

[Weak Duality] (i) \rightarrow its theorem \rightarrow Note: holds for every feasible solution!

(ii) \rightarrow holds for the primal & dual optimal not just opt. solution

This need to
check the written
notes!

\Downarrow
In particular, if we take

P-opt \rightarrow the Primal Prob. Opt. value

(can be $-\infty$)

D-opt \rightarrow the Dual Prob. Opt. value

(can be $+\infty$)

we have $D\text{-opt} \leq P\text{-opt}$

(iii) if you have $\tilde{x}, \tilde{\mu}$ which are primal & dual feasible
solution, s.t. $C^T \tilde{x} = b^T \tilde{\mu}$

\Downarrow

the optimal solutions are found!

(both Primal & Dual)

Geometry of LP.

Recall the standard form of an MILP.

$$\min C^T x + d^T y$$

$$\text{s.t. } Ax + By = b$$

$$x \geq \underline{0}, y \geq \underline{0}$$

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

the linear relaxation of the MILP is to ignore the integer constraints

$$\min C^T x + d^T y$$

$$\text{s.t. } Ax + By = b$$

$$x \geq \underline{0}, y \geq \underline{0}$$

Q: When are two solutions to these problems equal?

Fundamental to this question is to understand what the feasible region of a LP looks like.

↪ The feasible regions of LP's are known as \Rightarrow polyhedral.

$$P = \{x : Ax \leq b\}.$$

$$= \{x : a_i^T x \leq b_i \text{ for } 1 \leq i \leq m\}.$$

convex

Q: Can a polyhedral be unbounded?

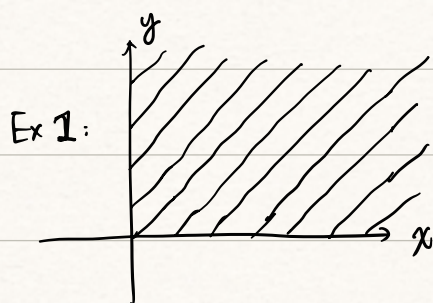
Yes. Example: half-space.

Then want to define the 'sharp points'.

○ Defn (Extreme Points) Let P be a polyhedron, we say that a point $y \in P$ is an extreme point if:

$$y = \theta z_1 + (1-\theta) z_2 \text{ where } 0 < \theta < 1 \text{ with } z_1, z_2 \in P.$$

$$\Rightarrow z_1 = z_2 = y.$$



↪ only have 1 extreme point (0,0)

pf: $(0,0)$ is extreme point

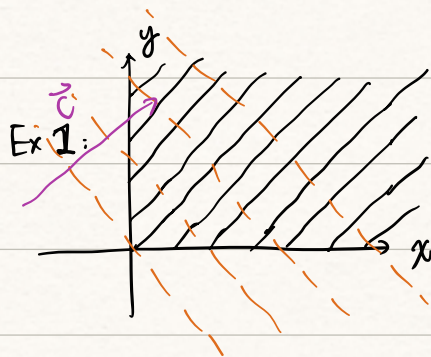
⊗ $\{(x,y) : x \geq 0, y \geq 0\} / \{(0,0)\}$ all not extreme points

○ Defn (Vertex) Let P be a polyhedron, we say that:

$\rightarrow y \in P$ is a vertex of P if there is a direction $c \in \mathbb{R}^n$

s.t. $c^T y \leq c^T z$ for all $z \in P / \{y\}$

must be strict inequality!



→ only have 1 vertex $(0,0)$

pf: choose $c = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$

Defn: Basic Feasible Solution (BFS)

Consider a polyhedron defined as $P = \{x: Ax=b, x \geq 0\} \subseteq \mathbb{R}^n$

where $A \in \mathbb{R}^{m \times n}$, $m \leq n$

Assume that:

(i) P is not empty.

(ii) A has full row rank $\Leftrightarrow \text{rank}(A) = m$

↪ if not, pick out linearly dependent part!

Pick m columns of A that are linearly independent.

↪ To simplify, let the last m columns are linearly independent

$$A = \begin{bmatrix} * & B \end{bmatrix}^m$$

$\underbrace{\quad}_{nm} \quad \underbrace{\quad}_m$

Define $\hat{x} = \begin{pmatrix} 0 \\ B^{-1}b \end{pmatrix} \in \mathbb{R}^n$

Notice that $A\hat{x} = b \rightarrow$ definition

$\Leftrightarrow \hat{x}$ lies in the $\{x: Ax=b\}$

↓
call this \hat{x} a Basic Solution!

(all other BS are obtained by using other choices of linearly independent columns \rightarrow different B)

However, we cannot, in general, know if $\hat{x} \geq 0$.

But if indeed $\hat{x} \geq 0$, then we call this a BASIC FEASIBLE SOLUTION!

Thm: Suppose $P = \{x: Ax=b, x \geq 0\}$ is a nonempty polyhedron. Let $y \in P$

The following are equivalent:

- (i) y is a vertex
- (ii) y is an extreme point
- (iii) y is a basic feasible solution.

$$\Leftrightarrow y = \begin{pmatrix} 0 \\ b^{-1}b \end{pmatrix} \in \mathbb{R}^n$$

- ★ Rmk: (i) There are analogous definitions of BFS for non-standard form.
(ii) vertex & extreme don't rely on A & b (parameters) (but not for today's lecture)

$$P = \{x: Ax=b, x \geq 0\} = \{x: \tilde{A}x = \tilde{b}, x \geq 0\}$$

\Rightarrow the BFS defined differently, but will end up being the same point because vertexes/extreme points are not defined with parametrization.

Pf: (i) \Rightarrow (ii) y is vertex $y \in P$ (if y is not an extreme point)

if $y = \theta z_1 + (1-\theta)z_2$ when $0 < \theta < 1$ and $z_1 \in P / \{y\}$ $z_2 \in P$

$$\begin{aligned} c^T y &= \theta c^T z_1 + (1-\theta) c^T z_2 < \theta c^T y + (1-\theta) c^T z_2 \\ &\leq \theta c^T y + (1-\theta) c^T y \quad \begin{array}{l} \rightarrow z_1 \neq y \\ \rightarrow z_2 \text{ can be } y \end{array} \\ &= c^T y \Rightarrow \text{Contradiction!} \end{aligned}$$

\downarrow
either $z_1 \neq y$ or $z_2 \neq y$.

(ii) \Rightarrow (iii) if y is an extreme point

$$A = [x \quad \underbrace{B}_k] \quad y = \begin{pmatrix} 0 \\ \underbrace{\tilde{y}}_k \end{pmatrix}$$

→ these k columns must be linearly independent

If not, there exists $d_1 \in \mathbb{R}^k$ s.t. $Bd_1 = 0$

we must have $y_1 = y + \alpha \begin{pmatrix} 0 \\ d_1 \end{pmatrix}$ α is enough small.
 $y_2 = y - \alpha \begin{pmatrix} 0 \\ d_1 \end{pmatrix}$

we can have $Ay_1 = b$, $Ay_2 = b$ and $y_1 \geq 0$, $y_2 \geq 0$
 $\Rightarrow y_1 \in P$, $y_2 \in P$

But we have $y = \frac{1}{2}(y_1 + y_2)$

→ contradicts to y is an extreme point

Then we have $k \leq m$.

① $k = m$ ✓

② $k < m$, then add other $m-k$ (linearly independent) columns to make B (invertible)

$$\Rightarrow B\bar{y} = b \rightarrow \bar{y} = B^{-1}b$$

then we finish $y = \begin{pmatrix} 0 \\ B^{-1}b \end{pmatrix}$.

(iii) \Rightarrow (i) if y is a BFS, $y = \begin{pmatrix} 0 \\ B^{-1}b \end{pmatrix} \geq 0$.

construct \underline{c} as follows:

$$\underline{c} = \begin{cases} +1, & \text{index } \underline{\{n\} \setminus B} \\ 0, & \text{else.} \end{cases}$$

Consider the Optimization prob.

$$\min c^T x$$

$$\text{s.t. } Ax = b, x \geq 0$$

(we need to show that $c^T x > c^T y \quad \forall x \in P \setminus \{y\}$)

(1) the obj. is always ≥ 0

(2) it attains 0 for the point y

(3) if $c^T x = 0$ and $Ax = b, x \geq 0$

then since \underline{c} takes +1 in entries not in B

$$x = \begin{pmatrix} 0 \\ * \end{pmatrix} \quad A = \begin{pmatrix} * & B \end{pmatrix}$$

$$\text{But } Ax=b \Rightarrow x=B^{-1}b$$

(1) & (2) & (3) shows that y is the unique point that
minimizes the optimization Problem
 $\Rightarrow y$ is a vertex.

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Numerical Solver for Optimization Instances.

{ MILP Solvers : IBM CPLEX, Gurobi. Proprietary.
Generic solvers : MATLAB, Scipy
Specialized Solvers :

Gurobi \rightarrow evaluation version \rightarrow solve problem instances of limited size

• knapsack problem (MILP).

$$\max \sum c_i x_i$$

$$\text{s.t. } \sum w_i x_i \leq B$$

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

• Faculty location Prob.

$$\min \sum c_j y_j + \sum_{i,j} d_{ij} x_{i,j}$$

$$\text{s.t. } \sum_j x_{i,j} = 1$$

$$x_{i,j} \leq y_j$$

$$\underline{x_{i,j} \in \{0, 1\}, y_j \in \{0, 1\}.$$

\hookrightarrow relaxed to $0 \leq x_{i,j} \leq 1.$