

Course logistics

- HW 1 due end of today.
- Solution key will be posted by midnight. You are allowed to submit 1 day late with a 15% late penalty.

Recap: Last week

- LP duality
- Totally unimodular matrices in linear programming

This week: Vertex Cover, Matchings, and More LP duality

Recap: LP duality

Let $\underline{c} \in \mathbb{Q}^n$, $\underline{b} \in \mathbb{Q}^m$, $A \in \mathbb{Q}^{m \times n}$, and consider the linear program (LP) in canonical form:

$$\begin{array}{ll} \min & \underline{c}^T \underline{x} \\ \text{subject to} & A \underline{x} \geq \underline{b} \\ & \underline{x} \geq 0 \end{array} \quad \begin{array}{l} (1) \\ \text{(primal)} \end{array}$$

The dual of LP (1) is

$$\begin{array}{ll} \max_{y \in \mathbb{Q}^m} & \underline{b}^T \underline{y} \\ & \boxed{A^T \underline{y} \leq \underline{c}} \\ & \underline{y} \geq 0 \end{array} \quad \begin{array}{l} \swarrow \\ (2) \\ \text{(dual)} \end{array}$$

Theorem (weak duality): Let \underline{x} be feasible for (1) and \underline{y} is feasible for (2), then

$$\underline{c}^T \underline{x} \geq \underline{b}^T \underline{y}$$

Proof: $\boxed{\underline{c}^T} \underline{x} \geq \boxed{\underline{y}^T A} \underline{x} \geq \underline{y}^T \boxed{\underline{b}}$

Theorem (strong duality): Let $(\underline{x}^*, \underline{y}^*)$ be optimal for LP (1) and LP (2) respectively,

then $\underline{c}^T \underline{x}^* = \underline{b}^T \underline{y}^*$

(assuming both LPs are feasible)

Find the dual

Strategy 1: learn a set of rules
and apply them

(1 variable for each constraint,
1 constraint for each variable)

Strategy 2: convert the LP into
standard or canonical form and
apply one of the following patterns

	Primal \longleftrightarrow Duals
canonical	$\begin{aligned} \min \quad & c^T x \\ & Ax \geq b \\ & x \geq 0 \end{aligned}$ $\begin{aligned} \max \quad & b^T y \\ & A^T y \leq c \\ & y \geq 0 \end{aligned}$
standard	$\begin{aligned} \min \quad & c^T x \\ & Ax = b \\ & x \geq 0 \end{aligned}$ $\begin{aligned} \max \quad & b^T y \\ & A^T y \leq c \end{aligned}$

Common examples in graph analysis

- The dual of the max s-t flow LP is the min s-t cut LP
- In bipartite graphs the dual of the max matching problem is the min vertex cover problem.

TU Matrices in Linear Programming

For the LP \downarrow

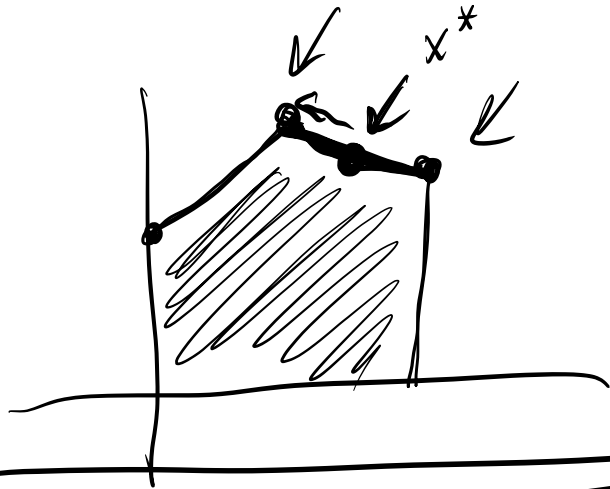
$$\begin{array}{ll} \min & c^T x \\ & Ax \geq b \\ & x \geq 0 \end{array}$$

(1)

$$x \in \mathbb{Z}^n$$

Theorem TU: If $\underline{b} \in \mathbb{Z}^m$ and A is totally unimodular (all square submatrices have determinant 0, 1, or -1) then

there exists $x^* \in \mathbb{Z}^n$ that is optimal for (1).



Vertex Cover and Matchings

Def: a matching $M \subseteq E$ of a simple graph $G = (V, E)$ is a vertex disjoint set of edges.

Def: a vertex cover $C \subseteq V$ of $G = (V, E)$ is a set of nodes such that every $e \in E$ is adjacent to at least one node in C .

i.e. $|e \cap C| \geq 0 \quad \forall e \in E$.

Lemma: Let $G = (V, E)$ be a simple graph, C a vertex cover, and M be a matching then

$$|M| \leq |C|$$

LP duality for Vertex Cover

The minimum vertex cover problem (Min-VC) is encoded by the binary linear program (BLP)

$$\min \sum_{v \in V} x_v \quad (1)$$

→ s.t. $x_u + x_v \geq 1 \quad \forall (u, v) \in E$

$$\boxed{x_u \in \{0, 1\}} \quad \forall u \in V$$

Min-VC is NP-hard.

Let BLP-VC be the optimal solution value.

The "LP relaxation" of this BLP is

↓
(2)
↗

$$\begin{array}{ll} \min & \sum_{v \in V} x_v \cdot 1 \\ \text{s.t.} & x_u + x_v \geq 1 \quad \forall (u,v) \in E \\ & 0 \leq x_u \leq 1 \quad \forall u \in V \end{array}$$

↘

Let LP-VC be the optimal solution value.

Observation: LP-VC \leq
 \geq BLP-VC
?

The dual of LP (2) is given by:

$$\begin{aligned}
 (3) \quad & \max \sum_{e \in E} y_e \cdot 1 \\
 & \text{s.t. } \forall u \in V \quad \sum_{e: u \in e} y_e \leq 1 \\
 & \quad y_e \geq 0
 \end{aligned}$$

Let $LP-M$ be the optimal solution value. Notice $LP-M = LP-VC$.

Consider the BLP obtained by forcing $y_e \in \{0, 1\}$ instead of

$y_e \geq 0$:

$$\begin{aligned}
 & \max \sum_{e \in E} y_e \\
 & \text{s.t. } \forall u \in V \quad \sum_{e: u \in e} y_e \leq 1
 \end{aligned}$$

$$y_c \in \{0, 1\}.$$

Let $BLP-M$ be the optimal solution value. Observe:

$$BLP-M \quad \boxed{\begin{matrix} \leq \\ \geq \end{matrix}} \quad LP-M$$

?

$$BLP-M \leq LP-M = LP-VC \leq \underline{BLP-VC}$$

Lemma: M and C are a matching and a cover, then

$$|M| \leq |C|$$

Theorem: If $G=(V,E)$ is a bipartite graph and M^* and C^* are optimal matching and cover, then $|M^*| = |C^*|$.

Proof: The constraint matrix for LP (3) is \hat{B} , the unsigned incidence matrix, which is TU. By Theorem TU,

$$|M^*| = \text{BLP-M} = \text{LP-M} = \text{LP-VC} = \text{BLP-VC} = |C^*|$$

(Application of LP duality and TU)