

# Notes for Graph Theory Course

Shuang Zhao

ACM Class: F0303026

Student ID: 5030309961

Shanghai Jiao Tong University

E-mail: shuangz@acm.org

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# Symbols

1. To any vector  $x \in \mathbb{R}^n$ , define  $\|x\|$  by the Euclidean length of vector  $x$ , namely

$$\|x\| := \sqrt{x_1^2 + \dots + x_n^2}$$

2. To any vectors  $x, y \in \mathbb{R}^n$ , define  $x \leq y$  by

$$x \leq y \iff x_1 \leq y_1, x_2 \leq y_2, \dots, x_n \leq y_n$$

3. Let  $A \in \mathbb{R}^{m \times n}$ . Define the the  $i$ -th row of  $A$  by vector  $a_i^\top \in \mathbb{R}^m$ , the  $j$ -th column of  $A$  by vector  $a'_j \in \mathbb{R}^n$ , and the  $j$ -th element on the  $i$ -th row by  $a_{ij} \in \mathbb{R}$ , where  $1 \leq i \leq m$  and  $1 \leq j \leq n$ .

4. Let  $A \in \mathbb{R}^{m \times n}$  and  $b \in \mathbb{R}^n$ . Define

$$\begin{aligned} P(A, b) &:= \{x \in \mathbb{R}^n \mid Ax \leq b\} \\ P^\equiv(A, b) &:= \{x \in \mathbb{R}^n \mid Ax = b\} \\ r_F^\equiv(A, b) &:= \{i \in \{1, 2, \dots, m\} \mid a_i^\top x = b_i, \forall x \in F\} \\ r_z^\equiv(A, b) &:= r_{\{z\}}^\equiv(A, b) \\ r^\equiv(A, b) &:= r_{P(A, b)}^\equiv(A, b) \end{aligned}$$

$A_{F, b} :=$  a submatrix of  $A$  containing  $a_i^\top$  for all  $i \in r_F^\equiv(A, b)$

$A_{z, b} :=$  a submatrix of  $A$  containing  $a_i^\top$  for all  $i \in r_z^\equiv(A, b)$

$A_b :=$  a submatrix of  $A$  containing  $a_i^\top$  for all  $i \in r^\equiv(A, b)$

# Chapter 1

## Polytopes, polyhedra, Farkas' lemma, and linear programming

### 1.1 Convex sets

First there are some base concepts within this course:

**Definition 1.1.** A subset  $C$  of  $\mathbb{R}^n$  is called *convex* if for all  $x, y \in C$  and any  $0 \leq \lambda \leq 1$  also  $\lambda x + (1 - \lambda)y \in C$ . So  $C$  is convex if with any two points in  $C$ , the whole line segment connecting  $x$  and  $y$  belongs to  $C$ .

**Definition 1.2.** Let set  $X \subseteq \mathbb{R}^n$ ,

$$\text{Conv.hull}(X) := \left\{ x \mid \exists t \in \mathbb{N}, \exists x_1, \dots, x_t \in X, \exists \lambda_1, \dots, \lambda_t \geq 0 : \right. \\ \left. x = \sum_{i=1}^t \lambda_i x_i, \sum_{i=1}^t \lambda_i = 1 \right\}$$

**Definition 1.3.** We call a subset  $H$  of  $\mathbb{R}^n$  a *hyperplane* if there exist a vector  $c \in \mathbb{R}^n$  with  $c \neq 0$  and a  $\delta \in \mathbb{R}$  such that:  $H = \{x \in \mathbb{R}^n \mid c^\top x = \delta\}$ .

**Definition 1.4.** We call a subset  $H$  of  $\mathbb{R}^n$  a *halfspace* (or an *affine halfspace*) if there exist a vector  $c \in \mathbb{R}^n$  with  $c \neq 0$  and a  $\delta \in \mathbb{R}$  such that

$$H = \{x \in \mathbb{R}^n \mid c^\top x \leq \delta\}$$

And following is the first important theorem in this chapter:

**Theorem 1.1 (Separating hyperplane theorem).** Let  $C$  be a closed convex set in  $\mathbb{R}^n$  and let  $z \notin C$ . Then there exists a hyperplane separating  $z$  and  $C$ .

**Basic idea.** To prove this theorem, firstly we choose a point  $y \in C$  such that  $y$  is nearest to  $z$  among all points in  $C$ . Since  $C$  is closed, such  $y$  always exists. Then we pick a hyperplane separates  $z$  and  $y$  with normal vector  $z - y$ . Without loss of generality, the hyperplane passes  $(z + y)/2$ . That is, we pick the hyperplane

$$H = \left\{ x \mid (z - y)^\top x = \frac{(z - y)^\top (z + y)}{2} = \frac{\|z\|^2 - \|y\|^2}{2} \right\}$$

Next we want to show  $H$  indeed separates  $z$  and  $C$ . A fast way to do this is to find a contradiction. Assume there exists an  $x \in C$  lying on the same side of  $H$  with  $z$ . Then

one can easily verify the existence of another point  $w$  on the line segment connecting  $x$  and  $y$ , such that  $\|w - z\| < \|y - z\|$ . This contradicts the fact that  $y$  is nearest to  $z$ . So the theorem follows.

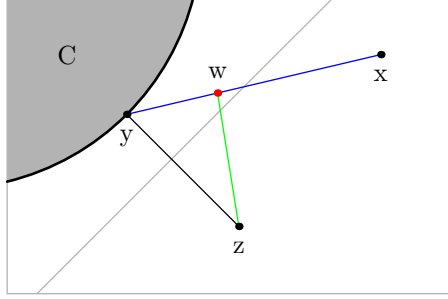


Figure: To prove separating hyperplane theorem

*Proof.* Since  $C$  is closed, there exists a  $y \in C$  such that for each  $x \in C$ ,  $\|y - z\| \leq \|x - z\|$ . Let  $c = z - y$ ,  $\delta = (\|z\|^2 - \|y\|^2)/2$  and  $H = \{x \mid c^\top x = \delta\}$ .

From  $c^\top z + c^\top y = 2\delta$  and  $c^\top(z - y) = \|c\|^2 > 0$ , one has  $c^\top z > \delta$  and  $c^\top y < \delta$ . Assume there exists an  $x \in C$ , such that  $c^\top x \geq \delta$ . Next we show there is a point  $w = \lambda x + (1 - \lambda)y$  satisfying  $0 \leq \lambda \leq 1$  and  $\|w - z\| < \|y - z\|$ .

$$\begin{aligned} \|w - z\|^2 &= \|\lambda x + (1 - \lambda)y - z\|^2 = \|\lambda(x - y) + (y - z)\|^2 \\ &= \|\lambda(x - y) + c\|^2 = \lambda^2\|x - y\|^2 - 2\lambda(x - y)^\top c + \|c\|^2 \end{aligned}$$

Let

$$0 < \lambda < \min \left\{ \frac{2c^\top(x - y)}{\|x - y\|^2}, 1 \right\}$$

Then  $\|w - z\|^2 < \|y - z\|^2 = \|c\|^2$ . This contradicts the fact that for each  $x \in C$ ,  $\|y - z\| \leq \|x - z\|$ . Thus for each  $x \in C$ ,  $c^\top x < \delta$ . Therefore  $H$  is a hyperplane separating  $z$  and  $C$ .  $\square$

Separating hyperplane theorem is a fundamental but very useful theorem. It is widely used in the proof of many propositions. We can obtain **Farkas' Lemma** by applying this theorem on a convex cone.

As a direct consequence of separating hyperplane theorem, we have

**Proposition 1.2 (Exercise [1] 2.1).** *Each closed convex set is the intersection of a collection of halfspaces, possibly infinite many of them.*

*Proof.* Let  $C$  be a closed convex set in  $\mathbb{R}^n$ . Then

$$\begin{aligned} C &= \mathbb{R}^n \setminus \bigcup_{z \notin C} \{z\} \\ &= \mathbb{R}^n \setminus \bigcup_{z \notin C} \{x \mid c_z^\top x > \delta_z\} \\ &= \bigcap_{z \notin C} \{x \mid c_z^\top x \leq \delta_z\} \end{aligned}$$

The second equality follows the separating hyperplane theorem.  $\square$

## 1.2 Polytopes, polyhedra and cones

Polytope and polyhedra are special cases of convex sets:

**Definition 1.5.** A subset  $P$  of  $\mathbb{R}^n$  is a *polyhedron* iff there exists an  $m \times n$  matrix  $A$  and a vector  $b \in \mathbb{R}^m$  such that

$$P = \{x \in \mathbb{R}^n \mid Ax \leq b\}$$

A polyhedron is the intersection of a finite number of halfspaces.

**Definition 1.6.** A subset  $P$  of  $\mathbb{R}^n$  is called a *polytope* iff  $P$  is the convex hull of a finite number of vectors. That is, there exists vectors  $x_1, \dots, x_t \in \mathbb{R}^n$  such that

$$P = \text{Conv.hull}\{x_1, \dots, x_t\}$$

Besides given the definitions of polytopes and polyhedra, we also show the relationship between them:

**Theorem 1.3.**  $P$  is a polytope iff  $P$  is a bounded polyhedron.

To prove Theorem 1.3, first we provide the definition of *extreme point*:

**Definition 1.7.** Let  $P$  be a convex set. A point  $z \in P$  is called a *extreme point* of  $P$  if  $z$  is not on the line segment connecting any two other points in  $P$ . That is, there do not exist points  $x, y$  in  $P$  such that  $x \neq z$ ,  $y \neq z$  and  $z = (x + y)/2$ .

Extreme points have an important property:

**Theorem 1.4.** Let  $A \in \mathbb{R}^{m \times n}$ ,  $b \in \mathbb{R}^m$  and  $P$  be the polyhedron  $P(A, b)$ . For each  $z \in P(A, b)$ ,  $z$  is an extreme point of  $P$ , iff  $\text{rank}(A_{z,b}) = n$ .

**Basic idea.** A simple method to prove this proposition is by contradiction.

First we suppose  $z$  is an extreme point of  $P(A, b)$  with  $\text{rank}(A_{z,b}) < n$ . By some simple calculations we can find  $x \neq z$  and  $y \neq z$  such that  $z = (x + y)/2$ .

Then we assume  $z$  is not an extreme point but with  $\text{rank}(A_{z,b}) = n$ . Let  $z = (x + y)/2$ , and we show  $x = y$ . Thus  $x = y = z$ .

*Proof. Necessity.* Suppose  $z$  is an extreme point of  $P$  with  $\text{rank}(A_{z,b}) < n$ . Then there exists a vector  $0 \neq c \in \mathbb{R}^n$  satisfying  $(A_{z,b})c = 0$ .

Then for each  $i \notin r_z^-(A, b)$ , it holds  $a_i^\top z < b_i$ . So there exists a small real  $\delta_i > 0$ , such that  $a_i^\top(z \pm \delta_i c) < b_i$ .

Now let  $\delta = \min\{\delta_i\}$ , and  $x = z - \delta c$ ,  $y = z + \delta c$ , then  $x, y \in P$ . Since  $c \neq 0$ ,  $\delta > 0$ , we have  $x \neq z$ ,  $y \neq z$  and  $z = (x + y)/2$ . This contradicts the fact that  $z$  is an extreme point of  $P$ .

*Sufficiency.* Assume  $z$  is not an extreme point of  $P$  but holds  $\text{rank}(A_{z,b}) = n$ . Then there exists  $x \neq z, y \neq z$ , such that  $z = (x + y)/2$ .

For each  $i \in r_z^-(A, b)$ , we have

$$\begin{aligned} a_i^\top x \leq b_i = a_i^\top z &\implies a_i^\top(x - z) = \frac{a_i^\top(x - y)}{2} \leq 0 \\ a_i^\top y \leq b_i = a_i^\top z &\implies a_i^\top(y - z) = \frac{a_i^\top(y - x)}{2} \leq 0 \\ \therefore a_i^\top(x - y) &= 0 \end{aligned}$$

So  $A_{z,b}(x - y) = 0$ . Since  $\text{rank}(A_{z,b}) = n$ , we have  $x - y = 0$ ,  $x = y$ . Therefore  $x = y = z$ . It contradicts  $x \neq z$  and  $y \neq z$ .  $\square$

And from this theorem, we can easily derive:

**Corollary 1.4.1.** *The total number of extreme points of a polyhedron is always finite.*

*Proof.* Let  $P = P(A, b)$  be a nonempty polyhedron where  $A \in \mathbb{R}^{m \times n}$  and  $b \in \mathbb{R}^n$ . Then there are at most  $2^m$  extreme points of  $P$ .  $\square$

Following Theorem 1.4, we can show something more:

**Theorem 1.5.** *Let  $P = P(A, b)$  be a bounded polyhedron, with extreme points  $x_1, \dots, x_t$ . Then*

$$P = \text{Conv.hull}(x_1, \dots, x_t)$$

**Basic idea.** To prove the equality, we need only to show

$$\text{Conv.hull}(x_1, \dots, x_t) \subseteq P$$

and

$$P \subseteq \text{Conv.hull}(x_1, \dots, x_t)$$

According to the convexity of  $P$ , we can easily obtain the former inclusion. Next we need only to show the latter one. That is, for each  $z \in P$ , we need to show  $z \in \text{Conv.hull}(x_1, \dots, x_t)$ . By the property of extreme points, if  $\text{rank}(A_{z,b}) = n$ ,  $z$  itself is an extreme point of  $P$ . So  $z$  is in the convex hull generated by all extreme points of  $P$ . If  $\text{rank}(A_{z,b}) = k < n$ , we use mathematical induction to show the inclusion. Namely, we are going to find two vectors  $y$  and  $z$  where  $\text{rank}(A_{x,b}) > k$  and  $\text{rank}(A_{y,b}) > k$ . By induction hypothesis,  $x, y \in \text{Conv.hull}(x_1, \dots, x_t)$ . Thus  $z \in \text{Conv.hull}(x_1, \dots, x_t)$ .

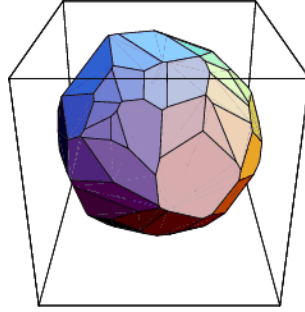


Figure: A bounded polyhedron, a polytope

*Proof.* Let  $C = \text{Conv.hull}(x_1, \dots, x_t)$ .

By the convexity of  $P$ , we know  $C \subseteq P$ . Next we need only to show  $P \subseteq C$ .

For each  $z \in P$ , if  $\text{rank}(A_{z,b}) = n$ ,  $z$  itself is an extreme point. Then  $z \in \{x_1, \dots, x_t\} \subseteq C$ . If  $\text{rank}(A_{z,b}) < n$ , there exists a vector  $c \neq 0$ , such that  $(A_{z,b})c = 0$ .

Let

$$\mu_0 = \max\{\mu \mid z + \mu c \in P\}$$

$$\nu_0 = \max\{\nu \mid z - \nu c \in P\}$$

And  $x = z + \mu_0 c$ ,  $y = z - \nu_0 c$ . Since  $P$  is bounded and closed,  $\mu_0$  and  $\nu_0$  exist and are both finite.

Let  $|r_z^-(A, b)| = t$ . Without loss of generality,  $r_z^-(A, b) = \{1, 2, \dots, t\}$ . Following the definition of  $\mu_0$ , we know

$$a_1^\top x = b_1, \dots, a_t^\top x = b_t$$

and

$$a_{t+1}^\top x \leq b_{t+1}, \dots, a_m^\top x \leq b_m$$

Since  $\mu_0$  attains maximum, we obtain there exists a  $t' > t$ , such that  $a_{t'}^\top x = b_{t'}$ . Thus  $A_{z,b}$  is a submatrix of  $A_{x,b}$ , and  $A_{x,b}$  has at least one more line than  $A_{z,b}$ . As  $a_{t'}^\top z < b_{t'}$  and  $a_{t'}^\top x = a_{t'}^\top (z + \mu_0 c) = b_{t'}$ ,  $a_{t'}^\top c \neq 0$ . So  $(A_{x,b})c \neq 0$ . This implies  $\text{rank}(A_{x,b}) > \text{rank}(A_{z,b})$ .

Similarly we can show  $\text{rank}(A_{y,b}) > \text{rank}(A_{z,b})$ . By our induction hypothesis,  $x, y \in C$ . So  $z$ , a convex combination of  $x$  and  $y$ , is a member of  $C$ .  $\square$

As a direct consequence, we have

**Corollary 1.5.1.** *Each bounded polyhedron is a polytope.*

To prove Theorem 1.3, we need only to prove backward:

**Theorem 1.6.** *Each polytope is a bounded polyhedron.*

*Proof.* Let  $P$  be a polytope in  $\mathbb{R}^n$ , say  $P = \text{Conv.hull}(x_1, \dots, x_t)$ . And we prove this theorem by induction on  $\dim(P)$ .

If  $P$  is contained in some hyperplane, namely  $\dim(P) < n$ , the theorem follows from the induction hypothesis.

If  $\dim(P) = n$ , this implies  $x_2 - x_1, \dots, x_t - x_1$  span  $\mathbb{R}^n$ . Thus there exists a  $x_0 \in P$  and a real number  $r > 0$ , such that  $B(x_0, r) := \{y : \|y - x_0\| \leq r\}$  is contained in  $P$ .

Without loss of generality,  $x_0 = 0$ . Define  $P^*$  by

$$P^* := \{y \in \mathbb{R}^n \mid x^\top y \leq 1 \quad \forall x \in P\}$$

For each  $y \in P^*$ , it holds  $x_j^\top y \leq 1$  for  $j = 1, \dots, t$ . At the same time, for each  $y$  satisfying  $x_j^\top y \leq 1$  for  $j = 1, \dots, t$ , we have

$$x^\top y = \sum_{j=1}^t \lambda_j x_j^\top y \leq \sum_{j=1}^t \lambda_j = 1$$

for each  $x \in P$ . Therefore,

$$P^* = \{y \in \mathbb{R}^n \mid x_j^\top y \leq 1 \quad j = 1, \dots, t\}$$

Moreover,  $P^*$  is bounded. As  $B(x_0, r) = B(0, r) \subseteq P$ , for each  $0 \neq y \in P^*$ , let

$$x' = r \cdot \|y\|^{-1} y$$

Then  $x' \in B(0, r) \subseteq P$ , hence  $x'^\top y = r \cdot \|y\| \leq 1$ . So  $\|y\| < 1/r$ , namely  $P^* \subseteq B(0, 1/r)$ .

By Corollary 1.5.1, we know  $P^*$  is a polytope. Thus

$$P^* = \text{Conv.hull}(y_1, \dots, y_s)$$

Next we show  $P = (P^*)^*$ , and this implies

$$P = \{x \in \mathbb{R}^n \mid y_j^\top x \leq 1 \quad \forall j = 1, \dots, s\}$$

By the definition of  $P^*$ , we know  $P \subseteq (P^*)^*$ . And for each  $z \notin P$ , by the separating hyperplane theorem, there exists a hyperplane  $H = \{x \mid c^\top x = \delta\}$  such that  $c^\top x < \delta$  for all  $x \in P$ , and  $c^\top z > \delta$ . As  $0 \in P$ , we have  $c^\top 0 = 0 < \delta$ . Without loss of generality,  $\delta = 1$ . So  $c \in P^*$ , and  $z \notin (P^*)^*$ . Therefore  $P = (P^*)^*$ , namely  $P$  is a polyhedron.  $\square$



**Comment.** In our proof of Theorem 1.6, we used a key concept  $P^*$ .  $P^*$  is call the *dual* of  $P$ . We will focus on the concept of Polarity and Duality in section 1.5.

**Theorem 1.3 follows from Corollary 1.5.1 and Theorem 1.6.**

Convex cone is another key concept in this course:

**Definition 1.8.** A subset  $C$  of  $\mathbb{R}^n$  is called a *convex cone* if for any  $x, y \in C$  and any  $\lambda, \mu \geq 0$  one has  $\lambda x + \mu y \in C$ .

**Definition 1.9.** For any  $X \subseteq \mathbb{R}^n$ ,  $\text{Cone}(X)$  is the smallest cone containing  $X$ . That is:

$$\text{Cone}(X) := \{\lambda_1 x_1 + \dots + \lambda_t x_t \mid x_1, \dots, x_t \in X; \lambda_1, \dots, \lambda_t \geq 0\}$$

A cone  $C$  is called *finitely generated* if  $C = \text{Cone}(X)$  for some finite set  $X$ .

And convex cone is kind of polyhedra:

**Proposition 1.7 (Exercise [1] 2.7).** Let  $C \subseteq \mathbb{R}^n$ . Then  $C$  is a convex cone, iff  $C$  is the intersection of a collection of linear halfspaces.

*Proof.* Let  $z \in \mathbb{R}^n$  and  $z \notin C$ . Then there exists a hyperplane

$$H = \{x \in \mathbb{R}^n \mid c^\top x = \delta\}$$

separating  $z$  and  $C$ . That is,  $c^\top z > \delta$  and for any  $x \in C$ ,  $c^\top x < \delta$ . Since  $C$  is a convex cone,  $0 \in C$ . So  $c^\top 0 = 0 < \delta$ .

If there exist an  $x' \in C$  such that  $c^\top x' = \theta > 0$ . Without loss of generality,  $\theta = 1$ . Then  $(2\delta)x' \in C$ . But

$$c^\top (2\delta x') = 2\delta(c^\top x') = 2\delta > \delta$$

This contradicts the fact that for all  $x \in C$ ,  $c^\top x < \delta$ . So for any  $x \in C$ ,  $c^\top x < 0$ , and for  $z \notin C$ ,  $c^\top z > 0$ . Therefore,

$$\begin{aligned} C &= \mathbb{R}^n \setminus \bigcup_{z \notin C} \{x \mid c^\top x > 0\} \\ &= \bigcap_{z \notin C} \{x \mid c^\top x \leq 0\} \end{aligned}$$

So  $C$  is the intersection of linear halfspaces. □

In fact, convex cones are polyhedra in one higher dimension. And we define another two useful symbols:

$$\begin{aligned} \text{lift}(P) &:= \left\{ \begin{pmatrix} x \\ 1 \end{pmatrix} \mid x \in P \right\} \\ \text{slice}(P) &:= \left\{ x \mid \begin{pmatrix} x \\ 1 \end{pmatrix} \in P \right\} \end{aligned}$$

**Proposition 1.8.**

$$\text{Conv.hull}(S) = \text{slice}(\text{Cone}(\text{lift}(S)))$$

*Proof.* Let  $Y = \text{lift}(S)$ . Then

$$\begin{aligned}
& \forall x \in \text{slice}(\text{Cone}(Y)) \\
& \iff \begin{pmatrix} x \\ 1 \end{pmatrix} \in \text{Cone}(Y) \\
& \iff \begin{pmatrix} x \\ 1 \end{pmatrix} = \sum_{p \in Y} \lambda_p p \quad \text{where } \lambda_p \geq 0 \text{ and } p = \begin{pmatrix} p' \\ 1 \end{pmatrix} \\
& \iff x = \sum_{p \in Y} \lambda_p p' \quad \text{where } \lambda_p \geq 0 \text{ and } \sum_{p \in Y} \lambda_p = 1 \\
& \iff x \in \text{Conv.hull}(S)
\end{aligned}$$

□

Now we know that statements about polytopes and polyhedra can be translated into statements about cones in one higher dimension. And next we use this **homogenization** technique to prove the first part of Caratheodory's theorem.

**Theorem 1.9 (Caratheodory's theorem).**

(i) Given a set  $S$ , for any point  $p$  in  $\text{Conv.hull}(S)$  there is a subset  $T$  with  $p$  in  $\text{Conv.hull}(T)$ , with  $|T| = \dim(S) + 1$ , and the points of  $T$  are affinely independent<sup>1</sup>.

(ii) Given a set  $S$ , for any point  $p$  in  $\text{Cone}(S)$  there is a subset  $T$  with  $p$  in  $\text{Cone}(T)$ , with  $|T| = \dim(S)$ , and the points of  $T$  are linearly independent.

*Proof.* (ii). Suppose there exists a subset  $T'$  with  $p$  in  $\text{Cone}(T')$  and the size  $T'$  is minimal, but  $|T'| > \dim(S)$ . Then

$$P = \sum_{s \in T'} c_s s \quad \text{where } c_s > 0$$

Since  $|T'| > \dim(S)$ , the vectors in  $T'$  are linearly dependent. Thus

$$\sum_{s \in T'} d_s c_s s = 0 \quad \text{where } d_s \neq 0$$

Pick the element  $s_0$  with the largest  $d_s = d_{s_0}$ . We have

$$c_{s_0} s_0 = \sum_{s \in T' \setminus \{s_0\}} -\frac{d_s}{d_{s_0}} c_s s$$

And we use this sum to express  $c_{s_0} s_0$ . This eliminates the appearance of  $s_0$  in the sum, and keep all the other coefficients nonnegative. This contradicts the choice of  $T'$ . □

*Proof.* (i). Let  $S' = \text{lift}(S)$ . Then by part (ii) of this theorem we know there exists a  $T' \subseteq S'$  such that

$$\begin{pmatrix} p \\ 1 \end{pmatrix} \in \text{Cone}(T')$$

and  $|T'| = \dim(S') = \dim(S) + 1$  with all vectors in  $T'$  are linearly independent.

Let  $T = \text{slice}(T')$ . Then  $T \subseteq S$ ,  $p \in \text{slice}(\text{Cone}(T')) = \text{Conv.hull}(T)$  and all vectors in  $T$  are affinely independent. Moreover,  $|T| = |T'| = \dim(S') = \dim(S) + 1$ . □

<sup>1</sup>We say  $n$  vectors  $x_1, \dots, x_n$  are affinely independent, iff  $\begin{pmatrix} x_1 \\ 1 \end{pmatrix} \dots \begin{pmatrix} x_n \\ 1 \end{pmatrix}$  are linearly independent.

**Theorem 1.10 (Exercise [1] 2.12, Polyhedron decomposition theorem).** *Let  $P$  be a subset of  $\mathbb{R}^n$ . Show that  $P$  is a polyhedron, iff  $P = Q + C$  for some polytope  $Q$  and some finitely generated convex cone  $C$ .*

*Proof. Necessity. (Minkowski's Theorem)*

$$\begin{aligned}
& P \text{ is a polyhedron} \\
\implies & P = \{x \mid x \in \mathbb{R}^n, b \in \mathbb{R}^m, A \in \mathbb{R}^{m \times n}, Ax \leq b\} \\
\implies & \text{Let } X = \text{lift}(P) \\
& \text{Then } \text{Cone}(X) = \left\{ x \mid x \in \mathbb{R}^{n+1}, \begin{pmatrix} -b & A \\ -1 & 0 \end{pmatrix} x \leq 0 \right\} \\
\implies & \text{cone}(X) \text{ is finitely generated} \\
\implies & \text{Cone}(X) = \{\lambda_1 x_1 + \dots + \lambda_t x_t \mid \lambda_1, \dots, \lambda_t \geq 0\} \\
& \text{Let } x_i = \begin{pmatrix} x'_i \\ a_i \end{pmatrix}, \text{ and } a_1, \dots, a_s > 0, a_{s+1}, \dots, a_t = 0 \\
\implies & \forall x \in P \\
& \begin{pmatrix} x \\ 1 \end{pmatrix} = \lambda_1 \begin{pmatrix} x'_1 \\ a_1 \end{pmatrix} + \dots + \lambda_t \begin{pmatrix} x'_t \\ a_t \end{pmatrix} \\
& = \sum_{i=0}^s \lambda_i a_i \begin{pmatrix} x'_i \\ 1 \end{pmatrix} + \sum_{i=s+1}^t \lambda_i \begin{pmatrix} x'_i \\ 0 \end{pmatrix} \quad \text{where } \sum_{i=0}^s \lambda_i a_i = 1 \\
\implies & x = (\lambda_1 a_1 \frac{x'_1}{a_1} + \dots + \lambda_s a_s \frac{x'_s}{a_s}) + (\lambda_{s+1} x'_{s+1} + \dots + \lambda_t x'_t)
\end{aligned}$$

Let

$$Q = \text{Conv.hull}\left(\frac{x'_1}{a_1}, \dots, \frac{x'_s}{a_s}\right) \quad \text{and} \quad C = \text{Cone}(x'_{s+1}, \dots, x'_t)$$

then we have

$$P = Q + C$$

*Sufficiency. (Weyl's Theorem)* If  $P = Q + C$  where

$$Q = \{a_1 x_1 + \dots + a_s x_s \mid a_1, \dots, a_s \geq 0, a_1 + \dots + a_s = 1\}$$

is a polytope and

$$C = \{b_1 x'_1 + \dots + b_t x'_t \mid b_1, \dots, b_t \geq 0\}$$

is a finitely generated convex cone.

Let  $X = \text{lift}(P)$ , then

$$\begin{aligned}
\forall \begin{pmatrix} x \\ 1 \end{pmatrix} \in X, \quad \begin{pmatrix} x \\ 1 \end{pmatrix} &= a_1 \begin{pmatrix} x_1 \\ 1 \end{pmatrix} + \dots + a_s \begin{pmatrix} x_s \\ 1 \end{pmatrix} + b_1 \begin{pmatrix} x'_1 \\ 0 \end{pmatrix} + \dots + b_t \begin{pmatrix} x'_t \\ 0 \end{pmatrix} \\
\text{Cone}(X) &= \text{Cone}\left\{ \begin{pmatrix} x_1 \\ 1 \end{pmatrix}, \dots, \begin{pmatrix} x_s \\ 1 \end{pmatrix}, \begin{pmatrix} x'_1 \\ 0 \end{pmatrix}, \dots, \begin{pmatrix} x'_t \\ 0 \end{pmatrix} \right\}
\end{aligned}$$

So  $\text{Cone}(X)$  is finitely generated, and therefore it is the intersection of a finite number of linear halfspaces. This implies  $P$  is the intersection of a finite number of halfspaces in one lower dimension.  $\square$

### 1.3 Farkas' Lemma

By applying the separating hyperplane theorem to a convex cone, we have:

**Theorem 1.11.** *Let  $C$  be a convex cone in  $\mathbb{R}^n$ . Then to any vector  $z \in \mathbb{R}^n$ , either*

$$z \in C$$

or

$$\exists c \in \mathbb{R}^n \text{ such that for each } x \in C, c^\top x \leq 0 \text{ and } c^\top z > 0$$

but not both.

*Proof.* For each  $z \notin C$ , by the separating hyperplane theorem, there exists a hyperplane  $H = \{x \in \mathbb{R}^n \mid c^\top x = \delta\}$  satisfying that for all  $x \in C$ ,  $c^\top x < \delta$  and  $c^\top z > \delta$ . If there is an  $x' \in C$  such that  $c^\top x' = \varepsilon > 0$ , we obtain the contradiction

$$\delta > c^\top \left( \frac{2\delta}{\varepsilon} x' \right) = \frac{2\delta}{\varepsilon} \cdot \varepsilon = 2\delta > 0$$

So for all  $x \in C$ ,  $c^\top x \leq 0 < \delta$  and  $c^\top z > \delta > 0$ . □

With Theorem 1.11 in hand, we can prove Farkas' Lemma by some translation:

**Theorem 1.12 (Farkas' Lemma).** *Let  $A$  be an  $m \times n$  matrix and  $b \in \mathbb{R}^m$ . Then either*

$$Ax = b \text{ has a nonnegative solution } x_0$$

or

$$\exists y_0 \in \mathbb{R}^m \text{ such that } y_0^\top A \leq 0 \text{ and } y_0^\top b > 0.$$

but not both.

*Proof.* To an  $m \times n$  matrix  $A$ , define  $\text{Cone}(A)$  by<sup>2</sup>

$$\text{Cone}(A) := \text{Cone}(a'_1, \dots, a'_m)$$

$$\begin{aligned} Ax = b \text{ does not have nonnegative solution} \\ \iff b \notin \text{Cone}(A) \\ \iff \exists y \text{ such that } \forall x \in \text{Cone}(A), y^\top x \leq 0 \text{ and } y^\top b > 0 \\ \iff \exists y \text{ such that } y^\top A \leq 0 \text{ and } y^\top b > 0 \end{aligned}$$

The second step follows Theorem 1.11. □

There are several variants of Farkas' Lemma, that can be easily derived from Theorem 1.12.

**Corollary 1.12.1.** *The system  $Ax \leq b$  has a solution  $x$ , iff there is no vector  $y$  satisfying  $y \geq 0$ ,  $y^\top A = 0$  and  $y^\top b < 0$ .*

<sup>2</sup>Please notice this symbol, as it will be used in further definitions and proofs.

*Proof.* Let  $A'$  be the matrix

$$A' = (A \quad -A \quad I)$$

Then

$$\begin{aligned} & \text{The system } Ax \leq b \text{ has a solution.} \\ \iff & \text{There exists } x_1, x_2, y \geq 0 \text{ such that } A(x_1 - x_2) + y = b \\ \iff & (A \quad -A \quad I) \begin{pmatrix} x_1 \\ x_2 \\ y \end{pmatrix} = b \quad \text{where } \begin{pmatrix} x_1 \\ x_2 \\ y \end{pmatrix} \geq 0 \\ \iff & \text{The system } A'x' = b \text{ has a nonnegative solution.} \end{aligned}$$

Applying Theorem 1.12 to the system  $A'x' = b$  gives the corollary.  $\square$

**Corollary 1.12.2.** *Suppose the system  $Ax \leq b$  has at least one solution. Then for every solution  $x$  of  $Ax \leq b$  one has  $c^\top x \leq \delta$ , iff there exists a vector  $y \geq 0$  such that  $y^\top A = c^\top$  and  $y^\top b \leq \delta$ .*

## 1.4 Linear programming

One of the standard forms of a linear programming (LP) problem is:

$$\begin{aligned} & \text{maximize } c^\top x \\ & \text{subject to } Ax \leq b \end{aligned}$$

So LP can be considered as maximizing a 'linear function'  $c^\top x$  over a polyhedron  $P = P(A, b)$ . Geometrically, this can be seen as shifting a hyperplane to its 'highest' level, under the condition that it intersects  $P$ .

Clearly, the minimization problem can be translated to the maximization problem:

$$\min\{c^\top x \mid x \in P(A, b)\} = -\max\{-c^\top x \mid x \in P(A, b)\}$$

One says the  $x$  is a *feasible solution* if  $x \in P(A, b)$ , namely  $Ax \leq b$ . If  $x$  attains the maximum, it is called an *optimum solution*.

The main theorem of this section is the Duality theorem of LP, due to von Neumann. The theorem states that if

$$\max\{c^\top x \mid Ax \leq b\}$$

is finite, then its duality

$$\min\{y^\top b \mid y \geq 0, y^\top A = c^\top\}$$

is finite, and the value of the maximum is equal to the value of another. In order to show this, we first prove:

**Lemma 1.1.** *Let  $P$  be a nonempty polyhedron in  $\mathbb{R}^n$  and let  $c \in \mathbb{R}^n$ . If  $\sup\{c^\top x \mid x \in P\}$  is finite, then  $\max\{c^\top x \mid x \in P\}$  is attained.*

*Proof.* Let  $P = P(A, b)$ , and  $\delta = \sup\{c^\top x \mid x \in P\}$ . Next we show there exists an  $x \in \mathbb{R}^n$  such that  $c^\top x \geq \delta$ .

$$\begin{aligned} & \text{There exists some } x \in P, \text{ such that } c^\top x \geq \delta \\ \iff & \text{The system } \begin{pmatrix} A \\ -c^\top \end{pmatrix} x \leq \begin{pmatrix} b \\ -\delta \end{pmatrix} \text{ has a solution} \end{aligned}$$

By Farkas' Lemma in the form of Corollary 1.12.1, we have either

$$\begin{pmatrix} A \\ -c^\top \end{pmatrix} x \leq \begin{pmatrix} b \\ -\delta \end{pmatrix} \quad \text{has a solution}$$

or

$$\exists y' \in \mathbb{R}^{n+1}, y' \geq 0 \quad \text{such that} \quad y'^\top \begin{pmatrix} A \\ -c^\top \end{pmatrix} = 0 \quad \text{and} \quad y'^\top \begin{pmatrix} b \\ -\delta \end{pmatrix} < 0$$

but not both. Next we show the latter case never occur.

Suppose such  $y'$  exists. Let

$$y' = \begin{pmatrix} y \\ \lambda \end{pmatrix} \quad \text{where } y \geq 0 \text{ and } \lambda \geq 0$$

If  $\lambda = 0$ , it follows  $y^\top A = 0$  and  $y^\top b < 0$ . This contradicts the fact that  $P$  is nonempty. So  $\lambda > 0$ . Without loss of generality,  $\lambda = 1$ . We have  $y^\top A = c^\top$  and  $y^\top b < \delta$  for all  $x \in P$ . And it follows a contradiction that for each  $x \in P$ ,

$$\delta = c^\top x = y^\top A x \leq y^\top b < \delta$$

□

From this we derive:

**Theorem 1.13 (Duality theorem of LP).** *Let  $A$  be an  $m \times n$  matrix  $b \in \mathbb{R}^m$  and  $c \in \mathbb{R}^n$ . Then*

$$\max\{c^\top x \mid Ax \leq b\} = \min\{y^\top b \mid y \geq 0, y^\top A = c^\top\}$$

*provided that both sets are nonempty.*

*Proof.* First note that

$$\sup\{c^\top x \mid Ax \leq b\} \leq \inf\{y^\top b \mid y \geq 0, y^\top A = c^\top\}$$

because for each  $x \in P(A, b)$  and  $y \in \mathbb{R}_+^m$  satisfying  $y^\top A = c^\top$ , it holds

$$c^\top x = y^\top A x = y^\top (Ax) \leq y^\top b$$

As both sets are nonempty, the supremum and infimum are finite. By Lemma 1.1, there exists an  $x_0 \in P(A, b)$  and a real  $\delta$  such that

$$c^\top x_0 = \max\{c^\top x \mid Ax \leq b\} = \delta$$

Next we want to find a vector  $y_0 \in \mathbb{R}_+^m$ ,  $y_0^\top A = c^\top$  such that  $y_0^\top b = \delta$ .

Let  $k = r_{x_0}^-(A, b)$ . Without loss of generality, we have

$$\begin{cases} a_1^\top x_0 = b_1 \\ \dots\dots\dots \\ a_k^\top x_0 = b_k \\ a_{k+1}^\top x_0 < b_{k+1} \\ \dots\dots\dots \\ a_m^\top x_0 < b_m \end{cases}$$

where  $0 \leq k \leq m$ . Then by Theorem 1.11, either

$$c \in \text{Cone}(a_1, \dots, a_k)$$

or

$$\exists y \in \mathbb{R}^m \text{ such that } y^\top a_i \leq 0 \text{ and } y^\top c > 0 \text{ for all } i = 1, \dots, k$$

Now we show that the latter case will never occur. Otherwise, if such  $y$  exists, we can find a small enough positive  $\varepsilon$  such that  $A(x_0 + \varepsilon y) \leq b$  and  $c^\top(x_0 + \varepsilon y) > c^\top x_0$ . This contradicts the choice of  $x_0$ .

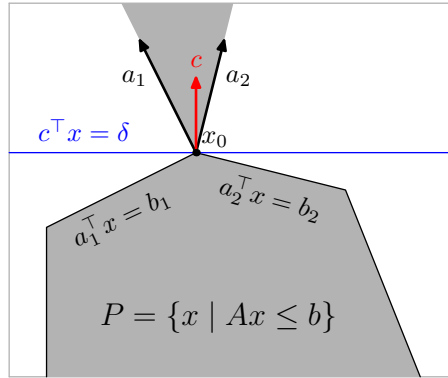


Figure:  $c$  always lies in  $\text{Cone}(a_1, \dots, a_k)$

Therefore, we have  $k \geq 1$  and  $c \in \text{Cone}(a_1, \dots, a_k)$ , say

$$c = \lambda_1 a_1 + \dots + \lambda_k a_k \quad \text{where } \lambda_1, \dots, \lambda_k \geq 0$$

Let

$$y_0 = (\lambda_1 \quad \dots \quad \lambda_k \quad 0 \quad \dots \quad 0)^\top \in \mathbb{R}_+^m$$

Then it is clear that  $y_0^\top A = c^\top$ , and

$$\begin{aligned} \delta &= c^\top x_0 \\ &= (\lambda_1 a_1^\top + \dots + \lambda_k a_k^\top) x_0 \\ &= \lambda_1 b_1 + \dots + \lambda_k b_k \\ &= y_0^\top b \end{aligned}$$

□

There are some variants of the Duality theorem:

**Corollary 1.13.1.** *Let  $A \in \mathbb{R}^{m \times n}$ ,  $b \in \mathbb{R}^m$  and  $c \in \mathbb{R}^n$ . Then both*

$$\max\{c^\top x \mid x \geq 0, Ax \leq b\}$$

and

$$\min\{y^\top b \mid y \geq 0, y^\top A \geq c^\top\}$$

exist and are equal, provided both sets are nonempty.

*Proof.*

$$\begin{aligned}
& \max\{c^\top x \mid x \geq 0, Ax \leq b\} \\
&= \max\left\{c^\top x \mid \begin{pmatrix} A \\ -I \end{pmatrix} x \leq \begin{pmatrix} b \\ 0 \end{pmatrix}\right\} \\
&= \min\left\{\begin{pmatrix} y_1^\top & y_2^\top \end{pmatrix} \begin{pmatrix} b \\ 0 \end{pmatrix} \mid \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} \geq 0, \begin{pmatrix} y_1^\top & y_2^\top \end{pmatrix} \begin{pmatrix} A \\ -I \end{pmatrix} = c^\top\right\} \\
&= \min\{y_1^\top b \mid y_1, y_2 \geq 0, y_1^\top A - y_2^\top = c^\top\} \\
&= \min\{y^\top b \mid y \geq 0, y^\top A \geq c^\top\}
\end{aligned}$$

Here the second equality follows the Duality theorem.  $\square$

**Corollary 1.13.2.** *Let  $A \in \mathbb{R}^{m \times n}$ ,  $b \in \mathbb{R}^m$  and  $c \in \mathbb{R}^n$ . Then both*

$$\max\{c^\top x \mid Ax \geq b\}$$

*and*

$$\min\{y^\top b \mid y \leq 0, y^\top A = c^\top\}$$

*exist and are equal, provided both sets are nonempty.*

*Proof.*

$$\begin{aligned}
& \max\{c^\top x \mid Ax \geq b\} \\
&= \max\{c^\top x \mid (-A)x \leq (-b)\} \\
&= \min\{y^\top (-b) \mid y \geq 0, y^\top (-A) = c^\top\} \\
&= \min\{(-y)^\top b \mid (-y) \leq 0, (-y)^\top A = c^\top\} \\
&= \min\{y^\top b \mid y \leq 0, y^\top A = c^\top\}
\end{aligned}$$

Here the second equality follows the Duality theorem.  $\square$

**Theorem 1.14 (Exercise [1] 2.25).** *Let a matrix, a column vector, and a row vector be given:*

$$\begin{pmatrix} A & B & C \\ D & E & F \\ G & H & K \end{pmatrix} \quad \begin{pmatrix} a \\ b \\ c \end{pmatrix} \quad (d \quad e \quad f)$$

*where  $A, B, C, D, E, F, G, H, K$  are matrices,  $a, b, c$  are column vectors, and  $d, e, f$  are row vectors (of appropriate dimensions). Then*

$$\begin{aligned}
& \max\{dx + ey + fz : x \geq 0, z \leq 0 \\
& \quad Ax + By + Cz \leq a \\
& \quad Dx + Ey + Fz = b \\
& \quad Gx + Hy + Kz \geq c\} \\
&= \min\{ua + vb + wc : u \geq 0, w \leq 0 \\
& \quad uA + vD + wG \geq d \\
& \quad uB + vE + wH = e \\
& \quad uC + vF + wK \leq f\}
\end{aligned}$$



*Proof.*

$$\begin{aligned}
& \max \{ dx + ey + fz & : & x \geq 0, z \leq 0 \\
& & & Ax + By + Cz \leq a \\
& & & Dx + Ey + Fz = b \\
& & & Gx + Hy + Kz \geq c \} \\
= & \max \left\{ (d \ e \ -e \ -f) \begin{pmatrix} x \\ y_1 \\ y_2 \\ -z \end{pmatrix} : \begin{pmatrix} x \\ y_1 \\ y_2 \\ -z \end{pmatrix} \geq 0 \right. \\
& & & \left. \begin{pmatrix} A & B & -B & -C \\ D & E & -E & -F \\ -D & -E & E & F \\ -G & -H & H & K \end{pmatrix} \begin{pmatrix} x \\ y_1 \\ y_2 \\ -z \end{pmatrix} \leq \begin{pmatrix} a \\ b \\ -b \\ -c \end{pmatrix} \right\} \\
= & \min \left\{ (u \ v_1 \ v_2 \ -w) \begin{pmatrix} a \\ b \\ -b \\ -c \end{pmatrix} : \begin{pmatrix} u^\top \\ v_1^\top \\ v_2^\top \\ -w^\top \end{pmatrix} \geq 0 \right. \\
& & & \left. \begin{pmatrix} A^\top & D^\top & -D^\top & -G^\top \\ B^\top & E^\top & -E^\top & -H^\top \\ -B^\top & -E^\top & E^\top & H^\top \\ -C^\top & -F^\top & F^\top & K^\top \end{pmatrix} \begin{pmatrix} u^\top \\ v_1^\top \\ v_2^\top \\ -w^\top \end{pmatrix} \geq \begin{pmatrix} d^\top \\ e^\top \\ -e^\top \\ -f^\top \end{pmatrix} \right\} \\
= & \min \{ ua + vb + wc & : & u \geq 0, w \leq 0 \\
& & & uA + vD + wG \geq d \\
& & & uB + vE + wH = e \\
& & & uC + vF + wK \leq f \}
\end{aligned}$$

Here, the first and last equality are doing translations and the middle one follows the Duality theorem of the form 1.13.1.  $\square$

**Theorem 1.15 (The Von Neumann's Minimax Theorem on two-person zero-sum game).** Let  $P_n = \{x \in \mathbb{R}_+^n \mid x_1 + \dots + x_n = 1\}$ . Then for every  $A \in \mathbb{R}^{m \times n}$ ,

$$\max_{x \in P_m} \min_{y \in P_n} x^\top Ay = \min_{y \in P_n} \max_{x \in P_m} x^\top Ay$$

*Proof.* Let

$$v_1 = \max_{x \in P_m} \min_{y \in P_n} x^\top Ay$$

and

$$v_2 = \min_{y \in P_n} \max_{x \in P_m} x^\top Ay$$

Next we show  $v_1 = v_2$  by linear programming.

Without loss of generality,  $a_{ij} > 0$  for all  $i, j$ .<sup>3</sup> For any fixed  $x$ ,  $\min_{y \in P_n} x^\top Ay$  is

<sup>3</sup>Let  $B$  be an  $m \times n$  matrix containing only 1's. Then for all  $x \in P_m$  and  $y \in P_n$ ,  $x^\top By = 1$ . So if the minimal element in  $A$  is smaller than or equal to 0, say  $t$ , let  $A' = A + (1-t)B$ . Then

$$\max_x \min_y x^\top A'y = \max_x \min_y x^\top Ay + (1-t) = v_1 + (1-t)$$

$$\min_y \max_x x^\top A'y = \min_y \max_x x^\top Ay + (1-t) = v_2 + (1-t)$$

Hence to prove  $v_1 = v_2$ , we need only to show  $\max_x \min_y x^\top A'y = \min_y \max_x x^\top A'y$ , where  $A'$  is an  $m \times n$  matrix with all its elements greater than 0.

attained at an extreme point of the polytope  $\{Ay \mid y \in P_n\}$ .<sup>4</sup> That is,

$$v_1 = \max_{x \in P_m} \min_{y \in P_n} x^\top Ay = \max_{x \in P_m} \min\{x^\top a'_1, \dots, x^\top a'_n\}$$

This follows  $v_1$  is the maximum of the LP problem:

$$\max_{v \in \mathbb{R}} v$$

subject to

$$\exists x \in P_m, x^\top a'_i \geq v, i = 1, 2, \dots, n$$

It is obvious that this problem has a feasible solution yielding  $v > 0$ . So by defining  $x'_i = x_i/v$  and  $x' = (x'_1 \ \dots \ x'_n)^\top$ , we have

$$v_1 = \max \frac{1}{\sum_{i=1}^n x_i/v} = \max \frac{1}{\sum_{i=1}^n x'_i}$$

Hence  $1/v_1$  is the minimum of the LP problem:

$$\min \sum_{i=1}^n x'_i = x'^\top \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$$

subject to

$$x'^\top A \geq (1 \ \dots \ 1) \quad \text{and} \quad x' \geq 0$$

Similarly,  $v_2$  is the minimum of the LP problem:

$$\min_{v \in \mathbb{R}} v$$

subject to

$$\exists y \in P_n, a_i^\top y \leq v, i = 1, 2, \dots, m$$

Define  $y'_i$  by  $y_i/v$  and  $y' = (y'_1 \ \dots \ y'_m)^\top$ , we know  $1/v_2$  is the maximum of the LP problem:

$$\max \sum_{i=1}^m y'_i = (1 \ \dots \ 1) y'$$

subject to

$$Ay' \leq \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} \quad \text{and} \quad y' \geq 0$$

According to the Duality Theorem of the form 1.13.1, we obtain  $1/v_1 = 1/v_2$ . This completes the proof.  $\square$

<sup>4</sup>We will give a strictly proof to this property in Section 1.6 (Corollary 1.24.1).

## 1.5 Polarity and duality

**Definition 1.10.** Let  $C$  be a convex cone in  $\mathbb{R}^n$ , define  $C^\circledast$  by

$$C^\circledast := \{y \in \mathbb{R}^n \mid x^\top y \leq 0 \quad \forall x \in C\}$$

And  $C^\circledast$  is called the *polar* of  $C$ .

**Theorem 1.16 (Exercise [1] 2.13).** For any subset  $C$  of  $\mathbb{R}^n$ ,

- (i) For each convex cone  $C$ ,  $C^\circledast$  is a closed convex cone.
- (ii) For each closed convex cone  $C$ ,  $C^{\circledast\circledast} = C$ .

*Proof.* (i). For any  $y_1, y_2 \in C^\circledast$ , it holds  $x^\top y_1 \leq 0, x^\top y_2 \leq 0$  for all  $x \in C$ . And for any  $\lambda, \mu \in \mathbb{R}_+$ , we have

$$x^\top (\lambda y_1 + \mu y_2) = \lambda(x^\top y_1) + \mu(x^\top y_2) \leq 0$$

Hence  $\lambda y_1 + \mu y_2 \in C^\circledast$ . So  $C^\circledast$  is a closed convex cone.  $\square$

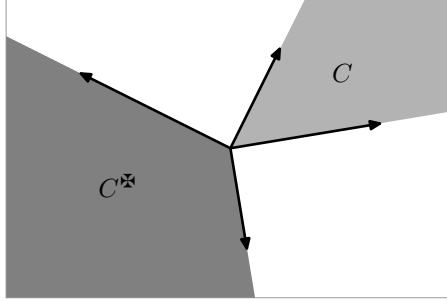


Figure:  $C$  and  $C^\circledast$

*Proof.* (ii). For any  $x \in C$ , by the definition of  $C^\circledast$ , we have  $y^\top x \leq 0$  for all  $y \in C^\circledast$ . So  $C \subseteq C^{\circledast\circledast}$ .

And for any  $x' \notin C$ , by Theorem 1.11, there exists a hyperplane  $c^\top x = 0$ , such that for all  $x \in C$ ,  $c^\top x \leq 0$  and  $c^\top x' > 0$ . From the definition of  $C^\circledast$ , we know  $c \in C^\circledast$ . And since  $c^\top x' > 0$ ,  $x' \notin C^{\circledast\circledast}$ . So  $C = C^{\circledast\circledast}$ .  $\square$

**Theorem 1.17.** Let  $A \in \mathbb{R}^{m \times n}$ , and  $C$  be the cone  $P(A, 0)$ . Then

$$C = \text{Cone}(A^\top)^\circledast$$

*Proof.* For each  $x \in C$ , that is,  $Ax \leq 0$ . And for all  $y \in \text{Cone}(A^\top)$ , that is,  $y = \lambda_1 a_1 + \dots + \lambda_m a_m$  where  $\lambda_1, \dots, \lambda_m \geq 0$ , we have

$$y^\top x = \sum_{i=1}^m (\lambda_i a_i^\top) x = \sum_{i=1}^m \lambda_i (a_i^\top x) \leq 0$$

So  $x \in \text{Cone}(A^\top)^\circledast$ . Thus  $C \subseteq \text{Cone}(A^\top)^\circledast$ .

For each  $x' \notin C$ , there exists an  $i \in \{1, 2, \dots, m\}$ , such that  $a_i^\top x' > 0$ . Let  $y = a_i \in \text{Cone}(A^\top)$ , then  $y^\top x' > 0$ . So  $x' \notin \text{Cone}(A^\top)^\circledast$ . Therefore  $C = \text{Cone}(A^\top)^\circledast$ .  $\square$

**Theorem 1.18 (Exercise [1] 2.28).** Let  $A$  be an  $m \times n$  matrix and let  $b \in \mathbb{R}^n$ . Let  $P = P(A, b)$ ,  $P \neq \emptyset$  and  $C$  be the convex cone  $P(A, 0)$ . Let the set  $\mathcal{C}$  consists of all vectors  $c$  for which  $\max\{c^\top x \mid x \in P\}$  is finite. Then  $\mathcal{C} = C^\circledast$ .

*Proof.* To prove  $\mathcal{C} = C^{\boxtimes}$ , we just show that  $\mathcal{C} \subseteq C^{\boxtimes}$  and conversely  $C^{\boxtimes} \subseteq \mathcal{C}$ . And by Theorem 1.16 and Theorem 1.17, we know  $C^{\boxtimes} = \text{Cone}(A^\top)$ .

For all  $c \in \mathcal{C}$ , by the Duality theorem of LP of the form Theorem 1.13 we obtain  $c^\top = y^\top A$  for some  $y \geq 0$ . That is,  $c \in \text{Cone}(A^\top)$ . So  $\mathcal{C} \subseteq C^{\boxtimes}$ .

Conversely, for each  $c \in C^{\boxtimes}$ , we have

$$c = \sum_{i=1}^m \lambda_i a_i \quad \text{where} \quad \lambda_1, \dots, \lambda_m \geq 0, \quad \sum_{i=1}^m \lambda_i = 1$$

Then for all  $x \in P$ ,

$$c^\top x = \sum_{i=1}^m \lambda_i a_i^\top x \leq \sum_{i=1}^m \lambda_i b_i \leq \sum_{i=1}^m b_i$$

So  $\max\{c^\top x \mid x \in P\}$  is finite, namely  $C^{\boxtimes} \subseteq \mathcal{C}$ . □

Next we extend the concept of polar to Polyhedra by define:

**Definition 1.11.** Let  $P$  be a polyhedron in  $\mathbb{R}^n$ , define  $P^*$  by

$$P^* := \{y \in \mathbb{R}^n \mid x^\top y \leq 1 \quad \forall x \in P\}$$

And  $P^*$  is called the **dual** of  $P$ .

**Proposition 1.19.** Let  $C$  be a convex cone in  $\mathbb{R}^n$ . Then  $C^{\boxtimes} = C^*$ .

*Proof.* By the definition of  $C^{\boxtimes}$  and  $C^*$ , we know  $C^{\boxtimes} \subseteq C^*$ . For each  $x \notin C^{\boxtimes}$ , namely there exists a  $c \in C$ , such that  $c^\top x = \delta > 0$ . Without loss of generality,  $\delta = 1$ . Then  $x \notin C^*$ . So  $C^{\boxtimes} = C^*$ . □

**Theorem 1.20 (Exercise [1] 2.14).** Let  $P$  be a polyhedron.

- (i)  $P^*$  is again a polyhedron.
- (ii)  $P$  contains the origin, iff  $(P^*)^* = P$ .
- (iii) The origin is an internal point of  $P$ , iff  $P^*$  is bounded.

*Proof.* (i). Let  $X = \text{lift}(P)$ ,  $Q = \text{Cone}(X)$ . Then by Theorem 1.16,  $Q^*$  is again a convex cone.

Since

$$x^\top y \leq 1 \iff (x \ 1) \begin{pmatrix} y \\ -1 \end{pmatrix} \leq 0$$

and it follows

$$y \in P^* \iff \begin{pmatrix} y \\ -1 \end{pmatrix} \in Q^*$$

Hence  $P^* = -\text{slice}(-Q^*)$  is a polyhedron<sup>5</sup>. □

*Proof.* (ii). *Necessity.* It is easy to show that  $\forall p \in P, p \in (P^*)^*$ . So  $P \subseteq (P^*)^*$ .

For any  $p' \notin P$ , there exists a hyperplane  $c^\top x = \delta$  such that  $\forall p \in P, c^\top p < \delta$ , and  $c^\top p' > \delta$ . Since  $P$  contains the origin,  $c^\top 0 = 0 < \delta$ . Without loss of generality,  $\delta = 1$ . It follows  $\forall p \in P, c^\top p < 1$ . So  $c \in P^*$ . As  $c^\top p' > 1, p' \notin (P^*)^*$ . So  $P = (P^*)^*$ .

*Sufficiency.* Since  $0 \in (P^*)^*$  and  $P = (P^*)^*$ , one has  $0 \in P$ . □

<sup>5</sup>Here we use  $-\mathcal{A}$  to express the set  $\{-x \mid x \in \mathcal{A}\}$ .

*Proof. (iii). Necessity.* If the origin is an internal point of  $P$ , that is there exists  $r > 0$ , such that  $B(0, r) \subseteq P$ . And for each  $y \neq 0$  in  $P^*$ , let  $x = r\|y\|^{-1}y$ . Since  $\|x\| = r$ ,  $x \in B(0, r) \subseteq P$ . So  $x^\top y \leq 1$ . That is,  $r\|y\| \leq 1$ ,  $\|y\| \leq 1/r$ . Hence  $P^* \subseteq B(0, 1/r)$ ,  $P^*$  is bounded.

*Sufficiency.* If  $P^*$  is bounded, that is,  $P^*$  is a polytope. Let

$$P^* = \text{Conv.hull}(y_1, \dots, y_t)$$

Then  $(P^*)^* = \{x \in \mathbb{R}^n \mid y_j^\top x \leq 1 \quad j = 1, \dots, t\}$ .

If  $0 \notin P$ , there exists a hyperplane  $c^\top x = \delta$ , such that for each  $p \in P$ ,  $c^\top p < \delta$ , and  $c^\top 0 = 0 > \delta$ . So  $kc \in P^*$ ,  $\forall k \in \mathbb{R}_+$ . This contradicts  $P^*$  is bounded. So  $0 \in P$ , therefore  $P = (P^*)^*$ , namely

$$P = \{x \in \mathbb{R}^n \mid y_j^\top x \leq 1 \quad j = 1, \dots, t\}$$

As  $y_j^\top 0 = 0 < 1$  for all  $j = 1, \dots, t$ , the origin is an internal point of  $P$ .  $\square$

Now we recall the basic idea of the proof of Theorem 1.6. In fact, the idea is quite simple.

We have a polytope  $P$ , and we want to prove it is also a bounded polyhedron. It is not so easy to do directly, so we use an indirect way to show this. First we show the polar of a polytope is a polyhedron, thus  $P^*$  is a polyhedron. And by Theorem 1.5.1, we know  $P^*$  is a polytope. This follows  $(P^*)^*$  is a polyhedron. Since  $P = (P^*)^*$ , we obtain  $P$  is a polyhedron.

## 1.6 Faces, edges and vertices

**Definition 1.12.** Let  $P = P(A, b)$  is a polyhedron with  $A \in \mathbb{R}^{m \times n}$  and  $b \in \mathbb{R}^m$ . Then  $x \in P(A, b)$  is called an *inner point* of  $P$ , iff  $a_i^\top x < b_i$  for all  $i \notin r^-(A, b)$ . That is,  $r_x^-(A, b) = r^-(A, b)$ .

**Proposition 1.21.** Every nonempty polyhedron has an inner point.

*Proof.* Let  $P$  be a polyhedron in  $\mathbb{R}^n$ , and we prove by induction on  $n$ .

If  $P$  is contained in some hyperplane, the induction hypothesis gives the proposition. So we may assume that  $P$  is not contained in any affine hyperplane. This follows there are  $t$  affinely independent vectors  $x_1, x_2, \dots, x_t \in P$ , namely  $x_2 - x_1, \dots, x_t - x_1$  span  $\mathbb{R}^n$ . It follows that there exists a vector  $x_0 \in P$  and a real  $r > 0$ , such that  $B(x_0, r)$  is contained in  $P$ . Then  $x_0$  is an inner point of  $P$ .  $\square$

Next, we give the definition of the dimension of a polyhedron:

**Definition 1.13.** A polyhedron  $P$  is of *dimension*  $k$ , denoted by  $\dim(P) = k$ , if the maximal number of affinely independent points in  $P$  is  $k + 1$ .

We say  $\dim(P) = -1$ , if  $P = \emptyset$ .

**Lemma 1.2.** Let  $A \in \mathbb{R}^{m \times n}$  and  $b \in \mathbb{R}^m$ . Then  $\dim(P(A, b)) = n - \text{rank}(A_b)$  provided that  $P(A, b)$  is nonempty.

*Proof.* The solution space for  $A_b x = 0$  is of dimension  $n - \text{rank}(A_b)$ . That is, there are  $n - \text{rank}(A_b)$  linearly independent vectors  $x_1, \dots, x_{n - \text{rank}(A_b)}$  satisfying  $A_b x = 0$ . And this follows  $0, x_1, \dots, x_{n - \text{rank}(A_b)}$  are affinely independent. According to Proposition 1.21, we can take an inner point in  $P(A, b)$ , say  $\tilde{x}$ . This implies that there exists a small enough

real  $\varepsilon > 0$ , satisfying  $\tilde{x}, \tilde{x} + \varepsilon x_1, \dots, \tilde{x} + \varepsilon x_{n-\text{rank}(A_b)}$  are affinely independent points in  $P(A, b)$ . So  $\dim(P(A, b)) \geq n - \text{rank}(A_b)$ .

Next we show that  $\dim(P(A, b)) \leq n - \text{rank}(A_b)$ . Let  $y_1, \dots, y_k$  be a set of  $k$  affinely independent points in  $P(A, b)$ . By the definition of  $A_b$ , let  $\beta \in \mathbb{R}^{|\overline{r}^-(A, b)|}$  be a vector containing all  $b_i$  where  $i \in \overline{r}^-(A, b)$ . Then to any  $x \in P(A, b)$ ,  $A_b x = \beta$ . Hence  $y_1, \dots, y_k$  are affinely independent solutions to the system  $A_b x = \beta$ . So  $k \leq n - \text{rank}(A_b) + 1$ . Therefore  $\dim(P(A, b)) \leq n - \text{rank}(A_b)$ .  $\square$

Before giving the first theorem in this section, we provide some definitions:

**Definition 1.14.** Let  $c \in \mathbb{R}^n$ ,  $\delta \in \mathbb{R}$  and  $P$  be a nonempty polyhedron. Then the halfspace  $\{x \in \mathbb{R}^n \mid c^\top x \leq \delta\}$  is called a **supporting halfspace** of  $P$ , iff it contains  $P$ .

If  $H = \{x \mid c^\top x \leq \delta\}$  is a supporting halfspace of  $P$ , then we say  $F := P \cap \{x \mid c^\top x = \delta\}$  is a **face** of  $P$ , and  $c^\top x \leq \delta$  **represents** it. A face  $F$  is said to be **proper** if  $F \neq \emptyset$  and  $F \neq P$ . If  $F \neq \emptyset$ , we say that  $Ax \leq b$  **supports**  $F$ .

The face of dimension  $\dim(P) - 1$  is called a **facet** of  $P$ . The face of dimension 0 is called a **vertex** of  $P$ .

The face  $F$  is supported by  $c^\top x \leq \delta$  iff  $\max\{c^\top x \mid x \in P\} = \delta$ , and in such a case it holds  $F$  is the set of optimal solutions to the LP program  $\max\{c^\top x\}$  subject to  $x \in P$ . By Lemma 1.1 on page 12, we know nonempty  $F$  exists if  $\max\{c^\top x \mid x \in P\}$  is finite.

And by Theorem 1.4 on page 5 and Theorem 1.2, we obtain:

**Theorem 1.22.** Let  $P$  be a nonempty polyhedron  $P(A, b)$  where  $A \in \mathbb{R}^{m \times n}$  and  $b \in \mathbb{R}^m$ . Then following assertions are equivalent:

1.  $z$  is an extreme point of  $P$ .
2.  $z$  is a vertex of  $P$ .
3.  $\text{rank}(A_{z, b}) = n$ .

**Theorem 1.23.** Let  $A$  be an  $m \times n$  matrix,  $b \in \mathbb{R}^m$ ,  $P = P(A, b)$  and  $F$  is a nonempty face of  $P$ . Then  $F$  is a polyhedron of the form

$$F = \left\{ x \in \mathbb{R}^n : \begin{array}{l} a_i^\top x = b_i \quad \forall i \in \overline{r}_F^-(A, b) \\ a_i^\top x \leq b_i \quad \forall i \notin \overline{r}_F^-(A, b) \end{array} \right\}$$

*Proof.* Let  $F$  be a face of  $P$  supported by  $c^\top x \leq \delta$ . Then by the definition of  $F$ , we have

$$\begin{pmatrix} A \\ c^\top \\ -c^\top \end{pmatrix} x \leq \begin{pmatrix} b \\ \delta \\ -\delta \end{pmatrix}$$

So  $F$  is a polyhedron.

Assume  $r_F^-(A, b) = k$ . Without loss of generality,  $r_F^-(A, b) = \{1, 2, \dots, k\}$ . Then let

$$F' = \{x \in \mathbb{R}^n \mid a_1^\top x = b_1, \dots, a_k^\top x = b_k, a_{k+1}^\top x \leq b_{k+1}, \dots, a_m^\top x \leq b_m\}$$

The definition of  $F'$  directly follows  $F \subseteq F'$ . Next we show that  $F' \subseteq F$ .

By Proposition 1.21, we can take an inner point of  $F$ , say  $x'$ . This follows:

$$\begin{aligned}
& r_{x'}^{\bar{}}(A, b) \\
&= r_{x'}^{\bar{}} \left( \begin{pmatrix} A \\ c^\top \\ -c^\top \end{pmatrix}, \begin{pmatrix} b \\ \delta \\ -\delta \end{pmatrix} \right) \setminus \{m+1, m+2\} \\
&= r_{\bar{F}}^{\bar{}} \left( \begin{pmatrix} A \\ c^\top \\ -c^\top \end{pmatrix}, \begin{pmatrix} b \\ \delta \\ -\delta \end{pmatrix} \right) \setminus \{m+1, m+2\} \\
&= r_{\bar{F}}^{\bar{}}(A, b)
\end{aligned}$$

So  $a_i^\top x' = b_i$  for  $i = 1, 2, \dots, k$  and  $a_i^\top x' < b_i$  for  $i = k+1, \dots, m$ . This gives  $c \in \text{Cone}(a_1, \dots, a_k)$ . Let  $c = \lambda_1 a_1 + \dots + \lambda_k a_k$  and  $y' = (\lambda_1 \ \dots \ \lambda_k \ 0 \ \dots \ 0)^\top$ , then  $y'^\top b = \delta$  and  $y'^\top A = c^\top$ . For all  $x \in F'$ , we have  $c^\top x = y'^\top Ax = y'^\top b = \delta$ . So  $F' \subseteq F$ .  $\square$

This theorem directly gives:

**Corollary 1.23.1.** *The number of distinct faces of a polyhedron is finite.*

*Proof.* To a polyhedron  $P = P(A, b)$  where  $A \in \mathbb{R}^{m \times n}$  and  $b \in \mathbb{R}^n$ , the number of all its distinct faces will not exceed  $2^m$ .  $\square$

This property shows that to a polyhedron  $P$ , although there can be infinite many of vector  $c$  which satisfies  $\delta = \max\{c^\top x \mid x \in P\}$  is finite, the number of distinct faces supported by  $c^\top x \leq \delta$  is finite.

Moreover, we have:

**Corollary 1.23.2.** *The intersection of two faces of  $P$  is again a face of  $P$ .*

**Corollary 1.23.3.** *If  $P$  is a polyhedron,  $F$  is a face of  $P$  and  $G$  is a face of  $F$ . Then  $G$  is also a face of  $P$ .*

**Theorem 1.24.** *Suppose  $P = P(A, b) \neq \emptyset$  and  $\text{rank}(A) = n - k$ . Then each minimal nonempty face of  $P$  under inclusion has dimension  $k$ .*

*Proof.* Let  $F$  be a minimal nonempty face of  $P$  under inclusion. If  $\dim(F) = 0$ , according to Lemma 1.2 and Theorem 1.23,  $0 = \dim(F) = n - \text{rank}(A_{F,b}) \geq n - \text{rank}(A)$ , so  $\text{rank}(A) = n$ ,  $k = 0$ . The theorem follows.

Next we assume  $\dim(F) > 0$ . By Proposition 1.21, we can take an inner point  $x'$  of  $F$ . Since  $\dim(F) > 0$ , there exists a  $y \in F$ ,  $y \neq x'$ . Consider the line  $L$  connecting  $x'$  and  $y$ :

$$L = \{x \mid x = x' + \lambda(y - x')\} \quad \text{where } \lambda \in \mathbb{R}$$

If  $L$  intersects with a hyperplane  $H = \{x \mid a_i^\top x = b_i\}$ , where  $i \notin r_{\bar{F}}^{\bar{}}(A, b) = r_{x'}^{\bar{}}(A, b)$ . Then the nonempty set  $F' = F \cap H$  does not contain  $x'$ . Thus  $r_{F'}^{\bar{}}(A, b) \supseteq r_{\bar{F}}^{\bar{}}(A, b) \cup \{i\}$ . And this implies  $\dim(F') < \dim(F)$ , which contradicts the choice of  $F$ .

So  $L$  does not intersect with any hyperplane  $H = \{x \mid a_i^\top x = b_i\}$  where  $i \notin r_{\bar{F}}^{\bar{}}(A, b)$ . This follows  $L$  is contained in  $P$ , namely  $Ax' + \lambda A(y - x') \leq b$  for all  $\lambda \in \mathbb{R}$ . So  $A(y - x') = 0$  for all  $y \in F$ . This gives  $F = \{y \mid Ay = Ax'\}$ . As  $\text{rank}(A) = n - k$ , by Theorem 1.23 we obtain  $\dim(F) = k$ .  $\square$

As a direct consequence of this theorem, we have

**Corollary 1.24.1 (Exercise [1] 2.22).** *Let  $P = P(A, b)$  be a nonempty polyhedron with at least one vertex. Then for all vector  $c$  such that*

$$\delta = \max\{c^\top x \mid x \in P\}$$

*is finite, there exists a vertex  $x'$  of  $P$ , satisfying  $c^\top x' = \delta$ .*

**Corollary 1.24.2.** *For  $A \in \mathbb{R}^{m \times n}$  and  $c \in \mathbb{R}$ ,  $P(A, b) \neq \emptyset$  has a vertex iff  $\text{rank}(A) = n$ .*

Since an  $m \times n$  matrix  $A$  with  $\text{rank}(A) = n$  has at most  $C_m^n$  invertible submatrices with the size of  $n \times n$ , we obtain that the polyhedron  $P(A, b)$  contains at most  $C_m^n$  vertices.



# Chapter 2

## Integer programming, totally unimodular matrices

### 2.1 Integer linear programming

Let  $b \in \mathbb{R}^m$ ,  $c, d \in \mathbb{R}^n$  and  $A, B \in \mathbb{R}^{m \times n}$ . To the LP problem

$$\max\{c^\top x + d^\top y\}$$

subject to

$$x, y \in \mathbb{R}_+^n, Ax + By \leq b$$

if we add one more restriction that  $y$  is an *integer* vector, namely  $y \in \mathbb{Z}_+^n$ , the LP problem is now called a *mixed-integer* linear programming (MIP) problem.

Moreover, an *integer* linear programming (IP) problem is a special case of MIP problem in which there are no continuous variables:

$$\max\{c^\top x \mid x \in \mathbb{Z}_+^n, Ax \leq b\}$$

Although LP is solvable in polynomial time, the general IP problem is  $\mathcal{NP}$ -complete. However, in some special classes of IP problem, polynomial-time algorithms have been found.

**Definition 2.1.** *To a polyhedron  $P = P(A, b)$ , if for each vector  $c$  satisfying  $\delta = \max\{c^\top x \mid x \in P\}$  is finite, there exists an integer vector  $x' \in P$ , such that  $c^\top x' = \delta$ , we say the polyhedron  $P$  is *integral*.*

By Definition 2.1, we know the IP problem over an integral polyhedron  $P$  collapses to an LP problem.

**Definition 2.2.** *Let  $P$  be a convex set in  $\mathbb{R}^n$ . Define the *integer hull* of  $P$  by*

$$\text{Conv.hull}(P \cap \mathbb{Z}^n)$$

*which is the convex hull generated by all integer points in  $P$ .*

**Proposition 2.1.** *A polyhedron  $P$  is integral iff the integer hull of  $P$  is  $P$  itself.*

*Proof. Necessity.* By Theorem 1.10 on page 10, we know  $P = Q + C$  where  $Q$  is a polytope and  $C$  is a finitely generated cone. Without loss of generality, each vertex of  $Q$  is also the vertex of  $P$ . Since  $P$  is integral,  $Q$  and  $C$  can both be generated by integer points. Therefore the integer hull of  $P$  equals to  $P$  itself.

*Sufficiency.* Since the integer hull of  $P$  is  $P$  itself, we know each face of  $P$  which is the set of solution to some optimization problem on  $P$ , contains an integer point.  $\square$

## 2.2 Totally unimodular matrices

**Definition 2.3.** A *unimodular matrix* is a square integer matrix whose determinant has magnitude 1.

A *totally unimodular matrix* is a matrix with all its square submatrix having determinant equals to 0, +1 or -1. That is, all nonsingular square submatrices of a totally unimodular matrix are unimodular.

**Proposition 2.2.** Let  $A$  be a totally unimodular  $n \times m$  matrix. Then

$$-A, A^\top, (A \ I_n), \begin{pmatrix} A \\ I_m \end{pmatrix}, (A \ -A) \text{ and } \begin{pmatrix} A \\ -A \end{pmatrix}$$

are also totally unimodular.

*Proof.* Firstly, it is quite clear that  $-A$  and  $A^\top$  are totally unimodular.

Secondly, we show  $(A \ I_n)$  is totally unimodular. For each square  $k \times k$  submatrix  $B$  of  $(A \ I_n)$ , suppose the first  $t$  columns of  $B$  come from  $A$ , and the other  $k - t$  ones come from  $I_n$ . Next we induction on  $t$ .

If  $t = k$ ,  $B$  is a submatrix of  $A$ . Since  $A$  is totally unimodular,  $|\det B|$  equals to 0 or 1. If  $t < k$ , the last column of  $B$  contains all 0's but one 1. Let the 1 be on the  $r$ -th row of  $B$ , then  $\det(B) = (-1)^{r+k}(\det B')$ , where  $B'$  is a  $(k - 1) \times (k - 1)$  matrix given by  $B$  omitting the  $r$ -th row and the  $k$ -th column. By our induction hypothesis,  $|\det B'|$  equals to 0 or 1. Hence  $|\det B|$  also equals 0 or 1. This follows  $(A \ I_n)$  is totally unimodular.

Similarly we can show  $\begin{pmatrix} A \\ I_m \end{pmatrix}$  is totally unimodular.

Next we prove  $(A \ -A)$  is totally unimodular. Let  $B$  be a submatrix of  $(A \ -A)$ . If there exists a column  $i$ , such that the  $i$ -th columns of  $A$  and  $-A$  both occur in  $B$ , we can easily derive that  $\det B = 0$ .

Otherwise  $B$  can be given by rearranging the columns of a submatrix of  $A$ , say  $C$ , then multiply  $-1$  to some of its columns. This implies  $|\det B| = |\det C|$ , namely  $|\det B|$  equals 0 or 1.  $\square$

Next we show the relationship between totally unimodular matrices and the IP problem:

**Lemma 2.1.** Let  $A$  be a totally unimodular  $m \times n$  matrix and let  $b \in \mathbb{Z}^m$ . Then each vertex of the polyhedron  $P = P(A, b)$  is an integer vector.

*Proof.* Let  $z$  be a vertex of  $P$ . By Theorem 1.22 on page 21, we know  $\text{rank}(A_{z,b}) = n$ . Hence  $A_{z,b}$  has a nonsingular  $n \times n$  submatrix  $A'$ . Let  $b'$  be the part of  $b$  corresponding to the rows of  $A$  that occur in  $A'$ . Then, we have  $A'z = b'$ .

Since  $A$  is totally unimodular,  $|\det A'| = 1$ . Because  $A'$  is an integer matrix,  $(A')^{-1}$  is also integer. Therefore  $z' = b'(A')^{-1}$  is an integer vector.  $\square$

**Theorem 2.3.** Let  $A$  be a totally unimodular  $m \times n$  matrix and let  $b \in \mathbb{Z}^m$ . Then the polyhedron  $P = P(A, b)$  is integral.

*Proof.* Let  $c \in \mathbb{R}^n$  and  $x = x^*$  be an optimum solution of the LP problem

$$\max\{c^\top x \mid x \in P\}$$

Choose  $d_1, d_2 \in \mathbb{Z}^n$  such that  $d_1 \leq x^* \leq d_2$ , and consider that polyhedron

$$Q := \{x \in \mathbb{R}^n \mid Ax \leq b, d_1 \leq x \leq d_2\}$$

Let

$$A' := \begin{pmatrix} A \\ -I \\ I \end{pmatrix} \quad \text{and} \quad b' := \begin{pmatrix} b \\ -d_1 \\ d_2 \end{pmatrix}$$

then

$$Q = \{x \in \mathbb{R}^n \mid A'x \leq b'\}$$

Since  $Q$  is of full column rank, by Theorem 1.24 on page 22,  $Q$  contains a vertex. And by Corollary 1.24.1 we obtain the maximum of LP problem  $\{c^\top x \mid x \in Q\}$  is attained at a vertex of  $Q$ , say  $\tilde{x}$ . By Proposition 2.2, we know  $A'$  is totally unimodular. Thus according to Lemma 2.1,  $\tilde{x}$  is integer.

As  $x^* \in Q$ ,  $c^\top \tilde{x} \geq c^\top x^*$ . Hence  $\tilde{x}$  is also an optimum solution of LP problem

$$\max\{c^\top x \mid x \in P\}$$

□

By Proposition 2.2 and Theorem 2.3, we can derive:

**Corollary 2.3.1.** *Let  $A$  be an  $m \times n$  totally unimodular matrix. Let  $b \in \mathbb{Z}^m$  and  $u \in \mathbb{Z}^n$ . Then each of the following polyhedra is integral:*

1.  $P(A, b)$
2.  $P(A, b) \cap \mathbb{R}_+^n$
3.  $P^=(A, b)$
4.  $P^=(A, b) \cap \{x \mid x \leq u\}$

*Proof.*  $P(A, b)$  being integral is directly given by Theorem 2.3.

Let

$$A' = \begin{pmatrix} A \\ -I \end{pmatrix} \quad \text{and} \quad b' = \begin{pmatrix} b \\ 0 \end{pmatrix}$$

we know  $A'$  is totally unimodular and  $b' \in \mathbb{Z}^{m+n}$ . Thus  $P(A', b') = P(A, b) \cap \mathbb{R}_+^n$  is integral.

Similarly, let

$$A' = \begin{pmatrix} A \\ -A \end{pmatrix} \quad \text{and} \quad b' = \begin{pmatrix} b \\ -b \end{pmatrix}$$

then  $A'$  is totally unimodular and  $b' \in \mathbb{Z}^{2m}$ . So  $P(A', b') = P^=(A, b)$  is integral.

Finally, let

$$A' = \begin{pmatrix} A \\ -A \\ I \end{pmatrix} \quad \text{and} \quad b' = \begin{pmatrix} b \\ -b \\ u \end{pmatrix}$$

then  $A'$  is totally unimodular and  $b' \in \mathbb{Z}^{2m+n}$ . So  $P(A', b') = P^=(A, b) \cap \{x \mid x \leq u\}$  is integral. □

In the following part of this section, we will prove the famous *Hoffman-Kruskal Theorem*. As a preparation, we prove:

**Lemma 2.2.** Let  $b \in \mathbb{Z}^m$ , and  $A$  be an integer  $m \times n$  matrix such that the polyhedron

$$P = P(A, b) \cap \mathbb{R}_+^n = \{x \mid Ax \leq b, x \geq 0\}$$

is integral. And let  $B = \begin{pmatrix} A & I \end{pmatrix}$ . Then for any  $c \in \mathbb{Z}^n$ , each vertex (if any) of the polyhedron

$$Q = P^=(B, c) \cap \mathbb{R}_+^n = \{x \mid Bx = c, x \geq 0\}$$

is integer.

*Proof.* Let

$$z = \begin{pmatrix} z_1 \\ z_2 \end{pmatrix}$$

be a vertex of  $Q$  where  $z_1 \in \mathbb{R}_+^n$  and  $z_2 \in \mathbb{R}_+^m$ . Since  $z \in Q$ , namely  $Bz = Az_1 + z_2 = c$ , we have  $Az_1 = c - z_2 \leq c$ . This means  $z_1 \in P$ . Moreover,  $z_1$  is an extreme point of  $P$ . If not so, namely there exists  $u, v \in P$ , such that  $u \neq v$  and  $z_1 = (u + v)/2$ , we have

$$z_2 = c - Az_1 = c - \frac{A(u + v)}{2} = \frac{1}{2}(c - Au) + \frac{1}{2}(c - Av)$$

Thus

$$z = \begin{pmatrix} z_1 \\ z_2 \end{pmatrix} = \frac{1}{2} \begin{pmatrix} u \\ c - Au \end{pmatrix} + \frac{1}{2} \begin{pmatrix} v \\ c - Av \end{pmatrix}$$

This contradicts the fact that  $z$  is a vertex of  $Q$ .

Since  $P$  is integral,  $z_1$  is integer. Therefore  $z_2 = c - Az_1$  is also integer.  $\square$

With Lemma 2.2 in hand, we can now start to prove *Hoffman-Kruskal Theorem*:

**Theorem 2.4 (Hoffman-Kruskal Theorem).** Let  $A \in \mathbb{Z}^{m \times n}$ . Then  $A$  is totally unimodular, iff for each  $b \in \mathbb{Z}^m$ , the polyhedron

$$P = P(A, b) \cap \mathbb{R}_+^n = \{x \mid Ax \leq b, x \geq 0\}$$

is integral.

*Proof. Necessity.* Let  $A' = \begin{pmatrix} A \\ I \end{pmatrix}$  and  $b' = \begin{pmatrix} b \\ 0 \end{pmatrix}$ , then  $A'$  is also totally unimodular and  $P = P(A', b')$ . By Theorem 2.3, we obtain  $P$  is integral.

*Sufficiency.* Let  $B = \begin{pmatrix} A & I \end{pmatrix} \in \mathbb{Z}^{m \times (n+m)}$ . Then  $A$  is totally unimodular iff each nonsingular  $m \times m$  submatrix of  $B$  has determinant  $\pm 1$ .

Let  $C \in \mathbb{Z}^{m \times m}$  be a nonsingular submatrix of  $B$ . Next we show  $C^{-1}$  is integer. To any  $v \in \mathbb{Z}^m$ , there exists another vector  $u \in \mathbb{Z}^m$  such that

$$z = u + C^{-1}v \in \mathbb{Z}_+^m$$

Let  $b = Cz$ , then  $b = Cz = Cu + CC^{-1}v = Cu + v$  is integer.

Without loss of generality,  $C$  contains first  $m$  columns of  $B$ , namely  $B = \begin{pmatrix} C & D \end{pmatrix}$ . And we raise  $z$  to  $z' \in \mathbb{Z}^{n+m}$ :

$$z' = \begin{pmatrix} z \\ \mathbf{0} \end{pmatrix}$$

where  $\mathbf{0}$  is an all-zero vector in  $\mathbb{R}^n$ .

Let

$$E = \begin{pmatrix} B \\ -B \\ -I \end{pmatrix} \quad \text{and} \quad f = \begin{pmatrix} b \\ -b \\ 0 \end{pmatrix}$$

Then for system

$$Ez' \leq f$$

the equality holds for the first  $m$  rows and last  $n$  rows of  $E$ . Since  $\text{rank}(C) = m$ , and the last  $n$  rows come from  $-I$ , we obtain  $\text{rank}(E_{z',f}) = m + n$ . By Theorem 1.4 on page 5,  $z'$  is a vertex of polyhedron  $P(E, f) = P^=(B, b) \cap \mathbb{R}_+^m$ . By Lemma 2.2,  $z'$  is integer. So  $z$  is integer.

Hence for any integer vector  $v$ ,  $C^{-1}v = z - u$  is integer. Therefore  $C^{-1}$  is integer. This implies  $C$  is integer.  $\square$

# Bibliography

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