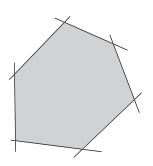
Geometry of Linear Programming

- extreme points
- vertices
- basic (feasible) solutions

Polyhedron (inequality form)

$$A = \begin{bmatrix} a_1 & \cdots & a_m \end{bmatrix}^T$$
 is $m \times n$, $b \in \mathbb{R}^m$
$$\mathcal{P} = \{ x \mid Ax \le b \} = \{ x \mid a_i^T x \le b_i, i = 1, \dots, m \}$$

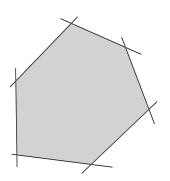


 $\ensuremath{\mathcal{P}}$ is convex because it's the intersection of halfspaces (the intersection of convex sets is convex)

Extreme points

 $x \in \mathcal{P}$ is an **extreme point** of \mathcal{P} if there **does not exist** two vectors $y, z \in \mathcal{P}$ such that

$$x = \lambda y + (1 - \lambda)z$$
 for any $\lambda \in (0, 1)$



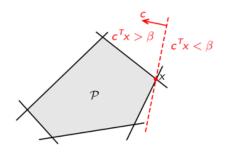
Vertices

 $x \in \mathcal{P}$ is a **vertex** of \mathcal{P} if there exists a vector $c \neq 0$ such that

$$c^T x < c^T y$$
 for all $y \in \mathcal{P}, y \neq x$

two equivalent points of view:

- given a **vertex** x, find c such that $c^Tx < c^Ty$ for all $y \in \mathcal{P}$, $y \neq x$
- given a **vector** c, find x such that $c^Tx < c^Ty$ for all $y \in \mathcal{P}$, $y \neq x$, ie, minimize c^Tx subject to $x \in \mathcal{P}$



Active constraints

define \mathcal{B} as the set of **active** or **binding** constraints (at x^*):

$$a_i^T x^* = b_i, \quad i \in \mathcal{B}$$
 (active constraints) $a_i^T x^* < b_i, \quad i \notin \mathcal{B}$ (inactive feasible constraints) or $a_i^T x^* > b_i, \quad i \notin \mathcal{B}$ (inactive infeasible constraints)

define the subset of active constraints

$$ar{A} = egin{bmatrix} ar{a}_{i_1}^T \ ar{a}_{i_2}^T \ draphi \ ar{a}_{i_k}^T \end{bmatrix}, \qquad ar{b} = egin{bmatrix} b_{i_1} \ b_{i_2} \ draphi \ b_{i_k} \end{bmatrix}, \qquad \mathcal{B} = \{i_1, i_2, \dots, i_k\} \end{pmatrix}$$

Basic solutions

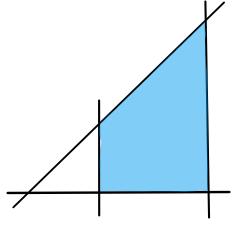
 x^* is a **basic solution** if one of the following equivalent conditions hold:

- $a_{i_1}, a_{i_2}, \ldots, a_{i_n}$ are linearly independent
- $\bar{A}x^* = \bar{b}$ has a unique solution
- $rank(\bar{A}) = n$

basic feasible solution: x^* is a basic solution and $x^* \in \mathcal{P}$

Theorem: the following are equivalent

- x* is a vertex
- x^* is an extreme point
- x* is a basic feasible solution



Example

$$\begin{bmatrix} -1 & 0 \\ 2 & 1 \\ 0 & -1 \\ 1 & 2 \end{bmatrix} x \le \begin{bmatrix} 0 \\ 3 \\ 0 \\ 3 \end{bmatrix}$$

- (1,1) is an extreme point
- (1,1) is a vertex: unique minimum of c^Tx with c=(-1,-1)
- (1,1) is a basic feasible solution: $\mathcal{B} = \{2,4\}$ and rank $\bar{A} = 2$, where

$$\bar{A} = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$$

Equivalence of definitions

$Vertex \implies extreme point$

Let x^* be a vertex of \mathcal{P} . Then there exists a $c \neq 0$ such that

$$c^T x^* < c^T x$$
 for all $x \in \mathcal{P}$ and $x \neq x^*$.

Then for all $y, z \in \mathcal{P}$ with $y \neq x^*$ and $z \neq x^*$,

$$c^T x^* < c^T y$$
 and $c^T x^* < c^T z$.

If $\lambda \in [0,1]$, then

$$c^T x^* < c^T (\lambda y + (1 - \lambda)z),$$

and $x^* \neq \lambda y + (1 - \lambda)z$. Therefore x^* is an extreme point.

Extreme point \Longrightarrow basic feasible solution

Suppose $x^* \in \mathcal{P}$ is an extreme point with

$$a_i^T x^* = b_i \quad i \in \mathcal{B}, \quad \text{and} \quad a_i^T x^* < b_i \quad i \notin \mathcal{B}.$$

Proceed by contradiction. Suppose x^* is not a basic feasible solution. Thus, a_i for $i \in \mathcal{B}$ are not linearly independent. Then there exists a $d \neq 0$ with

$$a_i^T d = 0$$
 for every $i \in \mathcal{B}$ (ie, $\bar{A}d = 0$)

and for $\epsilon > 0$ small enough,

$$y = x^* + \epsilon d \in \mathcal{P}, \quad z = x^* - \epsilon d \in \mathcal{P}.$$

Summing, we have

$$x^* = \frac{1}{2}y + \frac{1}{2}z,$$

which contradicts the assumption that x^* is an extreme point.

Basic feasible solution \implies vertex

Suppose $x^* \in \mathcal{P}$ is a basic feasible solution and

$$a_i^T x^* = b_i \quad i \in \mathcal{B}, \quad \text{and} \quad a_i^T x^* < b_i \quad i \notin \mathcal{B}.$$

Take any $x \in \mathcal{P}$. For each $i \in \mathcal{B}$,

$$-a_i^T x \ge -b_i = -a_i^T x^*$$

Summing these all together:

$$c^T x = -\sum_{i \in \mathcal{B}} a_i^T x \ge -\sum_{i \in \mathcal{B}} b_i = c^T x^*, \qquad c := -\sum_{i \in \mathcal{B}} a_i$$

with equality only if $a_i^T x = b_i, i \in \mathcal{B}$. Since $\{a_i \mid i \in \mathcal{B}\}$ are linearly independent, that holds only when $x = x^*$. Thus, $c^T x^* < c^T x$ for all $x \in \mathcal{P}$, $x \neq x^*$, so x^* is a vertex.

Unbounded directions

 \mathcal{P} contains a **half-line** if there exists $d \neq 0$, x_0 such that

$$x_0 + \alpha d \in \mathcal{P}$$
 for all $\alpha \ge 0$

equivalent conditions for $\mathcal{P} = \{ x \mid Ax \leq b \}$:

$$Ax_0 \leq b$$
, $Ad \leq 0$

fact: \mathcal{P} unbounded $\iff \mathcal{P}$ contains a half line

 \mathcal{P} contains a **line** if there exists $d \neq 0$, x_0 such that

$$x_0 + \alpha d \in \mathcal{P}$$
 for all α

equivalent conditions for $\mathcal{P} = \{ x \mid Ax \leq b \}$:

$$Ax_0 \leq b$$
, $Ad = 0$

fact: \mathcal{P} has no extreme points $\Longleftrightarrow \mathcal{P}$ contains a line

Optimal set of an LP

minimize
$$c^T x$$
 subject to $Ax \le b$

- optimal value $p^* = \min \left\{ \left. c^T x \mid Ax \le b \right. \right\} \quad (p^* = \pm \infty \text{ is possible})$
- optimal point: x^* with $Ax^* \le b$ and $c^Tx^* = p^*$
- optimal set: $X^* = \{ x \mid Ax \leq b, c^Tx = p^* \}$

example

$$\begin{array}{ll} \text{minimize} & c_1x_1+c_2x_2\\ \text{subject to} & -2x_1+x_2\leq 1, \quad x_1\geq 0, \ x_2\geq 0 \end{array}$$

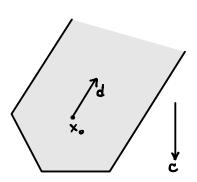
- c = (1,1): $X^* = \{ (0,0) \}, p^* = 0$
- c = (1,0): $X^* = \{ (0, x_2) \mid 0 \le x_2 \le 1 \}, p^* = 0$
- c = (-1, -1): $X^* = \emptyset$, $p^* = +\infty$

Existence of optimal points

• $p^* = -\infty$ if and only if there exists a feasible half line

$$\{x_0 + \alpha p \mid \alpha \ge 0\}$$

with $c^T p < 0$



- $p^* = +\infty$ if and only if $\mathcal{P} = \emptyset$
- p^* if finite if and only if $X^* \neq \emptyset$