MATH 567: Lecture 1 (01/07/2025)

Integer and Combinatorial Optimization

→ we will talk mostly about IP (integer programming)

I'm Bala Krishnamoorthy, call me Bala.

Today:
* syllabus, logistics...
* 2D LP example
* convexity, min-max as LP

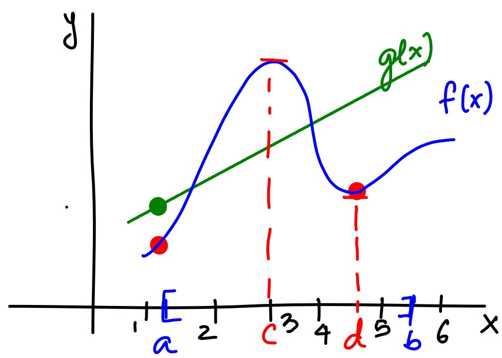
Optimization in Calculus

$\min f(x), \; x \in [a,b]$

$f'(x) = 0 \to$ critical points

$f''(x) > 0 \to$ minima

Also consider end points included in the interval.



$g(x)$: linear, $\min g(x), x \in [a,b] \Rightarrow$ just check end points!

Linear optimization generalizes the special linear 1D case to higher dimensions.

Integer optimization in 1D: $\min f(x)$, $x \in [a,b]$, $x \in \mathbb{Z}$

→ insist on finding integer optimal solutions

$\mathbb{Z}$ → set of integers

A standard linear program (LP)

$$\begin{aligned} \max \quad & \bar{c}^T \bar{x} \\ \text{s.t.} \quad & A\bar{x} \le \bar{b} \\ & \bar{x} \in \mathbb{R}^n_{\ge 0} \end{aligned}$$

$\bar{c}, \bar{x} \to$ vectors (lower-case letters w/ bar)

→ my notation in these notes!

$\le$ or $=$ (as used in many books)

Here is an example of LP formulation, and graphical solution.

(Taken from *Introduction to Mathematical Programming* by Winston and Venkataramanan.)

Farmer Jones must decide how many acres of corn and wheat to plant this year. An acre of wheat yields 25 bushels of wheat and requires 10 hours of labor per week. An acre of corn yields 10 bushels of corn and requires 4 hours of labor per week. Wheat can be sold at \$4 per bushel, and corn at \$3 per bushel. Seven acres of land and 40 hours of labor per week are available. Government regulations require that at least 30 bushels of corn need to be produced in each week. Formulate and solve an LP which maximizes the total revenue that Farmer Jones makes.

Decision variables (d.v.s):

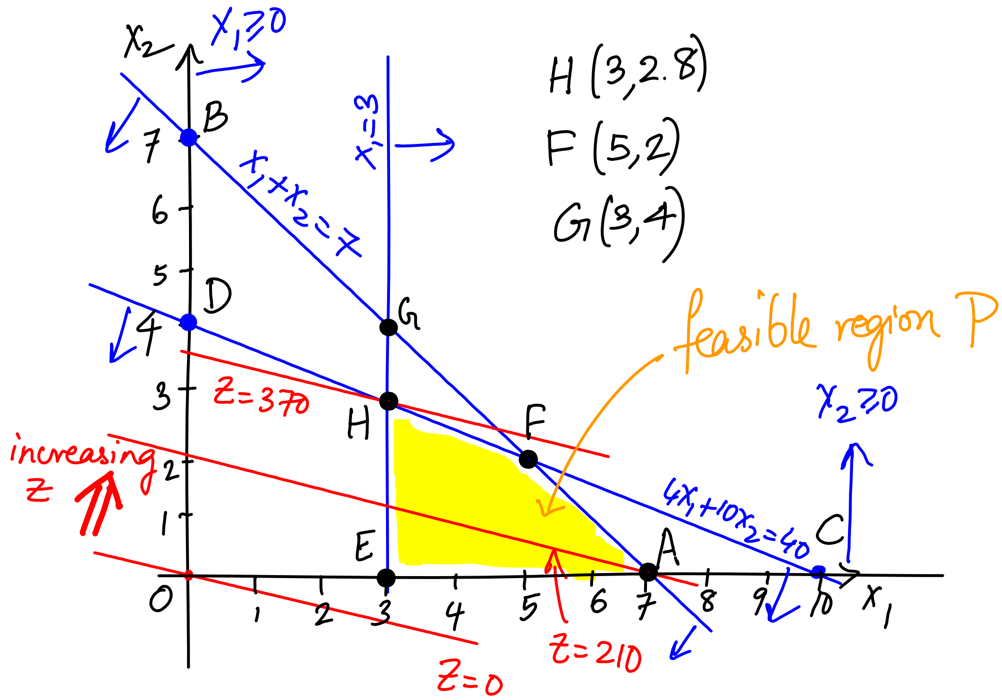
x_i = # acres of crop i, $i = 1, 2$ (1 = corn, 2 = wheat)

$$
\left.\begin{array}{llll}
\text{maximize} & z = 3\cdot 10\cdot x_1 + 4\cdot 25\cdot x_2 & & \text{(total revenue)} \\
\text{s.t.} & x_1 + x_2 & \leq 7 & \text{(total land)} \\
\text{subject to} & 4x_1 + 10x_2 & \leq 40 & \text{(total labor hrs)} \\
 & 10x_1 & \geq 30 & \text{(min corn)} \\
 & x_1, x_2 & \geq 0 & \text{(non-neg)}
\end{array}\right\} \text{linear program (LP)}
$$

The above model is an LP formulation. You need to specify the d.v.s, and describe the objective function and constraints as linear functions or (in)equalities in the d.v.'s.

Graphical Solution of the LP

slide z-line up (in the direction of increasing z)



Optimal solution is at $H(3, 2.8)$, with optimal $z^* = 370$.

Points to note

* Optimal solution (if one exists) occurs at a corner point (vertex)
* the feasible region P is convex

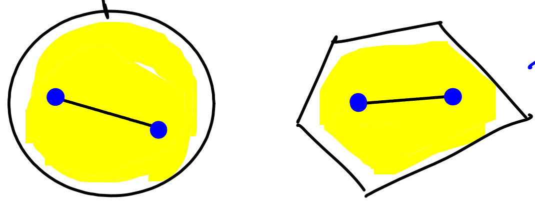
The first result depends on the fact that P is convex – indeed, we will strive hard to utilize convexity whenever possible!

Def P is convex if $\forall\ 0 \leq \lambda \leq 1$, $\bar{x}_1, \bar{x}_2 \in P$,

$$\lambda \bar{x}_1 + (1-\lambda) x_2 \in P.$$

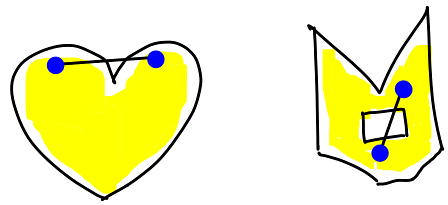
In words, the line segment connecting $\bar{x}_1$ and $\bar{x}_2$ lies in P.

Examples of convex regions:



We will talk a lot about polytopes and polyhedra

not convex!

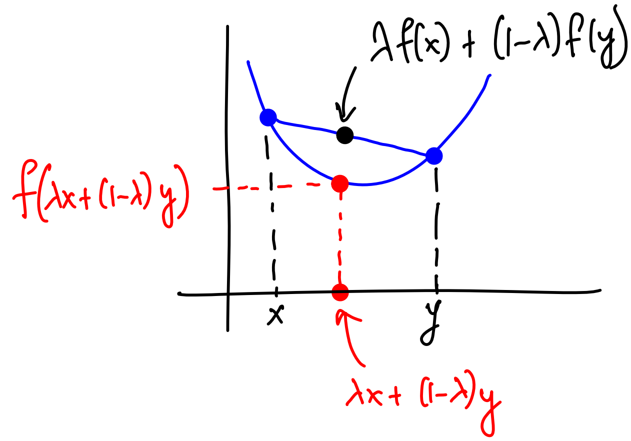


Convex function $f : \mathbb{R}^n \to \mathbb{R}$, is **convex** if

$\forall\, \bar{x}, \bar{y} \in \mathbb{R}^n$, $\lambda \in [0,1]$, we have

$$f(\lambda \bar{x} + (1-\lambda)\bar{y}) \leq \lambda f(\bar{x}) + (1-\lambda) f(\bar{y})$$

$\geq$ → concave



Again, convexity plays a critical role in how we formulate LPs and integer LPs. There are certain scenarios which could be modeled as LPs due to convexity, but other that cannot be!

Theorem: Let $f_1, \dots, f_m : \mathbb{R}^n \to \mathbb{R}$ be convex. Then

$$f(\bar{x}) = \max_{i=1,\dots,m} f_i(\bar{x}) \text{ is convex.}$$

We will stick to the finite cases in this class, i.e., m and n in the above theorem are finite.

Proof Let $\bar{x}, \bar{y} \in \mathbb{R}^n$, $\lambda \in [0,1]$.

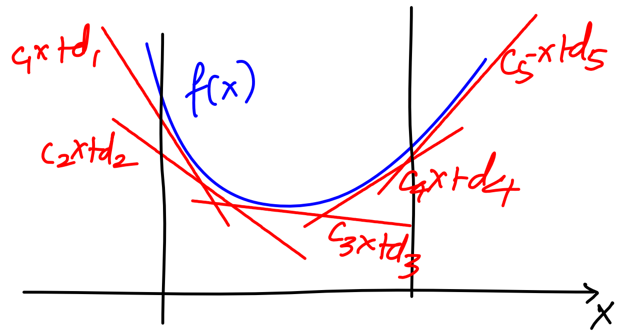
$$\begin{aligned}
f(\lambda\bar{x} + (1-\lambda)\bar{y}) &= \max_{1\le i\le m} f_i(\lambda\bar{x} + (1-\lambda)\bar{y}) \\
&\le \max_{1\le i\le m} \lambda f_i(\bar{x}) + (1-\lambda) f_i(\bar{y}) \quad \text{as each } f_i \text{ is convex} \\
&\le \lambda \underbrace{\left[\max_{1\le i\le m} f_i(\bar{x})\right]}_{f(\bar{x})} + (1-\lambda) \underbrace{\left[\max_{1\le i\le m} f_i(\bar{y})\right]}_{f(\bar{y})} \\
&= \lambda f(\bar{x}) + (1-\lambda) f(\bar{y})
\end{aligned}$$

□

Def $f(\bar{x}) = \max_{1\le i\le m} (\bar{c}_i^T \bar{x} + d_i)$, $\bar{c}_i \in \mathbb{R}^n$, $d_i \in \mathbb{R}$ is a **piecewise linear (PL) convex function**, with convexity following from the previous result.

A (general) convex function could be approximated efficiently using a PL convex function in certain optimization problems.

The more number of linear pieces we use, the finer the approximation of $f(x)$ is.



Consider the following generalization of LP:

$$\left.\begin{array}{lll} \min & \max\limits_{1\le i\le m} (\bar{c}_i^T\bar{x}+d_i) & \\ \text{s.t.} & A\bar{x}\le\bar{b} & \\ & \bar{x}\ge\bar{0} & \end{array}\right\}$$

not an LP as written (as the objective is not $\bar{c}^T\bar{x}$)

We can write an equivalent LP with an extra variable and m extra constraints:

$$\text{LP}\left\{\begin{array}{lll} \min & z & \\ \text{s.t.} & z\ge \bar{c}_i^T\bar{x}+d_i, & i=1,\dots,m \\ & A\bar{x}\le\bar{b} & \\ & \bar{x}\ge\bar{0} & \end{array}\right.$$

Note: We are able to model as an LP because the objective function is a min-max one.

What if it were a min-min or a max-max one?

We will have to use integer variables!

this LP is unbounded!

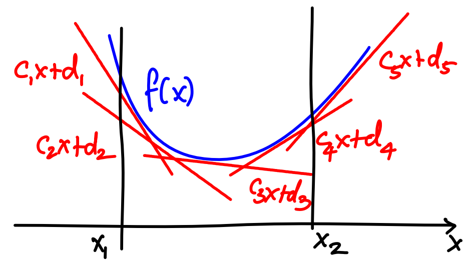
$$\left\{\begin{array}{l} \max\ z \\ z\ge\bar{c}_i^T\bar{x}+d_i \\ A\bar{x}\le\bar{b} \\ \bar{x}\ge\bar{0} \end{array}\right.$$

Analogy:

z models a "blanket" that stays above all the lines (linear "pieces") $\Leftarrow$ $z \geq \bar{c}_i^T \bar{x} + d_i$, $i = 1, \ldots, m$.

Minimizing z pushes the blanket plush against the pieces from above, and hence z models the function as desired.

If we maximize z instead, the blanket is pulled up, and there is no limit on how far it can be pulled up. The problem is unbounded in this case!



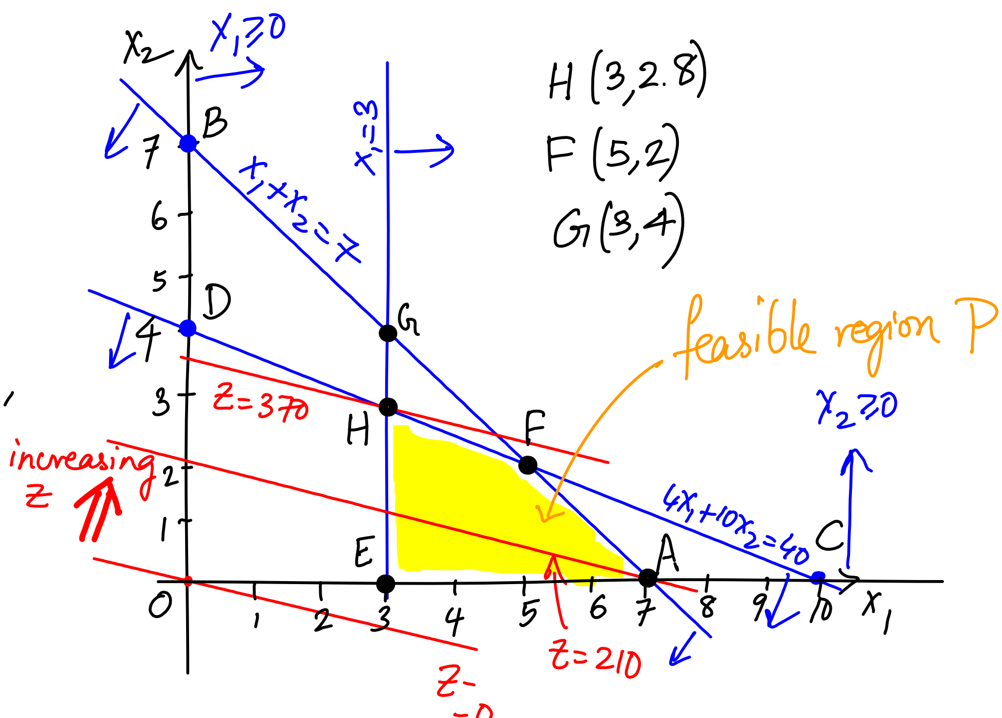
The first instinct on given an IP is to drop the integer restrictions and solve the underlying LP. May be then we can "round" the LP solution to a nearest integral solution to get a solution for the IP. But this idea fails in many cases.

Farmer Jones LP:

H(3, 2.8) is the optimal solution.

If $x_1, x_2 \in \mathbb{Z}$ on top, rounding H will put you outside P!

(3,3) $\notin$ P



Rounding down gives (3,2), which is feasible. But the optimal integer solution is F(5,2).

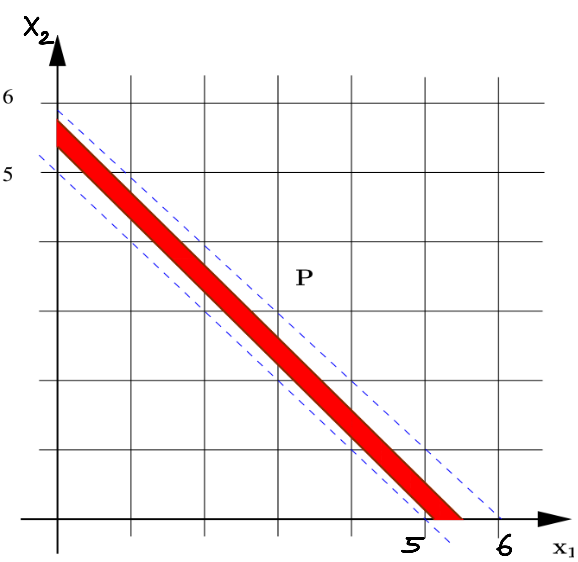
MATH 567: Lecture 2 (01/14/2025)

Today: * general forms of IP
* IP formulations

To round off (no pun intended!) the discussion on possibly rounding fractional solutions from LP relaxations to solve integer programs, we present another "extreme" example.

Consider the polytope P shown here, which is defined by the following constraints.

$$\left.\begin{cases} 106 \leq 21x_1 + 19x_2 \leq 113 \\ 0 \leq x_1, x_2 \leq 6 \end{cases}\right\} (P)$$



As is evident from the figure, $P \cap \mathbb{Z}^2 = \emptyset$! The idea of rounding for any IP defined on P is moot here.

for any objective function

We will return to such examples later on.

General Forms of integer (linear) Programs

Mixed integer Program (MIP)

$$\begin{aligned} \max \quad & z = \bar{c}^T \bar{x} + \bar{d}^T \bar{y} \\ \text{s.t.} \quad & A\bar{x} + B\bar{y} \leq \bar{b} \\ & \bar{x} \in \mathbb{Z}_{\geq 0}^{n_1}, \quad \bar{y} \in \mathbb{R}_{\geq 0}^{n_2} \end{aligned} \qquad \text{(MIP)}$$

Pure integer program (IP)

$$\begin{aligned} \max \quad & z = \bar{c}^T \bar{x} \\ \text{s.t.} \quad & A\bar{x} \leq \bar{b} \\ & \bar{x} \in \mathbb{Z}_{\geq 0}^{n} \end{aligned} \qquad \text{(IP)}$$

Special case of IP: Binary IP (BIP)

$$\begin{aligned} \max \quad & z = \bar{c}^T \bar{x} \\ \text{s.t.} \quad & A\bar{x} \leq \bar{b} \\ & \bar{x} \in \{0,1\}^{n} \end{aligned} \qquad \text{(BIP)}$$

Q When do we insist $x_i \in \mathbb{Z}$?

Should we build a new dorm? $\Rightarrow$ $x \in \{0,1\}$ insist on it.

fractional value does not make sense

How many rooms should we build?

$y = 385.6$ $\to$ 386, 385 } both are okay in the big scheme of things.

So, just set $y \in \mathbb{R}_{\geq 0}$.

We will now look at several BIP and MIP formulation problems. It is important to remember that one **need not write these formulations in standard form**. Later on, when we describe algorithms to solve these problem instances, it will make sense to describe them for problems in standard form. Similarly, when we study the geometry or other properties of the associated polytope, we will do so using a standard form. In fact, it is better to write formulations in non-standard form if they are more readable!

We will introduce AMPL, which is a state-of-the-art **modeling software**. The function of such a software is to convert formulations written in non-standard form to, sometimes more concise, standard form. Then AMPL sends the standard form problem to a solver, e.g., Gurobi, which runs linear-algebra based algorithms to solve the same. AMPL then "interprets" the solution to the standard form problem back to the original form before displaying the same.

We will first introduce several instances of the BIP, and then the MIP. Later on, we will describe some unified procedures to model most situations using only binary variables, or using binary and continuous variables. Further on, we will discuss how to "compare" formulations – as it turns out, there are multiple ways to formulate the same situation, and one formulation might be "tighter" than the rest.

BIP formulations

1. Assignment Problem

n persons, n jobs, c_{ij} = cost of person i doing job j

Goal: Assign each person to a job so that total cost is minimum.

Step 1 decision variables (d.v.s)

Let $x_{ij} = \begin{cases} 1 & \text{if person } i \text{ does job } j, \\ 0 & \text{o.w.} \end{cases}$ n^2 vars.

o.w. → "otherwise"

Step 2: Constraints

$$\sum_{j=1}^{n} x_{ij} = 1 \quad \forall i \ (i=1,\dots,n) \quad \text{(person } i \text{ gets one job)}$$

$$\sum_{i=1}^{n} x_{ij} = 1 \quad \forall j \ (j=1,\dots,n) \quad \text{(job } j \text{ gets one person)}$$

$$x_{ij} \in \{0,1\} \quad \forall i,j$$

Step 3 Objective function

$$\min \quad z = \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} x_{ij} \quad \text{(total cost)}$$

In summary

$$\min \quad z = \sum_{i} \sum_{j} c_{ij} x_{ij} \quad \text{(total cost)}$$

s.t.

$$\sum_{j} x_{ij} = 1 \ \forall i \quad \text{(person } i \text{ gets 1 job)}$$

$$\sum_{i} x_{ij} = 1 \ \forall j \quad \text{(job } j \text{ gets 1 person)}$$

$$x_{ij} \in \{0,1\} \quad \forall i,j$$

As you do more formulations, you will naturally go straight to the compact form, rather than write out the detailed steps. But do define the d.v.'s first in all cases!

2. The 0-1 knapsack problem

* n projects.
* total budget b.
* cost of project j is a_j.
* value of project j is c_j.

It is assumed that you cannot undertake a fraction, e.g., 0.4., of a project.

Decide which projects to choose within the budget such that total value is maximized.

d.v's $\quad x_j = 1$ if project j is selected, 0 o.w.

Constraints
$$\sum_{j=1}^{n} a_j x_j \le b \qquad \text{(budget)}$$
$$x_j \in \{0,1\} \quad \forall j \qquad \text{(binary vars).}$$

objective function
$$\max \sum_{j=1}^{n} c_j x_j.$$

$$\begin{aligned} \max \quad & \sum c_j x_j \\ \text{s.t.} \quad & \sum a_j x_j \overset{=}{\le} b \\ & x_j \in \{0,1\} \quad \forall j. \end{aligned}$$

equality knapsack problem: have to use up all the available budget

In feasibility knapsack, we want to find $x_j \in \{0,1\}$ s.t. $\sum a_j x_j = b$. (or, more generally, $\{ b' \le \underbrace{\bar{a}^T \bar{x}}_{\sum a_j x_j} \le b \}$)

There is no objective function specified.

Additional Restrictions

1. If project 2 is chosen, so must be project 5.

$$x_5 \geq x_2$$

If $x_2 = 1$, then we have $x_5 \geq 1$, which forces $x_5 = 1$, as $x_5 \in \{0,1\}$.
But if $x_2 = 0$, we get $x_5 \geq 0$, which is redundant.

Notice that the reverse implication that "if project 5 is chosen, then so must project 2" is not forced by this constraint. Indeed, if $x_5 = 1$, we get $x_2 \leq 1$, which is redundant.

Note that $x_2 = x_5$ is also not correct here, as that constraint models "either pick both projects 2 and 5, or neither one."

Must exactly

2. Can choose ~~(at most)~~ 2 out of projects 1, 3, 6, 7.

Must at least

$$x_1 + x_3 + x_6 + x_7 \overset{=}{\underset{\geq}{\leq}} 2$$

It is important to realize that these constraints work as intended only when all x_j's are binary. Further, we do not want to force more than what is required. We will first try to write the required constraints just using logic, but will later describe a more systematic approach.

3. Fixed Charge (continued...)

$$\min \; f(x_1) + c_2x_2 + \cdots + c_nx_n$$
$$A\bar{x} \le \bar{b}$$
$$0 \le x_1 \le M_1$$
$$f(x_1) = \begin{cases} 0, & x_1 = 0 \\ f_1, & x_1 > 0 \end{cases} \quad (f_1 > 0).$$

YES/NO question: Is $x_1 > 0$?

$\Longrightarrow$ model using $y_1 \in \{0,1\}$.

We want
$$y_1 = \begin{cases} 1 & \text{if } x_1 > 0 \\ 0 & \text{o.w.} \end{cases}$$

$$\boxed{\begin{aligned} \min \quad & f_1y_1 + c_2x_2 + \cdots + c_nx_n \\ \text{s.t.} \quad & A\bar{x} \le \bar{b} \\ & 0 \le x_1 \le M_1y_1 \\ & y_1 \in \{0,1\} \end{aligned}}$$

If $x_1 > 0$, y_1 is forced to 1. Else, $x_1 \le My_1$ will not hold (with $y_1 = 0$).

If $x_1 = 0$, $x_1 \le M_1y_1$ can hold with $y_1 = 0$ or $y = 1$. But the term f_1y_1 in the min objective function forces $y_1 = 0$ in the optimal solution.
Recall, $f_1 > 0$ here.

4. Interactive fixed charge → Included in HW1!

Similar to Problem 3 but

$$f(x_1, x_2) = \begin{cases} 0, & \text{if } x_1 = x_2 = 0 \\ f_1, & \text{if } x_1 > 0,\ x_2 = 0 \\ f_2, & \text{if } x_1 = 0,\ x_2 > 0 \\ f_{12}, & \text{if } x_1 > 0 \ \&\ x_2 > 0 \end{cases}$$

with $\begin{aligned} 0 \le x_1 \le M_1 \\ 0 \le x_2 \le M_2 \end{aligned}$, $\quad f_{12} \geq f_1 > 0,\ f_{12} \geq f_2 > 0,$

$f_{12} \neq f_1 + f_2$ → need not hold as equality; indeed $f_{12} \substack{> \\ = \\ <} f_1 + f_2$ are all ok.

Can we use $y_1, y_2 \in \{0,1\}$, and $y_1 \times y_2$? Yes, but $y_1 y_2$ is nonlinear, so you want to somehow linearize it — maybe define $y_{12} \in \{0,1\}$, and relate it to y_1 and y_2 using extra constraints.

Later on, we will talk about linearizing such nonlinear terms - products of binary variables, or x_i^2 when $x_i \in \{0,1\}$, etc.

MATH 567 : Lecture 3 (01/16/2025)

Today: * More MIP formulations
* modeling tools for BIPs

Recall : min-max objective functions and constraints — could be modeled as linear programs.

e.g., $\min\{|x|\} \longrightarrow \min\{\max\{x,-x\}\}$

$\longrightarrow \min\{z \mid z \geq x, z \geq -x\}.$

Similarly, we could model $\max\{\cdot,\cdot\} \leq b$ or $\min\{\cdot,\cdot\} \geq b$ constraints as equivalent linear systems. For instance,

$$|x| \leq 5 \longrightarrow \max\{x,-x\} \leq 5 \longrightarrow x \leq 5, \; -x \leq 5.$$

But $|x| \geq 4$ cannot be modeled as an LP. In particular,

~~$x \geq 4$ and $-x \geq 4$~~ is not what we want.

Will have to use an extra binary variable to model which of two options holds in this case.

Recall: Fixed charge :

$$\min f_1 y_1 + \cdots \qquad (f_i > 0)$$

s.t. ....

$$x_1 \leq M_1 y_1 \qquad y_1 \in \{0,1\}$$

We will see another problem class where fixed charge shows up. Later, we will see how to force the relation between x_1 and y_1 without relying on the $\min f_1 y_1$ objective function.

5. Uncapacitated lot sizing (ULS)

* 1 product, n time periods $(t = 1, \dots, n)$
* $d_1, \dots, d_n$: demand in each time period
* $f_1, \dots, f_n$: fixed cost for making any > 0 # items in each time period
* $c_1, \dots, c_n$: unit production cost in each time period
* $h_1, \dots, h_n$: unit holding (or storage) costs (h_t : cost for storing one unit from period t to $t+1$)

Goal: production plan that minimizes total cost.

Assumptions:
* infinite production capacity (no storage capacity as well)
* no units to start with, or at end

d.v.s:

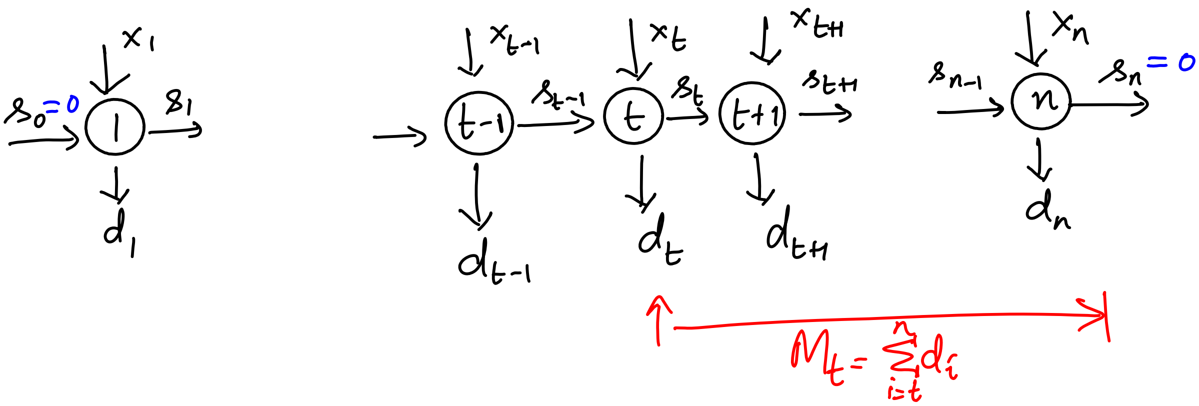
x_t = # units produced in period t, $t = 1, \dots, n$ (≥ 0, continuous)

s_t = # units stored from period t to $t+1$, $t = 0, \dots, n$ (≥ 0, continuous)

$$y_t = \begin{cases} 1 & \text{if } x_t > 0 \\ 0 & \text{o.w.} \end{cases}, \quad t = 1, \dots, n$$

→ to capture the fixed charge terms

Here is a schematic:



d_t's are data given to us

Here is the MIP: $\longrightarrow$ we do have an MIP, as s_t, x_t are continuous, while y_t is binary

$$\min \sum_{t=1}^{n} f_t y_t + \sum_{t=1}^{n} c_t x_t + \sum_{t=1}^{n} h_t s_t \qquad \text{(total cost)}$$

s.t.

$$s_0 = 0, \quad s_n = 0 \qquad \text{(no start/end inventory)}$$

$$\underbrace{s_{t-1} + x_t}_{\text{inflow}} = \underbrace{d_t + s_t}_{\text{outflow}}, \quad t = 1, \dots, n \qquad \text{(flow balance)}$$

$$x_t \leq M_t y_t \quad t = 1, \dots, n \qquad \text{(forcing constraints)}$$

$$s_t \geq 0, x_t \geq 0, \; y_t \in \{0,1\} \; \forall t \qquad \text{(var. restrictions).}$$

What should M_t be? Any large enough (>0) number will work, But ideally, use the smallest M_t that works.

$$M_t = \sum_{i=t}^{n} d_i \quad \text{will work here.}$$

We will spend a lot of time on details such as the choice of M_t, and how they affect the "strength" of the formulation.

If we allow backlogging, demand in period t could be Satisfied by (part of) x_j for $j > t$. In this case,

$$M_t = \sum_{i=1}^{n} d_i \quad \text{will work,}$$

since all the demand could potentially be satisfied by producing in the same single period.

6. (General) Piecewise linear function

(not convex in the interesting case)

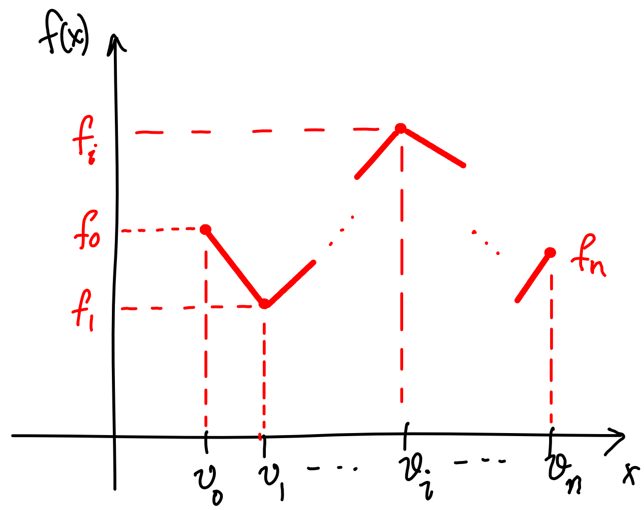
x : scalar

$$f(x) = \begin{cases} f_i, & \text{if } x = v_i \quad (i = 0, \dots, n) \\ \text{linear}, & \text{if } v_i \le x \le v_{i+1} \quad (i = 0, \dots, n-1) \end{cases}$$

If $x = \lambda_i v_i + \lambda_{i+1} v_{i+1}$

$\lambda_i, \lambda_{i+1} \ge 0$, $\lambda_i + \lambda_{i+1} = 1$, then

$f(x) = \lambda_i f_i + \lambda_{i+1} f_{i+1}$



Let $\delta_i = v_i - v_{i-1}$. We let

$s_i = \dfrac{f_i - f_{i-1}}{\delta_i}$, $i = 1, \dots, n$ (slopes, can be ≥ 0 or ≤ 0).

Let x_i be "the portion of x in $[v_{i-1}, v_i]$", $i = 1, \dots, n$.

If we

1. write $x = v_0 + \sum_{i=1}^{n} x_i$

$$g = f_0 + \sum_{i=1}^{n} s_i x_i$$

$$0 \le x_i \le \delta_i,$$

2. somehow enforce

"if $x_{i+1} > 0$ then $x_i \ge \delta_i$", for $i = 1, \dots, n-1$

3. plug in g for $f(x)$;

then we're done!

2. Equivalent logical expression:

"either $x_{i+1} \leq 0$ or $x_i \geq \delta_i$"

$$-x_i + \delta_i \leq 0$$

$A \Rightarrow B \equiv$
$\neg A$ or B
"not"

Let y_i and z_i are 0-1 variables

$$\boxed{\begin{aligned} x_{i+1} &\leq \delta_{i+1} y_i \\ -x_i + \delta_i &\leq \delta_i z_i \\ y_i + z_i &= 1 \\ y_i, z_i &\in \{0,1\} \end{aligned}}$$

if $x_{i+1} > 0$ then $y_i = 1$
$\Rightarrow z_i = 0$

$\forall i = 1, \ldots, n-1$

assuming XOR "exclusive OR"
A or B, but not both

If $x_{i+1} > 0$, then $y_i = 1 \Rightarrow z_i = 0$ (as $y_i + z_i = 1$).

$$\Rightarrow -x_i + \delta_i \leq 0 \Rightarrow x_i \geq \delta_i$$

Can simplify:

$$x_{i+1} \leq \delta_{i+1} y_i$$

$$-x_i + \delta_i \leq \delta_i (1 - y_i)$$

as $y_i + z_i = 1$

$$x_i \geq \delta_i y_i$$

i.e., $\delta_i y_i \leq x_i \leq \delta_i y_{i-1}$, $i = 1, \ldots, n-1$

$$x_{i+1} > 0 \Rightarrow y_i = 1 \Rightarrow y_{i-1} = 1, y_{i-2} = 1, \ldots, y_1 = 1.$$

So, we can force both implications for $y_i = \begin{cases} 1, & \text{if } x_i > 0 \\ 0 & \text{o.w} \end{cases}$ using constraints, i.e., do not have to rely on a $\min f_i y_i$ objective function.

We present one last formulation instance...

7. Semicontinuous variable

Need that "x does not take values that are too small".

e.g., if you buy any of a stock option, you need to buy at least 100 of them.

statement: x is zero or is at least ℓ (>0) (and $\leq M$)

Model: $\boxed{\ell y \leq x \leq My,\ y \in \{0,1\}}$

We now consider some themes/governing principles for writing all such formulations.

1. Modeling with only 0-1 variables

$x_1, x_2, \ldots$ are 0-1 (binary) variables

Notation

$L_i \equiv (x_i = 1)$

$\vee \equiv$ OR, $\wedge \equiv$ AND

$\Rightarrow \equiv$ "implies", $\Leftrightarrow \equiv$ "equivalent"

$\neg \equiv$ NOT (negation)

These are standard notation used in mathematical logic. We will start with statements, and then try to write the model, i.e., set of inequalities, that represents the statement.

Examples

statement	model (constraints)
1. $L_1 \vee L_2 \vee \cdots \vee L_n$	$x_1 + x_2 + \cdots + x_n \geq 1$
2. $L_1 \Rightarrow L_2$	$x_1 \leq x_2$
3. $L_1 \Leftrightarrow (L_2 \wedge L_3)$	

i.e.,

$$\begin{cases} L_1 \Rightarrow (L_2 \wedge L_3) & \to \quad x_1 \leq x_2, \; x_1 \leq x_3 \\ L_1 \Leftarrow (L_2 \wedge L_3) & \to \quad \text{think about it!} \end{cases}$$

We'll present the model in the next lecture...

MATH 567: Lecture 4 (01/21/2025)

Today:
* conjunctive normal form (CNF)
* model with 0-1 and continuous variables
* arbitrary disjunctions

Modeling with 0-1 variables (continued...)

3. $L_1 \Leftrightarrow (L_2 \wedge L_3)$

i.e.,

$$\begin{cases} L_1 \Rightarrow (L_2 \wedge L_3) \\ L_1 \Leftarrow (L_2 \wedge L_3) \end{cases}$$

$L_1 \Rightarrow (L_2 \wedge L_3)$: $x_1 \le x_2,\ x_1 \le x_3$ OR $2x_1 \le x_2 + x_3$

$L_1 \Leftarrow (L_2 \wedge L_3)$: $\cancel{x_1 \geq \frac{x_2+x_3}{2}}$ will force $x_1 = 1$ when $x_2=1, x_3=0$!

$\cancel{x_1 \geq x_2 x_3}$ nonlinear!

$\cancel{2x_1 = x_2 + x_3}$ $x_2 = x_3 = 0$ forces $x_1 = 0$!

$x_1 \geq x_2 + x_3 - 1$

Q. Is there a general method to model any logical statement?

YES! As long as the statement is in a "nice" form. And every statement has such a "nice" form!

Def A **literal** is an elementary statement, e.g., L_i, $\neg L_j$.

A **clause** is a set of literals connected with "OR" ($\vee$)

e.g., $L_1 \vee L_3$, $\neg L_2 \vee L_4 \vee \neg L_5$.

Def A logical statement is in **conjunctive normal form** (CNF) if it is a set of clauses connected by ANDs ($\wedge$).

e.g., $(L_1 \vee L_3) \wedge (\neg L_2 \vee L_3 \vee \neg L_5) \wedge (\neg L_3 \vee L_7)$

is in CNF.

If a statement is in CNF, it is easy to write down its representative model using inequalities.

e.g., $\left\{\begin{array}{r} x_1 + x_3 \geq 1 \\ (1-x_2) + x_3 + (1-x_5) \geq 1 \\ (1-x_3) + x_7 \geq 1 \end{array}\right\}$ is a model for the statement in CNF above.

Claim Every (finite) statement involving $\vee, \wedge, \neg, \Rightarrow, \Leftrightarrow$ has a CNF. The CNF may not be unique.

<u>Some Rules for doing transformations</u>

① $L_1 \wedge (L_2 \vee L_3) \equiv (L_1 \wedge L_2) \vee (L_1 \wedge L_3)$

$\quad \cdot \quad +$

② $L_1 \vee (L_2 \wedge L_3) \equiv (L_1 \vee L_2) \wedge (L_1 \vee L_3)$

$\quad \cdot \quad +$

③ $\neg (L_1 \wedge L_2) \equiv \neg L_1 \vee \neg L_2$

④ $\neg (L_1 \vee L_2) \equiv \neg L_1 \wedge \neg L_2$

⑤ $L_1 \Rightarrow L_2 \overset{\text{def}}{\equiv} \neg L_1 \vee L_2$

We could replace literals with clauses, or more general statements in the above rules, and they still hold, e.g., $C_1 \Rightarrow C_2 \equiv \neg C_1 \vee C_2$.

clauses

Examples

1. $(L_2 \wedge \cdots \wedge L_n) \Rightarrow L_1 \equiv \neg(L_2 \wedge \cdots \wedge L_n) \vee L_1$

$$\equiv (\neg L_2 \vee \neg L_3 \vee \cdots \vee \neg L_n) \vee L_1$$

$$\equiv \neg L_2 \vee \neg L_3 \vee \cdots \vee \neg L_n \vee L_1$$

which is in CNF.

model: $(1-x_2) + (1-x_3) + \cdots + (1-x_n) + x_1 \geq 1$

2. $(L_1 \wedge L_2) \vee (L_3 \wedge (L_4 \vee L_5))$

$$\equiv ((L_1 \wedge L_2) \vee L_3) \wedge ((L_1 \wedge L_2) \vee (L_4 \vee L_5))$$

$$\equiv ((L_1 \vee L_3) \wedge (L_2 \vee L_3)) \wedge [(L_1 \vee (L_4 \vee L_5)) \wedge (L_2 \vee (L_4 \vee L_5))]$$

$$\equiv (L_1 \vee L_3) \wedge (L_2 \vee L_3) \wedge (L_1 \vee L_4 \vee L_5) \wedge (L_2 \vee L_4 \vee L_5)$$

which is in CNF.

model: $\left\{ \begin{array}{l} x_1 + x_3 \geq 1 \\ x_2 + x_3 \geq 1 \\ x_1 + x_4 + x_5 \geq 1 \\ x_2 + x_4 + x_5 \geq 1 \end{array} \right\}$

2. Modeling with 0-1 and continuous variables

Let $y \in \{0,1\}$, $\bar{x} \in \mathbb{R}^n$

Statement : $y=1 \Longrightarrow A\bar{x} \leq \bar{b}$

Assume $\exists\, \bar{u} \geq \bar{0}$: $A\bar{x} \leq \bar{b}+\bar{u}$ is always true.

Then $\boxed{A\bar{x} \leq \bar{b} + \bar{u}(1-y)}$ is the model.

3. Modeling arbitrary disjunctions

$\bar{x} \in \mathbb{R}^n$

$$(A_1\bar{x} \leq \bar{b}^1) \vee (A_2\bar{x} \leq \bar{b}^2) \vee \cdots \vee (A_k\bar{x} \leq \bar{b}^k) \quad \text{—— } (*)$$

Assume $\{\bar{x} \mid A_i\bar{x} \leq \bar{b}^i\} \neq \emptyset$. if one system is $\emptyset$, then we could remove it from $(*)$

In words, $(*)$ says "$\bar{x}$ satisfies one of the k systems".

Note that some of the statements using literals L_i would fit this framework. At the same time, this is a much more general statement. We'll consider two approaches to model this statement. The first one looks quite similar to the previous case of $y=1 \Rightarrow A\bar{x} \leq \bar{b}$.

big-M representation

Assumption 1 $\exists\, \bar{u}^i \geq \bar{0}$ such that $\forall \bar{x}$ that satisfy $A_j\bar{x} \leq \bar{b}^j$ for some j, $A_i\bar{x} \leq \bar{b}^i + \bar{u}^i$ holds $\forall i$.

Let $y_i \in \{0,1\}$, $i = 1, \dots, k$. → models whether the i^{th} disjunction holds

$$\boxed{\begin{aligned} & A_i\bar{x} \leq \bar{b}^i + \bar{u}^i(1-y_i), \quad i=1,\dots,k \\ & y_1 + y_2 + \dots + y_k \geq 1 \\ & y_i \in \{0,1\}, \quad i = 1,\dots,k. \end{aligned}}$$

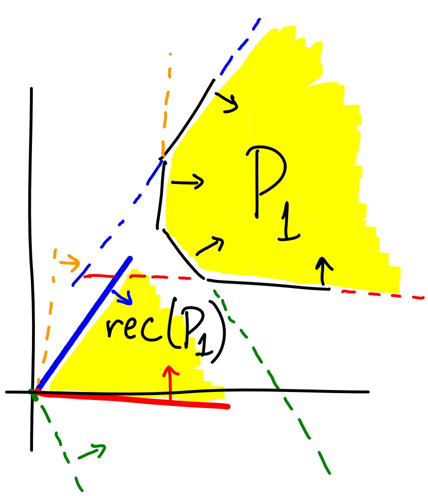
—— (x-bigM)

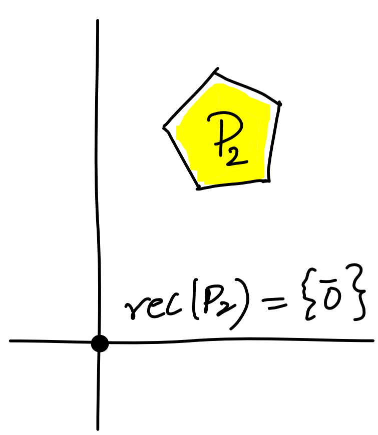
Sharp formulation

Assumption 2 $\exists\, C$ such that $C = \{\bar{x} \mid A_i\bar{x} \leq \bar{0}\}$, $i = 1,\dots,k$ is independent of i.

Def The **recession cone** of polyhedron $P = \{\bar{x} \mid A\bar{x} \leq \bar{b}\}$ is

$$\textbf{rec}(P) = \{\bar{x} \mid A\bar{x} \leq \bar{0}\}.$$





If P is a polytope, i.e., a closed polyhedron, then $\text{rec}(P) = \{\bar{0}\}$, the origin.

$$\boxed{\begin{array}{c} A_1\bar{x}^1 \le \bar{b}^1 y_1 \\ \vdots \\ A_k\bar{x}^k \le \bar{b}^k y_k \\ \bar{x}^1+\bar{x}^2+\cdots+\bar{x}^k = \bar{x} \\ y_1+y_2+\cdots+y_k = 1 \\ y_i \in \{0,1\} \end{array}} \quad (*\text{-sharp})$$

sharp, as exactly one (out of k) options is forced to hold

We now prove the correctness of ($*$-sharp).

Theorem 1 $\bar{x}$ satisfies $(*)$ $\iff \exists\, (\bar{x}^1,\dots,\bar{x}^k, y_1,\dots,y_k)$ such that $(\bar{x}, \bar{x}^1,\dots,\bar{x}^k, y_1,\dots,y_k)$ satisfies ($*$-sharp).

Proof ($\Rightarrow$) $\bar{x}$ satisfies $(*)$.

WLOG, Let $A_1\bar{x} \le \bar{b}^1$. We can choose

$$\left.\begin{array}{l} y_1=1,\ y_2=\cdots=y_k=0 \\ \bar{x}^1=\bar{x},\ \bar{x}^2=\cdots=\bar{x}^k=\bar{0} \end{array}\right\} \text{ satisfies } (*\text{-sharp}).$$

($\Leftarrow$) : in the next lecture...

MATH 567 : Lecture 5 (01/23/2025)

Today: * representing sets
* representing functions

Proof of Theorem 1 (continued..)

Recall...

Theorem 1 $\bar{x}$ satisfies (*) $\Longleftrightarrow$ $\exists\, (\bar{x}^1, \ldots, \bar{x}^k, y_1, \ldots, y_k)$ such that $(\bar{x}, \bar{x}^1, \ldots, \bar{x}^k, y_1, \ldots, y_k)$ satisfies (*-sharp).

$$\boxed{\begin{aligned} A_1 \bar{x}^1 &\le \bar{b}^1 y_1 \\ &\vdots \\ A_k \bar{x}^k &\le \bar{b}^k y_k \\ \bar{x}^1 + \bar{x}^2 + \cdots + \bar{x}^k &= \bar{x} \\ y_1 + y_2 + \cdots + y_k &= 1 \\ y_i &\in \{0,1\} \end{aligned}} \quad \text{(*-sharp)}$$

Proof ($\Rightarrow$): seen in the last lecture...

($\Leftarrow$) WLOG, let $y_1 = 1$, $y_i = 0$, $i = 2, \ldots, k$ in $(\bar{x}, \bar{x}^1, \ldots, \bar{x}^k, y_1, \ldots, y_k)$ that satisfies (*-sharp).

$$\Rightarrow \quad \begin{aligned} A_1 \bar{x}^1 &\le \bar{b}^1 \\ A_2 \bar{x}^2 &\le \bar{0} \\ &\vdots \\ A_k \bar{x}^k &\le \bar{0} \end{aligned} \quad \text{and} \quad \bar{x}^1 + \cdots + \bar{x}^k = \bar{x}$$

$$\Rightarrow \quad A_1 \bar{x} = A_1(\bar{x}^1 + \cdots + \bar{x}^k) = A_1 \bar{x}^1 + A_1 \bar{x}^2 + \cdots + A_1 \bar{x}^k \le \bar{b}^1 + \overbrace{\bar{0} + \cdots + \bar{0}}^{\text{from Assumption 2}}$$

$$\Rightarrow \quad A_1 \bar{x} \le \bar{b}^1, \text{ i.e., } \bar{x} \text{ satisfies } (*).$$

$\square$

Representing Sets in general

Q. In general, what all sets could we represent using 0-1 and/or general integer (GI) variables?

We need a few new definitions to address this question. In particular, we will formally define a formulation — so far, we have been studying them informally as MIP models.

Def A set S is **bounded MIP-representable** (b-MIP-r) if $\exists$ matrices A, B, C, D and a vector $\bar{f}$ such that

$$S = \{ (\bar{x},\bar{y}) \in \mathbb{Z}^n \times \mathbb{R}^m \mid \exists (\bar{u},\bar{v}) \in \mathbb{Z}^p \times \mathbb{R}^q \text{ such that } A\bar{x} + B\bar{y} + C\bar{u} + D\bar{v} \le \bar{f} \}$$ and

$A\bar{x} + B\bar{y} + C\bar{u} + D\bar{v} \le \bar{f}$ implies lower and upper bounds on $\bar{x}$ and $\bar{u}$ (the general integer (GI) variables). → hence the "bounded" in b-MIP-r

The set $P = \{ (\bar{x},\bar{y},\bar{u},\bar{v}) \in \mathbb{R}^{n+m+p+q} \mid A\bar{x} + B\bar{y} + C\bar{u} + D\bar{v} \le \bar{f} \}$ is called a **formulation** of S.

Note that all variables are continuous in this formal definition of a formulation.

Def $P = \{ \bar{x} \in \mathbb{R}^n \mid A\bar{x} \le \bar{b} \}$ is a **polyhedron**, where $A \in \mathbb{R}^{m \times n}$, $\bar{b} \in \mathbb{R}^m$, m, n are finite. → polyhedra are convex sets.

A bounded polyhedron is a **polytope**.

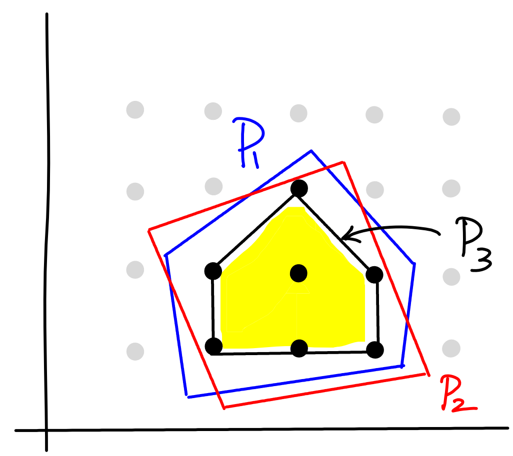
Examples of formulations

1. $S = \{\bar{x} \in \{0,1\}^n \mid (x_1 = 1) \vee \cdots \vee (x_n = 1)\}$ has a formulation

$$P = \{\bar{x} \in \mathbb{R}^n \mid 0 \le x_i \le 1 \; \forall i, \; x_1 + \cdots + x_n \ge 1\}.$$

2. $S = \{$7 lattice points shown as $\bullet\}$.

P_1, P_2, P_3 are all formulations for S.

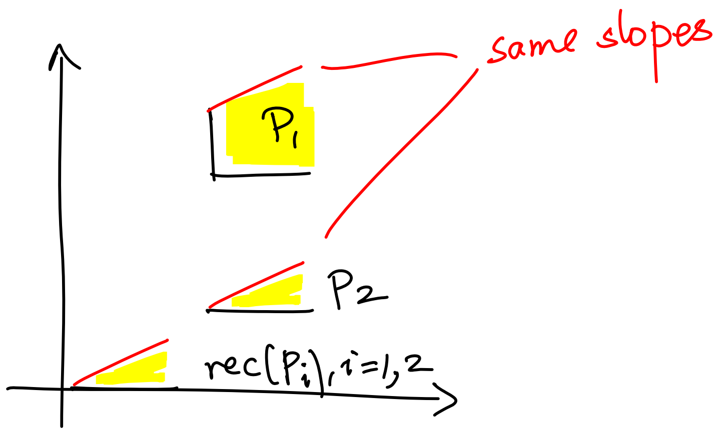


But P_3 is "better" than P_1 and P_2. Note that P_3 is the convex hull of the lattice points that is S. If we want to maximize a linear function over S, we could do the same over P_3 instead. The same claim cannot be made for P_1 or P_2. We will talk later about how to compare formulations.

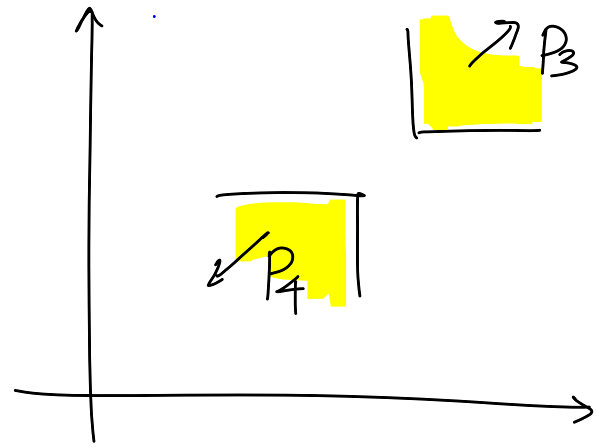
What kinds of sets S are b-MIP-r? Could we characterize them?

Theorem 2 (Jeroslow, Lowe): S is b-MIP-r iff $S = P_1 \cup \cdots \cup P_k$ for finite k, where P_i are polyhedra having the same recession cone i.e., $\mathrm{rec}(P_i)$ is independent of i, $i = 1, \ldots, k$.

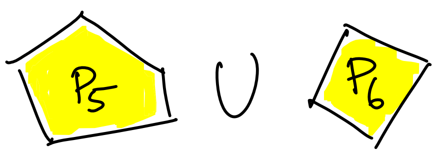
Here are some examples.



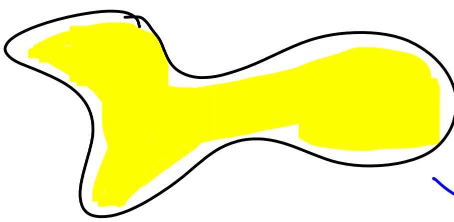
$P_1 \cup P_2$ is b-MIP-r.



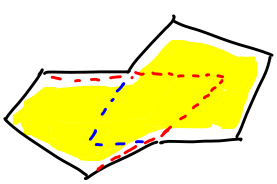
$P_3 \cup P_4$ is not okay as an MIP.
(as $\mathrm{rec}(P_3) \neq \mathrm{rec}(P_4)$)

$S =$ 

is okay as an MIP.
$(\mathrm{rec}(P_5) = \mathrm{rec}(P_6) = \{\bar{0}\})$

$S =$  is not okay as MIP, as it is not a polyhedron to start with.

→ S being non convex is not crucial here — it could've been an ellipse, and the conclusion is the same.

$S =$  → o.k. as MIP! → union of two polytopes.

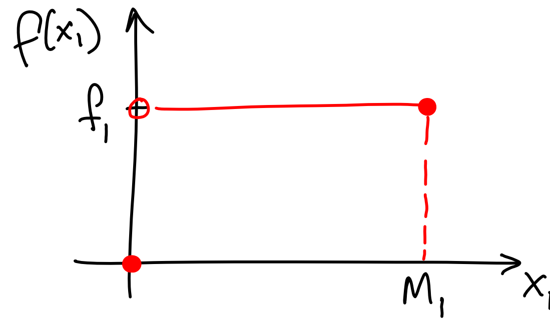
Can we use similar techniques to model functions, instead of sets?

Representing Sets v/s Functions

We already saw the case of fixed charge:

$$\left\{\begin{array}{ll} \min & f(x_1) \\ \text{s.t.} & 0 \le x_1 \le M_1 \\ & A\bar{x} \le \bar{b} \end{array}\right\}$$

and we wrote an MIP for the same.



It turns out we could use similar ideas to model some classes of functions appearing in certain optimization problems. Naturally, if $f(x_1)$ is nonlinear, e.g., x_1^3 or $\sqrt{x_1}$, we will not get an integer linear program! We need some definitions first.

Def Given $f : \mathbb{R}^n \to \mathbb{R}$, we define the **graph**, **epigraph**, and **hypograph** of f as follows.

$$\text{graph}(f) = \{ (z, \bar{x}) \in \mathbb{R}^{n+1} \mid z = f(\bar{x}) \},$$

$$\text{epi}(f) = \{ (z, \bar{x}) \in \mathbb{R}^{n+1} \mid z \ge f(\bar{x}) \}, \text{ and}$$

$$\text{hypo}(f) = \{ (z, \bar{x}) \in \mathbb{R}^{n+1} \mid z \le f(\bar{x}) \}.$$

Notice that graph(f), epi(f), and hypo(f) are sets, and we could consider when each of them is b-MIP-r — instead of talking about representability of $f(\cdot)$ itself.

Suppose we have $\left\{\begin{array}{l}\min f(\bar{x}) \\ \text{s.t. } A\bar{x} \le \bar{b}\end{array}\right\}$ where epi(f) is b-MIP-r.

Then we can write $\left\{\begin{array}{l}\min\ z \\ \text{s.t. } A\bar{x} \le \bar{b} \\ \quad (z, \bar{x}) \in \text{epi}(f)\end{array}\right\}$ as the MIP representation.

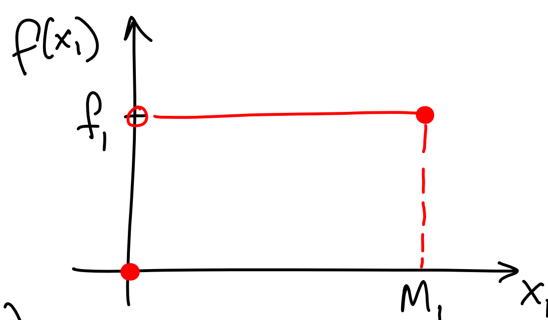
Since epi(f) is b-MIP-r, we can write down an MIP representation of epi(f), which completes the MIP model above.

Q. Why not require graph(f) being b-MIP-r?

Theorem 3 graph(f) is b-MIP-r iff both epi(f) and hypo(f) are b-MIP-r.

Example

The fixed charge function.

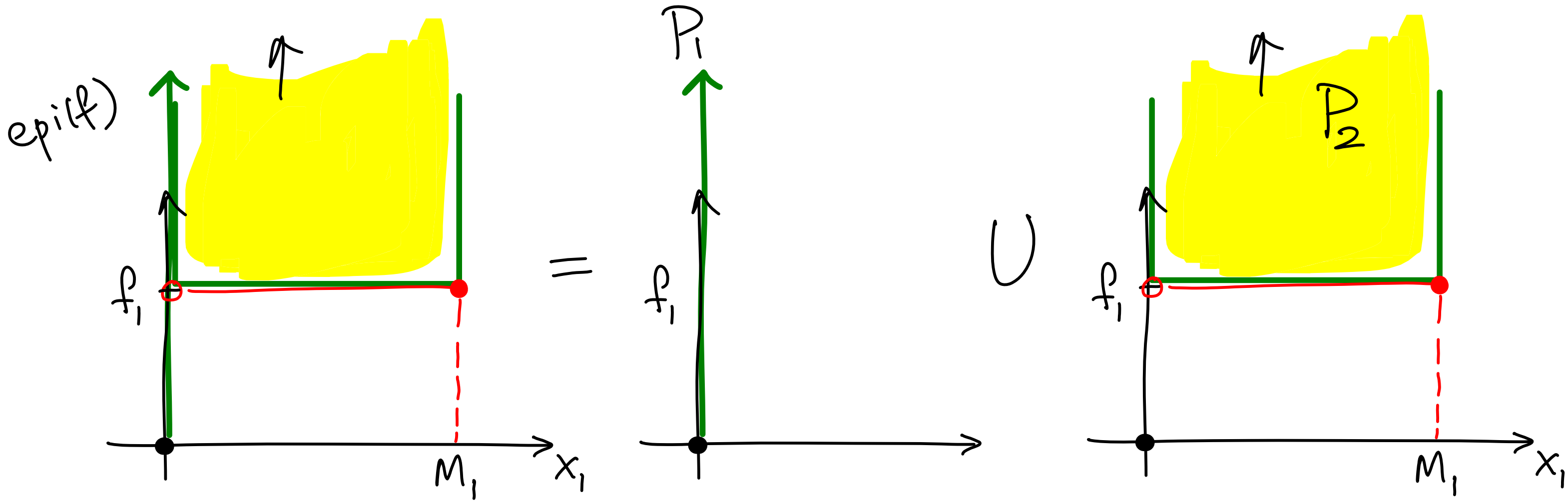


graph(f), i.e., $f(x_1)$ as drawn, is not b-MIP-r.

graph(f) is the union of origin ($\bullet$) and and the half-open line segment ($\circ$———$\bullet$).

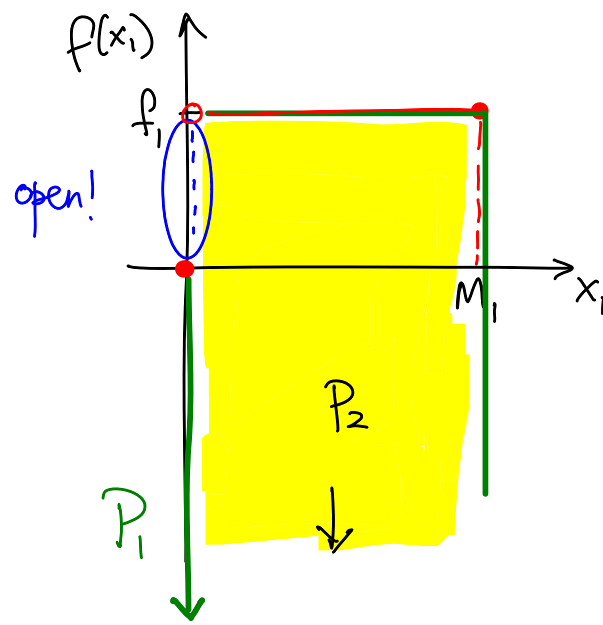
This second piece is not a polyhedron to start with.

But epi(f) turns out to be b-MIP-r here, and hypo(f) is not b-MIP-r at the same time.



Here $rec(P_1) = rec(P_2) = P_1$. Hence epi(f) is b-MIP-r.

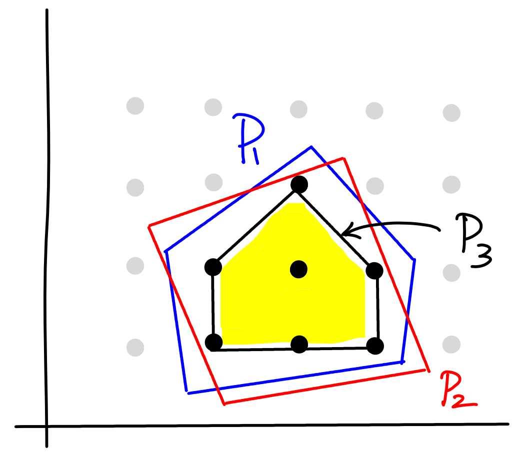
Here, hypo(f) is not b-MIP-r, as it is the union of P_1 and P_2, where P_2 is not a polyhedron (same reason as that for graph(f)).



What if $f_1 < 0$ here? Then hypo(f) will be b-MIP-r and epi(f) will not be b-MIP-r (the roles are reversed).

Comparing Formulations

Q. What is a good/bad formulation?



We could say here P_3 is better than both P_1 and P_2, but cannot compare P_1 to P_2. More generally, we want to compare formulations with different sets (and hence different numbers) of extra variables. To this end, we need to introduce some basic results.

pronounced "Farkash"; feasibility of alternative systems

Farkas' Lemma

① $\exists \bar{x} : A\bar{x} \le \bar{b}$ then

$A\bar{x} \le \bar{b}$ implies $\bar{a}^T\bar{x} \le \beta \iff$

$\exists \bar{u} \ge \bar{0}$ such that $\bar{u}^T A = \bar{a}^T$, $\bar{u}^T\bar{b} \le \beta$

multipliers using which we could derive $\bar{a}^T\bar{x} \le \beta$ from $A\bar{x} \le \bar{b}$

② $\exists \bar{x} : A\bar{x} \le \bar{b} \iff \nexists \bar{u} \ge \bar{0}$, $\bar{u}^T A = \bar{0}^T$, $\bar{u}^T\bar{b} < 0$.

(cannot derive $\bar{0}^T\bar{x} \le -1$ from $A\bar{x} \le \bar{b}$)

MATH 567: Lecture 6 (01/28/2025)

Today: * comparing formulations
* sharp/ideal formulation

Recall Farkas' lemma. We present one more version now.

(3) $\exists \bar{x} : A\bar{x} = \bar{b} \iff \nexists \bar{u} \neq \bar{0} : \bar{u}^T A = \bar{0}^T, \; \bar{u}^T \bar{b} = -1$ can be any nonzero #

$A\bar{x} = \bar{b}$: $[A \mid \bar{b}] \xrightarrow{\text{EROs}} [\;\;]$ echelon form

If the echelon form has as row of the form $[0\,0 \cdots 0 \mid \blacksquare]$, $\neq 0$
the system $A\bar{x} = \bar{b}$ is inconsistent.

Naturally, we can prove the other versions if we assume one version of Farkas' lemma (i.e., they are equivalent).

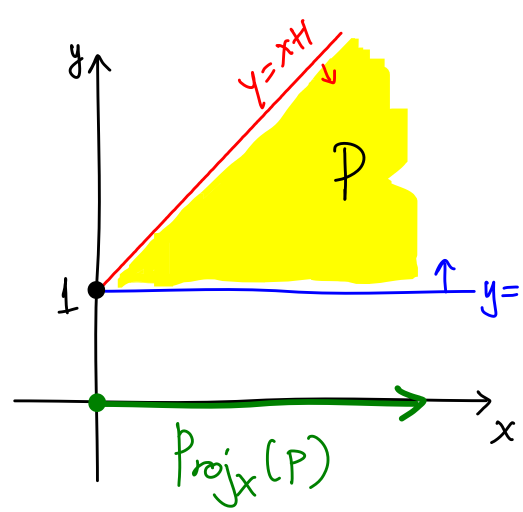
Def If $P = \{(\bar{x}, \bar{y}) \mid A\bar{x} + B\bar{y} \leq \bar{b}\}$, then the **projection of P** onto the space of $\bar{x}$ variables is

$$\text{Proj}_{\bar{x}}(P) = \{\bar{x} \mid \exists \bar{y} : (\bar{x}, \bar{y}) \in P\}.$$

$\Downarrow$ "push down" P onto the x-axis

e.g., $P = \{(x,y) \mid y \geq 1, y \leq x+1\}$

$$\text{Proj}_x(P) = \{x \mid x \geq 0\}.$$



Theorem 4 $\text{Proj}_{\bar{x}}(P) = \underbrace{\{\bar{x} \mid \bar{v}^T A\bar{x} \leq \bar{v}^T \bar{b} \ \forall \bar{v} \geq \bar{0}, \ \bar{v}^T B = \bar{0}^T\}}_{(RHS)}.$

In words, all nonnegative linear combinations of $A\bar{x} + B\bar{y} \leq \bar{b}$ that eliminate the "unwanted" $\bar{y}$ variables.

Proof '$\subseteq$': $\bar{x} \in \text{Proj}_{\bar{x}}(P) \Rightarrow \exists \bar{y} \mid A\bar{x} + B\bar{y} \leq \bar{b}$

$\Rightarrow \bar{v}^T A\bar{x} \leq \bar{v}^T \bar{b}$ holds $\forall \bar{v} \geq 0, \ \bar{v}^T B = \bar{0}^T$.

'$\supseteq$': Show that if $\bar{x} \notin \text{Proj}_{\bar{x}}(P)$, then $\bar{x} \notin (RHS)$.

Can use Farkas' lemma!

$\nexists \bar{y}: B\bar{y} \leq \bar{b} - A\bar{x}$, i.e., the system $B\bar{y} \leq \bar{b} - A\bar{x}$ has no solutions (in $\bar{y}$).

$\Rightarrow \exists \bar{v} \geq \bar{0}, \quad \bar{v}^T B = \bar{0}^T$ and $\bar{v}^T (\bar{b} - A\bar{x}) < 0$.

$\Rightarrow \exists \bar{v} \geq \bar{0}, \ \bar{v}^T B = \bar{0}^T$ for which $\bar{v}^T A\bar{x} > \bar{v}^T \bar{b}$.

$\Rightarrow \bar{x} \notin (RHS)$. $\square$

Back to 2D example:

$$\begin{matrix} y \geq 1 \\ y \leq x+1 \end{matrix} \Rightarrow \left.\begin{matrix} -y \leq -1 \\ y \leq x+1 \end{matrix}\right\} \xRightarrow{\text{ADD}} x \geq 0, \text{ which is } \text{Proj}_x(P).$$

Equivalently, $\left\{ \begin{array}{rl} -y & \le -1 \\ -x+y & \le 1 \end{array} \right\} \equiv \underbrace{\begin{bmatrix} 0 \\ -1 \end{bmatrix}}_{A} x + \underbrace{\begin{bmatrix} -1 \\ 1 \end{bmatrix}}_{B} y \le \underbrace{\begin{bmatrix} -1 \\ 1 \end{bmatrix}}_{\bar{b}}$.

What $\bar{v} \geq \bar{0}$ with $\bar{v}^T B = 0$ can we take to eliminate y?

$\bar{v} = \begin{bmatrix} \lambda \\ \lambda \end{bmatrix}$, $\lambda \geq 0$ works! Or, $\bar{v} = \lambda \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, $\lambda \geq 0$ are all the multipliers!

Could we generalize this result illustrated in the example, i.e., could we describe $\text{Proj}_{\bar{x}}(P)$ using only a finite # $\bar{v}^i$'s?

Theorem 5 If $\{\bar{v} \geq \bar{0},\ \bar{v}^T B = \bar{0}^T\} = \underbrace{\textbf{cone}\{\bar{v}^1, \ldots, \bar{v}^k\}}_{\text{the projection cone is finitely generated}}$

$\stackrel{\text{def}}{\equiv} \left\{ \sum_{i=1}^{k} \lambda_i \bar{v}^i \,\middle|\, \lambda_i \geq 0 \right\}$, then

$$\text{Proj}_{\bar{x}}(P) = \left\{ \bar{x} \,\middle|\, (\bar{v}^i)^T A \bar{x} \le (\bar{v}^i)^T \bar{b},\ i = 1, \ldots, k \right\}.$$

Def The set $\{\bar{v} \mid \bar{v} \geq \bar{0},\ \bar{v}^T B = \bar{0}^T\}$ is called the **projection cone** of $\text{Proj}_{\bar{x}}(P)$.

Example (continued): The projection cone of $\text{Proj}_x(P)$ is

$$\left\{ \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \,\middle|\, \begin{array}{l} v_1, v_2 \geq 0 \\ -v_1 + v_2 = 0 \end{array} \right\} = \left\{ \lambda \begin{bmatrix} 1 \\ 1 \end{bmatrix} \,\middle|\, \lambda \geq 0 \right\}.$$

Definition of Comparison

Let $S \subseteq \mathbb{Z}^n \times \mathbb{R}^m$ have two formulations

$$P_1 = \{(\bar{x}, \bar{y}, \bar{u}^1, \bar{v}^1) \in \mathbb{R}^{n+m+p_1+q_1} \mid A_1\bar{x} + B_1\bar{y} + C_1\bar{u}^1 + D_1\bar{v}^1 \le \bar{b}^1\}$$

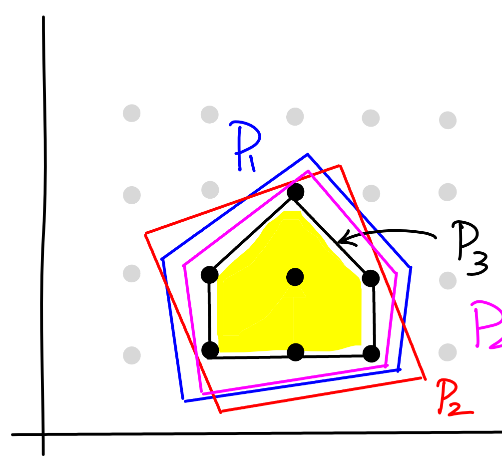
and

$$P_2 = \{(\bar{x}, \bar{y}, \bar{u}^2, \bar{v}^2) \in \mathbb{R}^{n+m+p_2+q_2} \mid A_2\bar{x} + B_2\bar{y} + C_2\bar{u}^2 + D_2\bar{v}^2 \le \bar{b}^2\}$$

where $p_1 \neq p_2$, $q_1 \neq q_2$ and $p_1+q_1 \neq p_2+q_2$.

Then P_1 is a **better (stronger, tighter)** formulation than P_2 if $\text{Proj}_{(\bar{x},\bar{y})}(P_1) \subset \text{Proj}_{(\bar{x},\bar{y})}(P_2)$.

P_j, $j=1,2,3,4$ are formulations of S.



Here, $P_3 \subset P_j$, $j=1,2,4$.

So, P_3 is stronger than P_j.

Similarly, $P_4 \subset P_1$, so is stronger than P_1.

Example

$$S = \{ \bar{x} \mid \bar{x} \in \{0,1\}^n, (x_1 = 1) \Rightarrow (x_2=1) \wedge \cdots \wedge (x_n = 1) \}.$$

$$P_1 = \{ \bar{x} \mid x_1 \le x_2, \ldots, x_1 \le x_n, \quad 0 \le x_i \le 1, \quad i=1,\ldots,n \}$$ and

$$P_2 = \{ \bar{x} \mid (n-1)x_1 \le x_2 + \cdots + x_n, \quad 0 \le x_i \le 1, \quad i=1,\ldots,n \}$$

are formulations for S. ($P_i \cap \mathbb{Z}^n$ gives S for $i=1,2$).

P_1 is the **disaggregated** formulation, while P_2 is an **aggregated** formulation.

Claim $P_1 \subset P_2$.

$P_1 \subseteq P_2$ is trivial — just add up $x_1 \le x_i$, $i=2,\ldots,n$, to get $(n-1)x_1 \le x_1 + \cdots + x_2$.

To show $P_1 \subset P_2$, identify one point in P_2 / P_1.

$\left(\frac{1}{n-1}, 1, 0, \ldots, 0\right) \in P_2 / P_1$. For instance, $x_3 \ge x_1$ is violated here.

In fact, P_1 is the strongest formulation for S here!

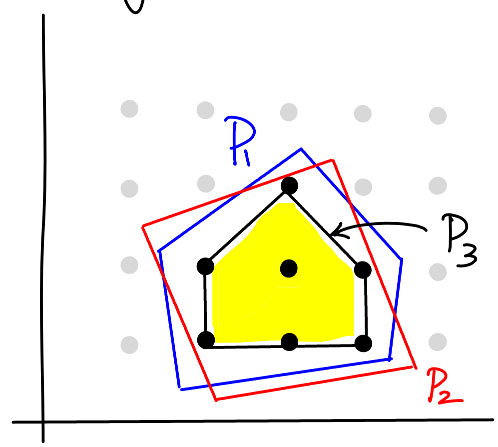
Def Given $S \in \mathbb{Z}^n \times \mathbb{R}^m$, $P \subseteq \mathbb{R}^n \times \mathbb{R}^m$ is a **sharp** or **ideal formulation** for S if

(1) $\forall \begin{bmatrix}\bar{c}\\ \bar{d}\end{bmatrix} \in \mathbb{R}^{n+m}$ such that $\max\left\{ [\bar{c}^T \bar{d}^T]\begin{bmatrix}\bar{x}\\ \bar{y}\end{bmatrix} \,\middle|\, \begin{bmatrix}\bar{x}\\ \bar{y}\end{bmatrix} \in P \right\}$ is finite, the optimum is obtained for some element of S.

(2) An extended formulation of S (using extra variables) is sharp if its projection to $(\bar{x}, \bar{y})$-space is sharp in the sense of (1) above.

Intuitively, all corner points of P are integral.

P_3 is the sharp formulation of S here:



More generally, P is the convex hull of S.

Def For $X \subseteq \mathbb{R}^n$, the **convex hull** is defined as

$$\text{conv}(X) = \left\{ \bar{x} \in \mathbb{R}^n \,\middle|\, \bar{x} = \sum_{i=1}^{k} \lambda_i \bar{x}^i,\ \lambda_i \geq 0,\ \sum_{i=1}^{k} \lambda_i = 1, \text{ for all finite subsets } \{\bar{x}^1, \ldots, \bar{x}^k\} \text{ of } X \right\}.$$

To show a formulation P is sharp for a set S, we can show every corner point of P is integral, i.e., all their entries are integers.

In 2D, any two non-parallel lines representing equations from P **could** intersect at a corner point, assuming it is feasible.

In general, in $\mathbb{R}^n$, we get a corner point from n linearly independent (LI) equations that define P, assuming their intersection is feasible.

We saw that $\left(\frac{1}{n-1}, 1, 0, 0, \ldots, 0\right) \in P_2$ (aggregated formulation). In fact, this point is a corner point of P_2, defined by the n LI constraints.

$\to$ more on this and other details in the next lecture...

MATH 567: Lecture 7 (01/30/2025)

Today: * sharp formulations
* TSP Formulations

Example $\left[(x_1=1) \Rightarrow \bigwedge_{j=2}^{n}(x_j=1),\ x_i \in \{0,1\} \forall i\right]$, P_1, P_2, (continued...)

We saw that $\left(\frac{1}{n-1}, 1, 0, 0 \dots, 0\right) \in P_2$ (aggregated formulation). In fact, this point is a corner point of P_2, defined by the n LI constraints

$$(n-1)x_1 \leq x_2 + \dots + x_n \text{ — (1)}$$
$$x_2 \leq 1 \text{ — (2)}$$
$$x_j \geq 0,\ j=3,\dots,n \text{ — } (n-2)$$

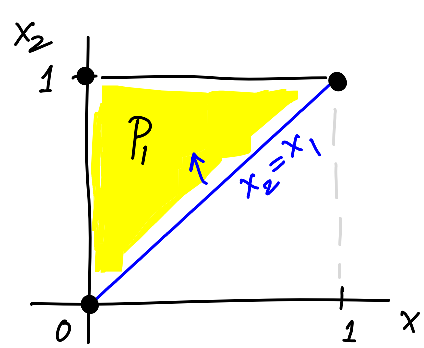
satisfied as equations. Hence P_2 is not sharp for S.

To show P_1 (disaggregated formulation) is sharp for S, we show each corner point of P_1 is integral. The inequalities defining P_1 can be broken down into 3 groups:

$$x_i \geq x_1,\ i=2,\dots,n \text{ — (1)}$$
$$x_i \geq 0,\ i=1,\dots,n \text{ — (2)}$$
$$x_i \leq 1,\ i=1,\dots,n \text{ — (3)}$$

First, check intuition in 2D:

$$P_1 = \{\bar{x} \in \mathbb{R}^2 \mid x_2 \geq x_1,\ 0 \leq x_i \leq 1,\ i=1,2\}.$$



Indeed, all three corner points are integral!

In general, we consider a few cases:

(i) All $(n-1)$ inequalities from (1), and one from (2) or (3):

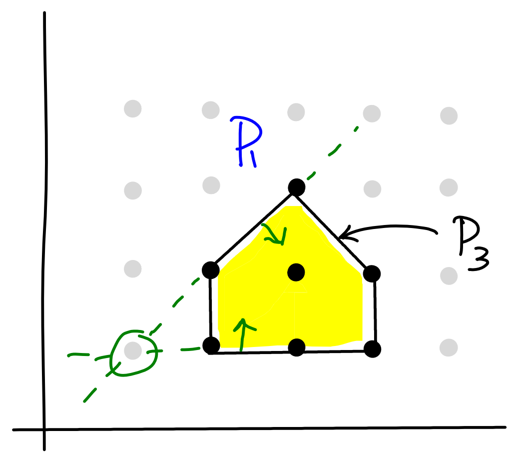
$$\Rightarrow \quad x_i = 0 \ \forall i \quad \text{or} \quad x_i = 1 \ \forall i.$$

(ii) All n inequalities from (2) or (3): $\Rightarrow$ trivial.

(iii) $2 \leq j < n$ inequalities from (1) and $n-j$ inequalities from (2) or (3) $\Rightarrow$ Can show $x_i \in \{0,1\} \ \forall i$.

Recall that we need to consider equality versions of the constraints and their intersections to enumerate all potential corner points.

For instance, the two LI lines corresponding to two constraints indicated by green dashed lines here meet at a point that is not feasible, and hence is not a corner point of P_3.



If we can provide a sharp formulation with a "small", i.e., a polynomial number, of inequalities, then we can solve any linear optimization problem over S "easily", i.e., in polynomial time.

But for many problems, e.g., the traveling salesman problem (TSP), the sharp formulation has exponentially many inequalities.

We now consider several examples of sharp formulation.

More Examples of Sharp Formulations

1. Given a bipartite graph $G = (V_1 \cup V_2, E)$, let $S_M \subseteq \mathbb{Z}^{|E|}$ be the collection of incidence vectors of all matchings.

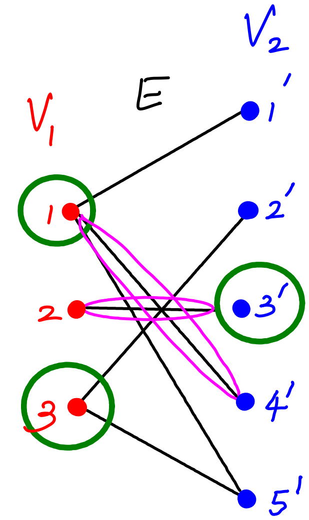
M for matching

Then $P_m = \{ \bar{x} \in \mathbb{R}^{|E|} \mid \bar{x} \geq \bar{0},$

$$\sum_{e \ni i} x_e \leq 1 \;\; \forall i \in V_1,$$

$$\sum_{e \ni j} x_e \leq 1 \;\; \forall j \in V_2 \}$$

is a sharp formulation for S_m.



$\{(1,4'), (2,3')\}$ is a matching, and $\{1,3,3'\}$ is a node cover.

2. Given $G = (V_1 \cup V_2, E)$ as above, let $S_N \subseteq \mathbb{Z}^{|V|}$ be the

$V = V_1 \cup V_2$

collection of incidence vectors of all node covers, i.e., subsets of nodes that cover all edges. Then

$$P_N = \{ \bar{x} \in \mathbb{R}^{|V|} \mid 0 \leq \bar{x} \leq \bar{1}, \sum_{i \in e} x_i \geq 1 \;\; \forall e \in E \}$$

$x_i + x_j \geq 1 \;\; \forall (i,j) \in E$

is a sharp formulation for S_N.

The default problems ask to identify the maximum (cardinality) matching, and the minimum (cardinality) node cover.

3. Define S_{ij} and P_{ij} as follows, using $x_1, x_2, x_3 \in \{0,1\}$.

$$S_{ij} = \{ \bar{x} \mid \bar{x} \in \{0,1\}^3, \; (x_i = 0) \vee (x_j = 0) \} \text{ and}$$

$$P_{ij} = \{ \bar{x} \mid \bar{x} \in \mathbb{R}^3, \; 0 \le \bar{x} \le \bar{1}, \; x_i + x_j \le 1 \}, \text{ for } i,j = 1,2,3, \; i \neq j.$$

We can show P_{ij} is a sharp formulation for S_{ij}.

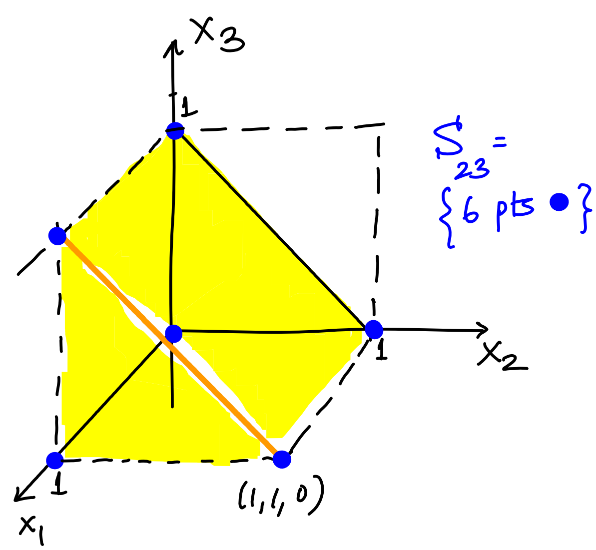
For instance,

$$S_{23} = \{ (0,0,0), (1,0,0), (0,1,0), (1,1,0), (0,0,1), (1,0,1) \} \text{ and}$$

$$P_{23} = \left\{ \bar{x} \in \mathbb{R}^3 \;\middle|\; x_2 + x_3 \le 1, \; \begin{array}{l} x_1 \ge 0, \; x_2 \ge 0, \; x_3 \ge 0 \\ x_1 \le 1, \; \underbrace{x_2 \le 1, \; x_3 \le 1}_{\text{could remove!}} \end{array} \right\}.$$

Could check all subsets of 3 LI inequalities $\left(\le \binom{7}{3} = 35 \text{ choices} \right)$.

We could also just plot P_{23}!



In another formulation, we could drop $x_2 \le 1$ and $x_3 \le 1$, since we have $x_2 + x_3 \le 1$, which implies $x_2 \le 1$ and $x_3 \le 1$ along with $x_2 \ge 0$ and $x_3 \ge 0$.

Now, let

$$S = S_{12} \cap S_{23} \cap S_{31} = \{ \bar{x} \in \{0,1\}^3 \mid (x_1=0) \vee (x_2=0) \wedge (x_2=0) \vee (x_3=0) \wedge (x_3=0) \vee (x_1=0) \}$$

and

$$P = P_{12} \cap P_{23} \cap P_{31} = \{ \bar{x} \in \mathbb{R}^3 \mid 0 \le \bar{x} \le \bar{1},\ x_1+x_2 \le 1,\ x_2+x_3 \le 1,\ x_3+x_1 \le 1 \}.$$

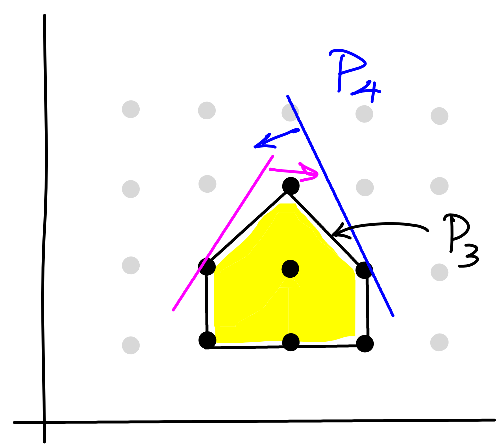
Is P a sharp formulation for S? No!

For instance, $\max \{ x_1+x_2+x_3 \mid \bar{x} \in P \}$ has a unique optimal solution at $(1/2, 1/2, 1/2) \notin S$.

Notice that in S, no point can have two x_j's set to 1, as $(x_i=0) \vee (x_j=0)$ is true for all three pairs. So we cannot get $x_1+x_2+x_3 = 2$. But $(1/2,1/2,1/2) \in P$, and indeed gives a higher value for $x_1+x_2+x_3$.

Also, $(1/2,1/2,1/2)$ is a corner point of P: it is the point of intersection of $x_1+x_2=1$, $x_2+x_3=1$, $x_3+x_1=1$, which are LI.

There was question about whether the sharp formulation P is unique. As a set, it captures the convex hull of S and conv(S) itself is unique. But there could be alternative descriptions of P, e.g., by adding redundant constraints, as shown here with the case of P_4, which adds two redundant constraints to P_3.



Traveling Salesman Problem (TSP)

* n cities
* c_{ij} : cost (or distance) from city i to city j is defined on a directed graph $G=(V,E)$.
  directed

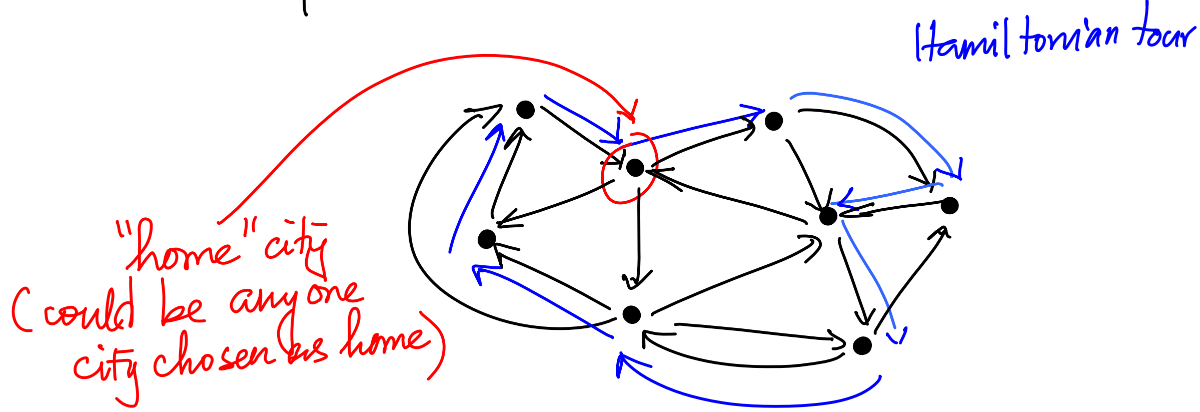
smallest total costs

Goal: find a shortest Hamiltonian tour, i.e., a single directed cycle that contains all n nodes (cities), and each node is visited exactly once.

TSP is perhaps the most widely studied combinatorial optimization problem. We will consider a few different formulations for the TSP.

Forget c_{ij}'s for now.

Goal: Formulations for $S \subseteq \mathbb{Z}^{|E|}$, the set of incidence vectors of all Hamiltonian tours



$$S = \{\bar{x} \mid \bar{x} \text{ is the incidence vector of a Hamiltonian tour}\}.$$

$x_{ij} = 1$ if $(i,j) \in$ tour

$\bar{x} \in S \Rightarrow$

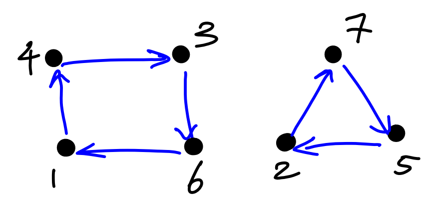
$$\left.\begin{array}{l} \displaystyle\sum_{j:(i,j)\in E} x_{ij} = 1 \quad \forall i \\ \displaystyle\sum_{j:(i,j)\in E} x_{ji} = 1 \quad \forall i \\ 0 \le x_{ij} \le 1, \quad \bar{x} \in \mathbb{Z}^{|E|} \end{array}\right\} \text{———} (1)$$

remove to get formulation, i.e., the polytope

Assume $x_{ii} = 0 \ \forall i$.

But (1) is not enough, as it allows subtours.

Here is a collection of two subtours, which together satisfy (1):



We have to avoid subtours. We examine a few different ways to avoid them. One option involves adding some extra variables, and extra constraints. The other option involves adding extra constraints using the original variables (x_{ij}).

We have to avoid subtours!

<u>First approach</u> We add u_i, $i = 1, \dots, n$, node variables.

$u_i \equiv$ position of node i in tour.

any node could be the "home city"

We assume node 1 is the "home city". $u_1 = 1$.

$u_3 = 5 \Rightarrow$ Node 3 is the 5^{th} node in the tour, starting from node 1.

MATH 567 : Lecture 8 (02/04/2025)

Today: TSP formulations and comparisons

Recall $u_i \equiv$ position of node i in tour.

We want to impose

if $x_{ij}=1$ then $u_j \geq u_i+1$ for $i\neq 1, j\neq 1$.

We write

$$u_i - u_j + 1 \leq n(1-x_{ij}), \ \forall i\neq 1, \forall j \neq 1 \quad \text{——— (2)}$$

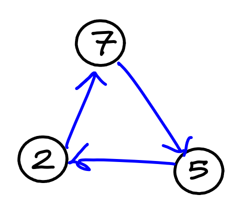
Let's check:

if $x_{ij}=1$ (2) $\Rightarrow$ $u_i - u_j + 1 \leq 0 \implies u_j \geq u_i+1$. ✓

if $x_{ij}=0$ (2) $\Rightarrow$ $u_i - u_j \leq n-1$. ✓

Notice that u_j need not represent the position of node j in the tour exactly. But u_j will be at least u_i+1 when $x_{ij}=1$. Thus, we could have $u_j = u_i+5$, for instance. But even such values eliminate subtours, as they will not allow split (sub)tours as illustrated previously.

$$\{u_7 \geq u_2+1, \ u_2 \geq u_5+1, \ u_5 \geq u_7+1\}$$



$\hookrightarrow$ cannot hold together!

But if we add $2 \leq u_j \leq n$, $\forall j \neq 1$, we get u_j representing the position of node j exactly.

Claim $S = \{\bar{x} \in \mathbb{Z}^{|E|} \mid \exists \bar{u} : (\bar{x}, \bar{u}) \text{ satisfies (1) and (2)}\}$.

Proof '$\subseteq$': If $\bar{x}$ is a tour, take u_i = position of node i in $\bar{x}$.

If $x_{ij} = 1$ (2) $\Rightarrow$ $u_j \geq u_i + 1$. ✓

$x_{ij} = 0$ (2) $\Rightarrow$ $u_i - u_j + 1 \leq n$. ✓

'$\supseteq$': $\bar{x} \notin S \overset{\text{want to show}}{\Longrightarrow} \bar{x}$ violates (1) or

$\bar{x}$ satisfies (1), but there is no $\bar{u}$ to satisfy (2).

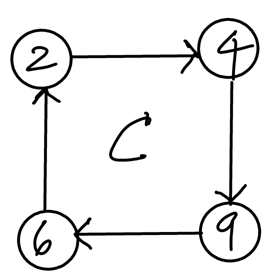
Case 1: $\bar{x}$ violates (1): trivial.

Case 2: $\bar{x}$ satisfies (1), but is not a tour.

Let C be a subtour with $1 \notin C$. In more detail,

$$C = \Big\{\{\overbrace{i_1, i_2, \ldots, i_k}^{\text{nodes}}\} \text{ along with edges } (i_r, i_{r+1}),\ r = 1, \ldots, k-1 \text{ and } (i_k, i_1), \text{ where } i_r \neq 1.\Big\}$$

e.g.,



Consider

$$u_i - u_j + 1 \leq n(1 - x_{ij}) \quad \text{— (2)}$$

for each $i, j \in C$.

Add (2) around $C \Rightarrow |C| \leq n\,(|C| - X(C))$ where

$X(C) = \sum_{(i,j) \in C}' x_{ij}$. Hence $X(C) \leq \left(1 - \frac{1}{n}\right)|C|$.

But x_{ij}'s violate this inequality!

there will be exactly $|C|$ x_{ij}'s set to 1!

□

Remark If we use (1), and instead of (2), write

$$\left.\begin{array}{ll} 1 \le u_i \le n & \text{(a)} \\ u_i - u_j + 1 \le n(1 - x_{ij}), \ \forall i, \ \forall j \ne 1 & \text{(b)} \\ n - u_i \le (n-1)(1 - x_{i1}), \ \forall i \ne 1 & \text{(c)} \end{array}\right\} \ (3),$$

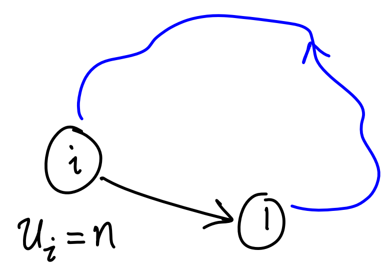
then (1) & (3) together give a valid formulation for S.

3 (b) forces $x_{ij} = 1 \Rightarrow u_j \ge u_i + 1, \ \forall i, \ \forall j \ne 1.$

3 (c) forces $x_{i1} = 1 \Rightarrow u_i \ge n \quad \forall i \ne 1.$

forces $u_i = n$, with 3(a)

u_i for node i in the are $(i, 1)$ coming into node 1 is forced to n, making i the last node in the tour.



$$S = \left\{ \bar{x} \in \mathbb{Z}^{|E|} \;\middle|\; \exists \bar{u} : (\bar{x}, \bar{u}) \text{ satisfy (1) \& (3)} \right\}.$$

(1)+(2) and (1)+(3) are quite similar to each other in terms of strength, as well as in computation.

(1)+(2) is the **Miller-Tucker-Zemlin (MTZ)** formulation.

Subtour Formulation

$$\boxed{\forall W \subseteq V,\ |W|>1,\ \sum_{\substack{i,j\in W\\(i,j)\in E}} x_{ij} \le |W|-1} \qquad (4)$$

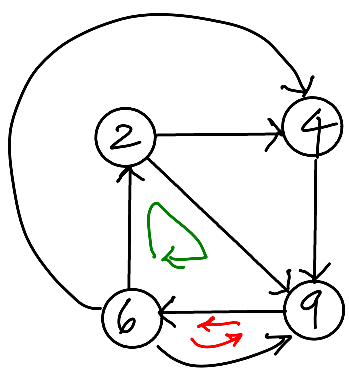
?

more on this point in a bit...

(4) has exponentially many constraints in $|V|=n$.

(1)+(4) is a valid formulation for S, i.e.,

$$S = \{\bar{x} \in \mathbb{Z}^{|E|} \mid \bar{x} \text{ satisfies (1) and (4)}\}.$$



$W = \{2,4,6,9\}$

$$\sum_{\substack{i,j\in W\\(i,j)\in E}} x_{ij} \le 3$$

7 x_{ij} terms here

This constraint will avoid **all** possible subtours of length 4 in G which use $\{2,4,6,9\}$, and not just the obvious one, i.e., 2-4-9-6-2.

At the same time, this constraint will allow subtours of length 2 or 3 in W, e.g., 6-9-6 or 2-9-6-2. We need the subtour constraints for $W' = \{6,9\}$ and $W'' = \{2,6,9\}$ to eliminate them.

Now, let's consider the $W \underset{?}{\subsetneq} V$ question...

Q. Should we write the subtour constraint for $W = V$? Wouldn't that eliminate all possible Hamiltonian tours?

The answers are YES and YES, as it does not matter much when considering formulations for S. The default option is that we write the subtour constraints for all $W \subset V$, i.e., with $|W| \leq n-1$. In this case, we will indeed capture the Hamiltonian tours.

On the other hand, we could write the subtour constraint for $W = V$, in which case the Hamiltonian tours are avoided. But Hamiltonian paths are still permitted, and we could add the last missing arc in any Hamiltonian path to get the corresponding tour.

But once we involve the costs c_{ij}, we should ideally not write the subtour constraint for $W = V$. The last connecting arc (to complete the tour) could have a huge cost, affecting the minimality computations.

Also, notice that (4) is valid for $|W| = 1$, since we assume that there are no self loops, i.e., no arcs (i,i). Equivalently, $x_{ii} = 0 \; \forall i$.

Comparing MTZ and Subtour formulations

First guess

If C is a subtour (cycle) with $1 \notin C$, adding (2) around C got us

$$X(C) \leq \left(1 - \frac{1}{n}\right)|C| \quad \text{———} \quad (\Delta)$$

If $n=100$, $X(C) \leq 0.99|C|$, which is not very effective.

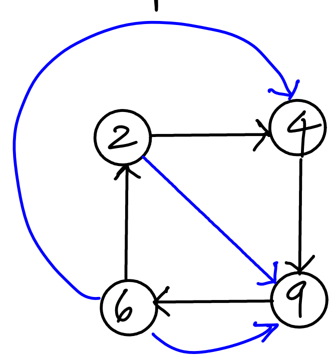
Notice that $X(C) \leq |C|$ holds trivially (and from (1)). So, as n becomes larger and larger, the right-hand side value becomes closer and closer to $|C|$, while still remaining strictly smaller than $|C|$.

In the subtour formulation, using $W = C$, we get

$$\underbrace{\sum_{\substack{i,j \in W \\ (i,j) \in E}}}_{\text{more } x_{ij} \text{ terms than included in } X(C).} x_{ij} \leq \underbrace{|C| - 1}_{\text{almost "1 better than } (\Delta)\text{".}} \quad \text{———} \quad (*)$$

Thus $(*)$ is stronger than (Δ) in both the left-hand and the right-hand sides. But we now make this comparison more formal.

not just the 4 arcs in C (2-4-9-6-2)



We consider

$$P_{MTZ} = \{ (\bar{x}, \bar{u}) \in \mathbb{R}^{|E|} \times \mathbb{R}^{|V|} \mid (\bar{x}, \bar{u}) \text{ satisfy } (1) \text{ and } (2) \},$$ and

$$P_{subtour} = \{ \bar{x} \in \mathbb{R}^{|E|} \mid \bar{x} \text{ satisfies } (1) \text{ and } (4) \}.$$

To compare, we compute $\mathrm{Proj}_{\bar{x}}(P_{MTZ})$.

Theorem 6 $\mathrm{Proj}_{\bar{x}}(P_{MTZ}) = \{ \bar{x} \mid \exists \bar{u} : (\bar{x}, \bar{u}) \text{ satisfies } (1) \,\&\, (2) \}$

$$= \{ \bar{x} \mid \bar{x} \text{ satisfies } (\triangle) \text{ for all cycles } C, 1 \notin C \}.$$

there could be exponentially many such cycles.

Indeed, P_{MTZ} is described by a small (polynomial in m, n) number of constraints using the n extra variables u_i. But an exponential number of constraints are needed to describe $\mathrm{Proj}_{\bar{x}}(P_{MTZ})$.

Proof P_{MTZ} is given by (1) and

$$u_i - u_j + 1 \le n(1 - x_{ij}) \quad \forall i \ne 1, \forall j \ne 1. \quad \text{——— } (2)$$

$$\Rightarrow \quad u_i - u_j + n x_{ij} \le n - 1, \quad \forall i \ne 1, \forall j \ne 1.$$

Recall: Projection of $P = \{ (\bar{x}, \bar{y}) \mid A\bar{x} + B\bar{y} \le \bar{b} \}$ to $\bar{x}$:

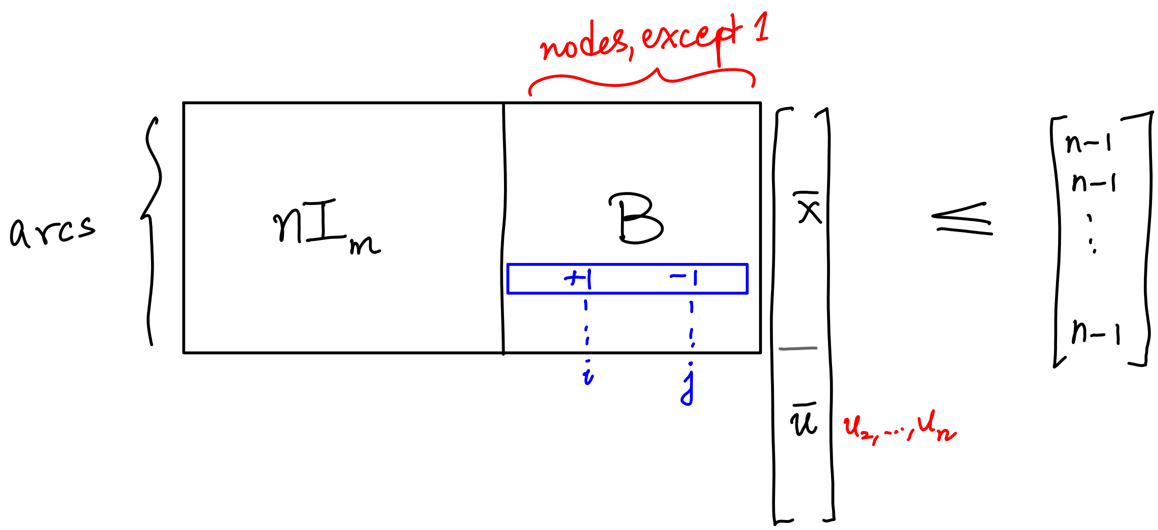
$$\mathrm{Proj}_{\bar{x}}(P) = \{ \bar{x} \mid \exists \bar{y} : (\bar{x}, \bar{y}) \in P \}.$$

$$u_i - u_j + n x_{ij} \leq n-1 \quad \forall i \neq 1, \forall j \neq 1,$$

Can be written in matrix form as

$$nI\bar{x} + B\bar{u} \leq (n-1)\bar{1}, \quad \text{where}$$

I is the identity matrix, B is the arc-node incidence matrix of G, with column for node 1 removed, and any non-zero entry corresponding to arcs incident to node 1 zeroed out, and $\bar{1}$ is the vector of ones.



MATH 567: Lecture 9 (02/06/2025)

Today: * TSP: MTZ v/s subtour formulations
* sharp formulation of a disjunction

Recall: $\mathrm{Proj}_{\bar{x}}(P_{MTZ})$ to compare with $P_{subtour}$

$$u_i - u_j + n x_{ij} \le n-1 \quad \forall i \ne 1, \forall j \ne 1; \longrightarrow \text{matrix form is}$$

$$nI\bar{x} + B\bar{u} \le (n-1)\bar{1}, \quad \text{where}$$

I is the identity matrix, B is the arc-node incidence matrix of G, with column for node 1 removed, and any non-zero entry corresponding to arcs incident to node 1 zeroed out, and $\bar{1}$ is the vector of ones.

$$\begin{array}{c} \\ \text{arcs} \left\{ \right. \end{array} \begin{bmatrix} nI_m & \overbrace{B}^{\text{nodes, except 1}} \end{bmatrix} \begin{bmatrix} \bar{x} \\ \bar{u} \end{bmatrix} \le \begin{bmatrix} n-1 \\ n-1 \\ \vdots \\ n-1 \end{bmatrix}, \qquad \bar{u}: u_2, \dots, u_n$$

$$\text{row of } B: \begin{array}{cc} +1 & -1 \\ i & j \end{array}$$

The **node-arc incidence matrix** of a directed graph $G=(V,E)$ with $|V|=n$, $|E|=m$ is an $n \times m$ matrix with a row for each node and a column for each arc, with entries in $\{-1,0,1\}$. The column corresponding to arc (i,j) has a $+1$ in row i and a -1 in row j, and other entries are zero. B above is the transpose of this matrix, with the modifications made as specified.

Also, recall the definition of projection – we went from $A\bar{x}+B\bar{y} \le b$ to the space of $\bar{x}$ variables by eliminating the "unwanted" $\bar{y}$ variables.

Let $C = \{\bar{v} \geq \bar{0} \mid \bar{v}^T B = \bar{0}^T\}$ be the projection cone.

$\bar{v}$?

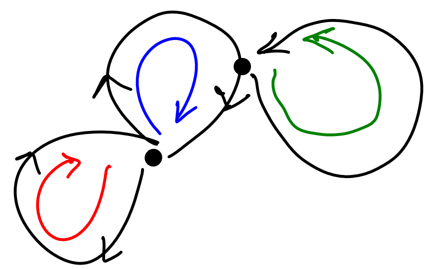
$$C = \{\bar{v} \geq \bar{0} \mid \forall i \neq 1, \overbrace{\sum_j{}' v_{ij} = \sum_j{}' v_{ji}}^{\text{come in and go out at } i \text{ equal \# times}}\}$$

$= \{\bar{v} \mid \bar{v} \text{ is a } \underline{\text{circulation}} \text{ in } G\}$

or circuit, generalization of a cycle

$\bar{v}$ is the incidence vector of a circulation.

$\bar{v} \in \{0,1\}^m$, $m = \#$ arcs.



It turns out we can describe all circulations as unions of a finite set of "basic" cycles. In other words, the projection cone is finitely generated.

$$C = \{\sum_{i=1}^{k} \lambda_i \bar{v}^i \mid \lambda_i \geq 0\} \quad \text{where}$$

$\bar{v}^1, \dots, \bar{v}^k$ are the incidence vectors of a set of basic cycles.

$$\Rightarrow \operatorname{Proj}_{\bar{x}}(P_{MTZ}) = \left\{ \bar{x} \,\middle|\, \begin{array}{l} (\bar{v}^i)^T (n I)\bar{x} \le (\bar{v}^i)^T (n-1)\bar{1}, \ i=1,\dots,k, \\ \text{and system (1)} \end{array} \right\}.$$

We do not get any inequalities stronger than $\triangle$ here.

If $(\bar{v}^i)^T = [0, 0, \dots, 0, \underbrace{1, 1 \dots, 1}, 0, \dots, 0]$,

1's for $(i,j) \in C$; assumed to be set all together here WLOG.

then

$$(\bar{v}^i)^T (n I)\bar{x} \le (\bar{v}^i)^T (n-1)\bar{1}$$

$$n\, x(C) \le (n-1)\,|C|$$

$$\Rightarrow \quad x(C) \le \left(1 - \frac{1}{n}\right)|C|, \text{ which is } \triangle.$$

$\Rightarrow$ The subtour formulation is stronger!

Sharp Formulation of a Disjunction

Let $S = Q_1 \cup \cdots \cup Q_k$ where $Q_i = \{\bar{x} \mid A_i \bar{x} \le \bar{b}^i\}$, $i=1,\ldots,k$.
$\bar{x} \in \mathbb{R}^n$, are non-empty polyhedra with the same recession cone. Then $P \subseteq \underbrace{\mathbb{R}^n}_{\bar{x}} \times \underbrace{\mathbb{R}^k}_{\bar{y}} \times \underbrace{(\mathbb{R}^n \times \cdots \times \mathbb{R}^n)}_{k \text{ copies, for } \bar{x}^1,\ldots,\bar{x}^k}$

defined as the set of all vectors $(\bar{x}, \bar{y}, \bar{x}^1, \ldots, \bar{x}^k)$ that satisfy

$$P = \left\{ \begin{array}{l} A_1 \bar{x}^1 \le \bar{b}^1 y_1 \\ \quad \vdots \qquad \vdots \\ A_k \bar{x}^k \le \bar{b}^k y_k \\ \bar{x}^1 + \cdots + \bar{x}^k = \bar{x} \\ y_1 + \cdots + y_k = 1 \\ 0 \le y_i \le 1 \ \forall i \end{array} \right\}$$

could ignore, as $y_1 + \cdots + y_k = 1$ implies the same with $y_i \ge 0$.

is a sharp formulation for S.

S is the same (∗) set for which we wrote (∗- big-M) and (∗- sharp) formulations.

Q: How do we prove P is indeed a sharp formulation?

To show P is a sharp formulation for S, we have to show $\quad \text{Proj}_{\bar{x}}(P) = \text{conv}(S)$.

We need $\mathrm{conv}\left(\bigcup_{i=1}^{k} Q_i\right)$ to be closed, but we'll assume that.

It appears the approach to identify all corner points will not work here. Could we use another approach?

Def An inequality $\bar{a}^T\bar{x} \le \beta$ is a **valid inequality** for $X \subseteq \mathbb{R}^n$ if $\bar{a}^T\bar{x} \le \beta \;\; \forall \bar{x} \in X$.

We can try to derive conditions that guarantee an inequality is valid for $\mathrm{conv}(S)$ iff it is valid for $\mathrm{Proj}_{\bar{x}}(P)$.

$$\bar{a}^T\bar{x} \le \beta \text{ is valid for } \mathrm{conv}(Q_1 \cup \dots \cup Q_k)$$

$$\Longleftrightarrow \bar{a}^T\bar{x} \le \beta \text{ is valid for each of } Q_1, \dots, Q_k.$$

$$\Longleftrightarrow \exists\, \bar{u}^i \ge \bar{0}, \quad \bar{a}^T = (\bar{u}^i)^T A_i, \quad (\bar{u}^i)^T \bar{b}^i \le \beta, \text{ i.e.,}$$

we can derive $\bar{a}^T\bar{x} \le \beta$ from $A_i\bar{x} \le \bar{b}^i$.

$\bar{a}^T\bar{x} \le \beta$ is valid for $\mathrm{Proj}_{\bar{x}}(P) \iff \exists$ multipliers that derive $\bar{a}^T\bar{x} \le \beta$ from P by eliminating $\bar{x}^1,\dots,\bar{x}^k, y_1,\dots,y_k$.

$$
\begin{array}{l|lllllllllll}
\bar{a}^T & \bar{x} & -\bar{x}^1 & -\bar{x}^2 & \cdots & -\bar{x}^k & & & & & = & \bar{0} \\
\bar{v}^{1T} & & A_1\bar{x}^1 & & & & -\bar{b}^1 y_1 & & & & \le & \bar{0} \\
\bar{v}^{2T} & & & A_2\bar{x}^2 & & & & -\bar{b}^2 y_2 & & & \le & \bar{0} \\
\vdots & & & & \ddots & & & & & & & \vdots \\
\bar{v}^{kT} & & & & & A_k\bar{x}^k & & & & -\bar{b}^k y_k & \le & \bar{0} \\
\beta' & & & & & & y_1 & +\, y_2 & + \cdots + & y_k & = & 1 \\
\beta'_1 & & & & & & -y_1 & & & & \le & 0 \\
\beta'_2 & & & & & & & -y_2 & & & \le & 0 \\
\vdots & & & & & & & & \ddots & & & \vdots \\
\beta'_k & & & & & & & & & -y_k & \le & 0
\end{array}
$$

We need

$$\bar{a}^T = (\bar{v}^1)^T A_1 \rightarrow \text{eliminates } \bar{x}^1$$

$$\vdots$$

$$\bar{a}^T = (\bar{v}^k)^T A_k \rightarrow \text{eliminates } \bar{x}^k$$

We need

$\bar{a} \ge \bar{0}$, $\bar{v}^i \ge \bar{0}$,

$\beta' \ge 0$, $\beta'_i \ge 0$

and $\beta' \le \beta$

and

$$(-\bar{v}^1)^T\bar{b}^1 + \beta' - \beta'_1 = 0 \rightarrow \text{eliminate } y_1$$

$$\vdots$$

$$(-\bar{v}^k)^T\bar{b}^k + \beta' - \beta'_k = 0 \rightarrow \text{eliminate } y_k$$

$$\left\}\begin{array}{l} (-\bar{v}^1)^T\bar{b}^1 + \beta' \ge 0 \\ \vdots \\ (-\bar{v}^k)^T\bar{b}^k + \beta' \ge 0 \end{array}\right.$$

Notice we need $\beta_i' \geq 0$, and hence could scale the right-hand sides of these inequalities to get rid of β_i's.

$$\left\{ \begin{array}{ll} \bar{a}^T = (\bar{v}^i)^T A_i , & i = 1, \dots, k \\ \beta' \geq (\bar{v}^i)^T \bar{b}^i , & i = 1, \dots, k \\ \beta' \leq \beta & \end{array} \right\}$$

Need to show this system has non-negative solution in $(\bar{v}^i, \beta')$.

We could use this approach for specific instances in which the A_i and $\bar{b}^i$ are provided.

Definitions and Results on Polyhedra

We collect several relevant definitions and results related to polyhedra here. We will use these result in further elucidating properties and strengths of formulations, as well as comparing them.

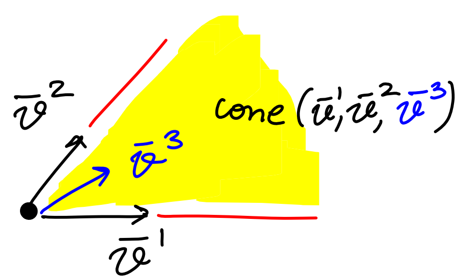
* $C \subseteq \mathbb{R}^n$ is convex if $\lambda \bar{x} + (1-\lambda)\bar{y} \in C \;\forall\, \bar{x}, \bar{y} \in C,\ \lambda \in [0,1]$.

* $C \subseteq \mathbb{R}^n$ is a convex cone if $\lambda \bar{x} + \mu \bar{y} \in C \;\forall\, \bar{x}, \bar{y} \in C$, and $\lambda, \mu \geq 0$.

* $\text{cone}(\{\bar{v}^1, \ldots, \bar{v}^k\}) = \{\bar{x} \mid \bar{x} = \sum_{i=1}^{k} \lambda_i v^i,\ \lambda_i \geq 0 \;\forall i\}$.

  the smallest cone containing $\bar{v}^1, \ldots, \bar{v}^k$.

  k is finite $\Longrightarrow$ C is a finitely generated cone.



* A cone C is polyhedral if $C = \{\bar{x} \mid A\bar{x} \leq \bar{0}\}$. Here, C is the intersection of finitely many linear half-spaces. $\{\bar{x} \mid \bar{a}^T \bar{x} \leq 0\}$

* A convex cone is polyhedral iff it is finitely generated.

MATH 567: Lecture 10 (02/11/2025)

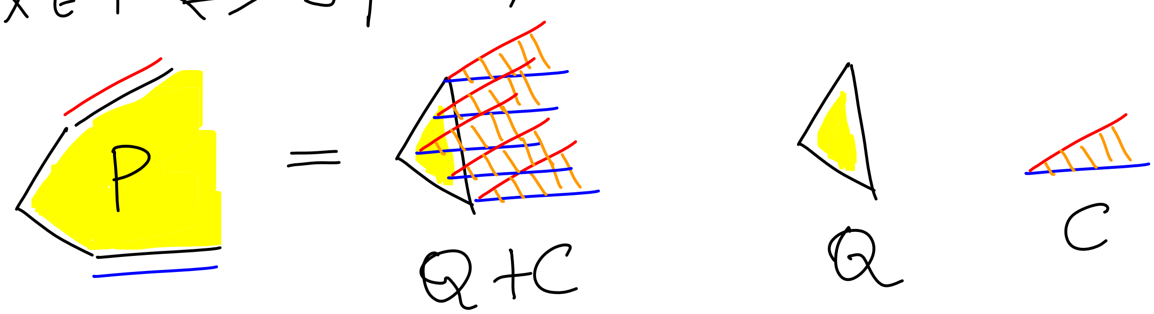
Today: * Definitions on polyhedra
* Integral polyhedra

---

* $P \subseteq \mathbb{R}^n$ is a (convex) polyhedron if $P = \{\bar{x} \mid A\bar{x} \le \bar{b}\}$.
P is the intersection of finitely many affine half-spaces $\{\bar{x} \mid \bar{a}^T\bar{x} \le \beta\}$, $\bar{a} \ne \bar{0}$, $\beta \ne 0$.
some entries in $\bar{b}$ are $\neq 0$ (not necessary to have all entries $\neq 0$)

* $P \subseteq \mathbb{R}^n$ is a (convex) polytope if it is the convex hull of finitely many vectors.
$$P = \text{conv}(\bar{v}^1, \ldots, \bar{v}^k) = \left\{ \bar{x} \;\middle|\; \bar{x} = \sum_{i=1}^{k} \lambda_i \bar{v}^i,\ 0 \le \lambda_i \le 1,\ \sum_{i=1}^{k} \lambda_i = 1 \right\}.$$
P is a bounded polyhedron.

* Motzkin's decomposition theorem: P is a polyhedron iff $P = Q + C$ for some polytope Q and convex cone C.
$\bar{x} \in P \iff \exists\, \bar{y} \in Q,\ \bar{z} \in C$, s.t. $\bar{x} = \bar{y} + \bar{z}$.

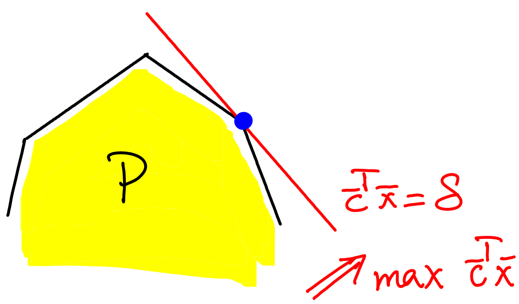


Polytopes and convex cones both have several nice structural properties that might not always hold for general polyhedra. But because of this decomposition theorem, we could present results in terms of polytopes and convex cones.

* Farkas' lemma: $\quad \exists \bar{x} \mid A\bar{x} \leq \bar{b} \iff$

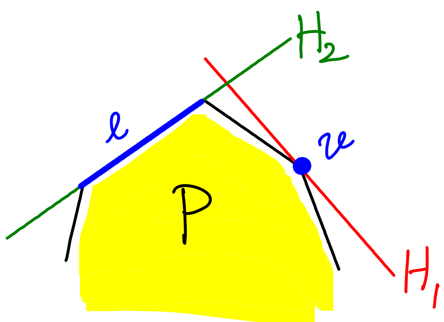
$$\nexists \bar{u} \geq \bar{0}, \quad \bar{u}^T A = \bar{0}^T, \quad \bar{u}^T \bar{b} < 0.$$

* ① Let $P = \{\bar{x} \mid A\bar{x} \leq \bar{b}\}$, $\delta = \max\{\bar{c}^T\bar{x} \mid \bar{x} \in P\}$, $\bar{c} \neq \bar{0}$.
Then the affine hyperplane $\{\bar{x} \mid \bar{c}^T\bar{x} = \delta\}$ is a **supporting hyperplane** of P.



The line $\bar{c}^T\bar{x} = \delta$ "supports" the polyhedron here.

② $F \subseteq P$ is called a **face** of P if $F = P$ or if $F = P \cap H$ for some supporting hyperplane H of P.



Vertex v and line segment ℓ are faces of P here

We give an alternative definition for a face of P.

③ If $\bar{a}^T\bar{x} \leq \beta$ is a valid inequality for P, and $F = \{\bar{x} \in P \mid \bar{a}^T\bar{x} = \beta\}$, then F is a face of P.

(4) F is a **proper face** of P if $F \neq \phi$, $F \neq P$, and F is a face of P.

$\bar{a}^T\bar{x} \leq \beta$: $[\bar{a}, \beta]$ represents the face defined by $\bar{a}^T\bar{x} = \beta$.

valid inequality

Also $[\bar{a}, \beta]$ supports P.

compact notation

* Alternatively, F is a face of $P \Longleftrightarrow F = \{\bar{x} \mid \bar{x} \in P, A'\bar{x} = \bar{b}'\}$ where $A'x \leq \bar{b}'$ is a subsystem of $A\bar{x} \leq \bar{b}$.

(i) P has only finitely many faces;

(ii) each face is a nonempty polyhedron; and

(iii) if F is a face of P, then $F' \subseteq F$ is a face of $P \Longleftrightarrow F'$ is a face of F.

* Active (tight) constraint : A constraint $\bar{a}^T\bar{x} \leq \beta$ from $A\bar{x} \leq \bar{b}$ is **tight** or **active** in a face F if $\bar{a}^T\bar{x} = \beta \quad \forall \bar{x} \in F$.

also, binding

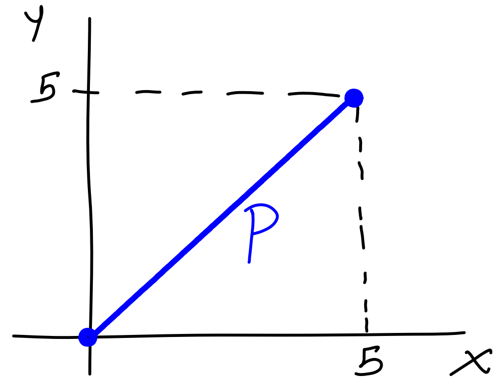
* An inequality $\bar{a}^T\bar{x} \leq \beta$ from $A\bar{x} \leq \bar{b}$ is an **implicit equality** if $A\bar{x} \leq \bar{b} \Longrightarrow \bar{a}^T\bar{x} = \beta$.

* Let $A'\bar{x} \leq \bar{b}'$ be the subsystem of implicit equalities in $A\bar{x} \leq \bar{b}$. Then the **dimension** of P is

$$\dim(P) = n - \operatorname{rank}(A').$$

Example

$y \geq x$
$y \leq x$
$x \leq 5$
$x \geq 0$



Both $y \geq x$ and $y \leq x$ are implicit equalities here. We get $x - y \leq 0$ and $-x + y \leq 0$, to give $A' = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$, which has rank $(A') = 1$. Thus, $\dim(P) = 2 - 1 = 1$, which agrees with our intuition.

* P is **full-dimensional** if $\dim(P) = n$, i.e., it has no implicit equalities.

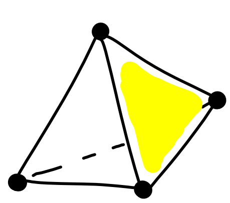
* $\dim\{\bar{v}\} = 0$. (one point/vertex)

* by convention, $\dim(\emptyset) = -1$.

* The **affine hull** of P is $\text{affhull}(P) = \{\bar{x} \mid A'\bar{x} = \bar{b}'\}$.

* **facet**: inclusionwise minimal face F of P with $F \neq P$.

* If F is a facet of P, then $\dim(F) = \dim(P) - 1$.



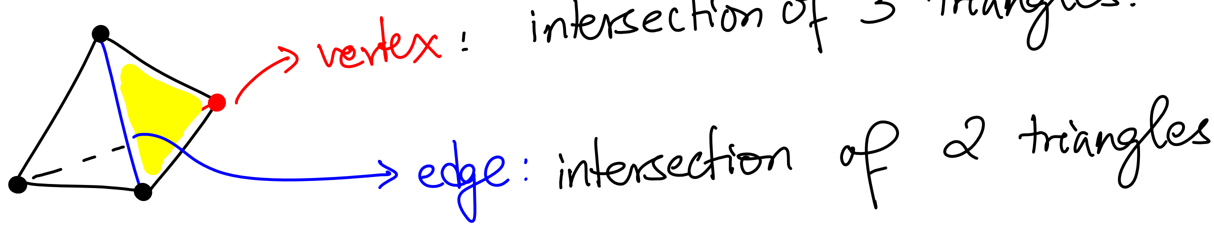
P is a solid tetrahedron.
Each triangle is a facet.
Each vertex and edge is a face, but not a facet.

Let $A'\bar{x} \le \bar{b}'$ be the subsystem of implicit equalities in $A\bar{x} \le \bar{b}$, and $A^{+}\bar{x} \le \bar{b}^{+}$ be the remaining inequalities.

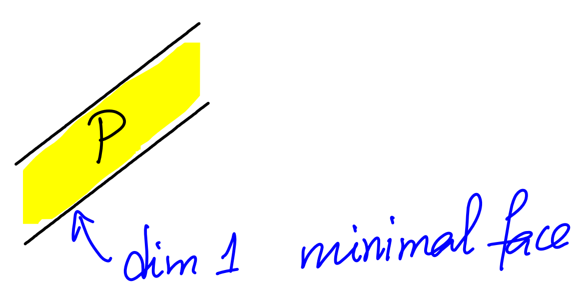
If no inequality in $A^{+}\bar{x} \le \bar{b}^{+}$ is redundant in $A\bar{x} \le \bar{b}$, then for any facet F of P,
$F = \{\bar{x} \in P \mid \bar{a}^{+T}\bar{x} = \beta^{+}\}$ for an inequality $\bar{a}^{+T}\bar{x} \le \beta^{+}$ from $A^{+}\bar{x} \le \bar{b}^{+}$.

In this case, $\bar{a}^{+T}\bar{x} = \beta^{+}$ **determines** the facet F.

* Each face of P, except P itself, is the intersection of facets of P.

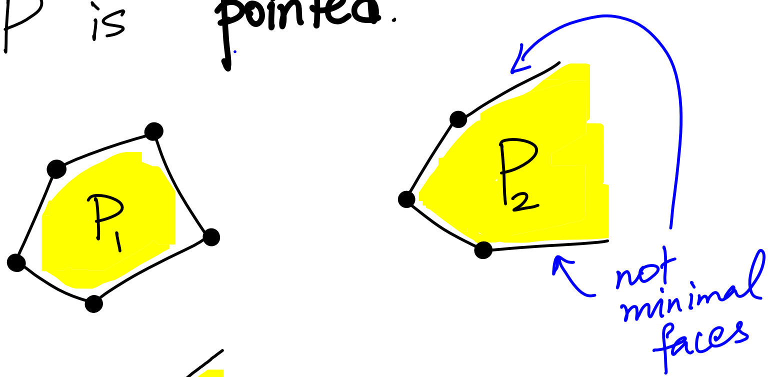


* A **minimal face** of P is a face of P not containing any other face of P.
For the tetrahedron, vertices are minimal faces.

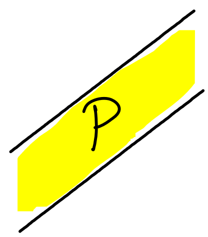


* A vertex of P is $\bar{z} \in P$ such that $\{\bar{z}\}$ is a minimal face of dimension zero.

* If each minimal face of P has dimension zero, then P is **pointed**.



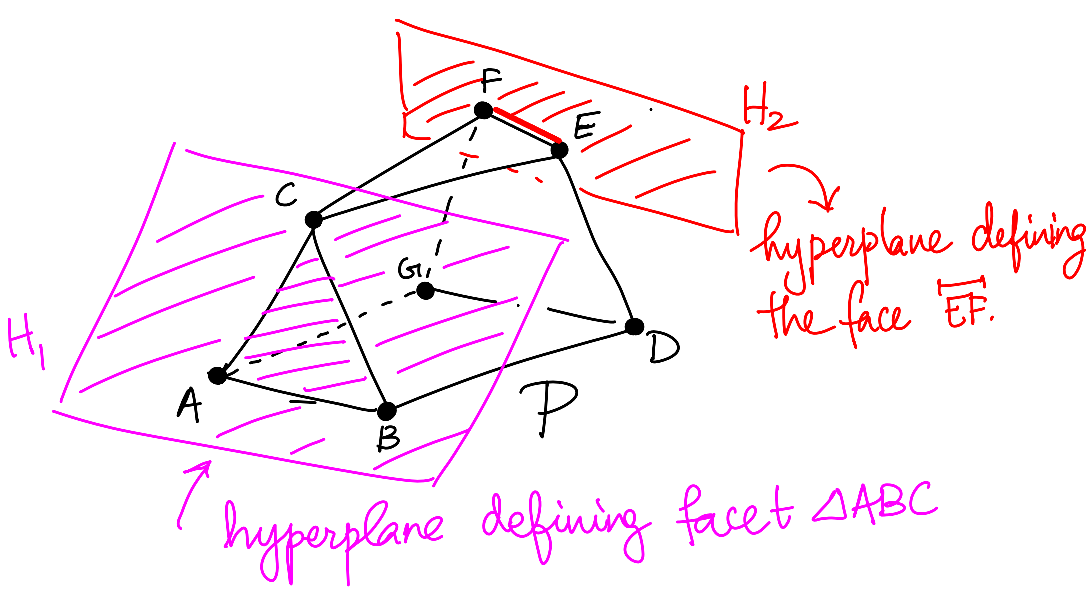
P_1 and P_2 are pointed.



P_3 is not pointed

Here is another example illustrating several of these definitions

P is the solid object in $\mathbb{R}^3$.



$\dim(P) = 3$, and it has no implicit equalities.

All the vertices, edges (line segments), triangles, and quardilaterals are all faces of P.

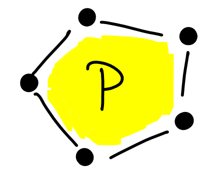
The triangles and quardilaterals are facets of P, and their dimension is 2 each.

The vertices are minimal faces of P. Also, $\dim(\text{edge}) = 1$.

H_1 is the supporting hyperplane defining face $\triangle ABC$, and H_2 defines the face which is edge $\overline{EF}$.

Special Cases: Well-Solved IPs

Recall: A polytope is the convex hull of its vertices.



We study problems of the form

$$\max\{\bar{c}^T\bar{x} \mid \bar{x} \in X\} = \max\{\bar{c}^T\bar{x} \mid \mathrm{conv}(X)\},$$

where conv(X) is "efficiently" described, i.e., using a polynomial # inequalities in a polynomial # variables. Then we can solve as an LP efficiently (in polynomial time), and get integrality for free.

We restrict our attention to rational polyhedra, i.e., $P = \{\bar{x} \mid A\bar{x} \le \bar{b}\}$ where entries in A, $\bar{b}$ are rational.

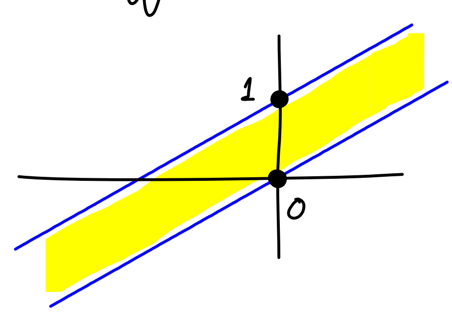
The subtour formulation with **all** subtour constraints added will describe the convex hull, but there are exponentially many constraints.

Integral Polyhedra

Def A rational polyhedron is called **integral** if every non-empty face contains an integer vector.

We need to consider only minimal faces.

A pointed rational polyhedron is integral iff **every vertex is integral**.



A polyhedron could be integral even if it is not pointed, e.g., the infinite band as shown here.

MATH 567: Lecture 11 (02/13/2025)

Today: * unimodularity and total unimodularity

Recall: integral polyhedra...

Theorem 7 (Hoffman 1974) A rational polytope P is integral iff for all integral vectors $\bar{w}$, the optimal value of $\max\{\bar{w}^T\bar{x} \mid \bar{x} \in P\}$ is an integer.

optimal $\bar{w}^T\bar{x}$

Proof ($\Rightarrow$) Let P be integral, i.e., all vertices are integral. Then $\max\{\bar{w}^T\bar{x} \mid \bar{x} \in P\}$ is integral for integral $\bar{w}$, as it occurs at a vertex.

($\Leftarrow$) Let $\max\{\bar{w}^T\bar{x} \mid \bar{x} \in P\}$ be integral for all integral $\bar{w}$.

Let $\bar{v} = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix}$ be a vertex of P,

and let $\bar{w}$ be an integral vector such that $\bar{v}$ is the unique optimal solution to $\max\{\bar{w}^T\bar{x} \mid \bar{x} \in P\}$.

We can assume $\bar{w}^T\bar{v} > \bar{w}^T\bar{u} + u_1 - v_1$ for all other vertices $\bar{u}$ of P. We can scale $\bar{w}$ by a large integer if needed (i.e., when $u_1 - v_1 < 0$).

Then we have $\bar{w}^T\bar{v} + v_1 > \bar{w}^T\bar{u} + u_1$ for all other vertices $\bar{u}$ of P.
This inequality gives the following result.

$\Rightarrow \bar{v}$ is the unique optimal solution for the objective function vector $\bar{w}' = [w_1+1, w_2, \ldots, w_n]^T = \bar{w} + \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$, as

we get $\bar{w}'^T \bar{v} > \bar{w}'^T \bar{u}$ for all other vertices $\bar{u} \in P$.

By assumption, $\bar{w}^T \bar{v}$ and $\bar{w}'^T \bar{v}$ are integral.
Also, $\bar{w}, \bar{w}' \in \mathbb{Z}^n$. $\Rightarrow v_1 \in \mathbb{Z}$.

We repeat the argument for $v_2, v_3, \ldots, v_n$. $\square$

Can extend result to unbounded pointed polyhedra easily, and also to polyhedra in general (i.e., not pointed).

While this theorem specifies an if and only if condition for P to be integral, it does not appear easy to check. We will have to certify integrality of the optimal value for all $\bar{w} \in \mathbb{Z}^n$, for which the optimum exists. But could we specify some easier to check conditions which guarantee integrality?

Unimodularity and Total Unimodularity (TU)

We assume $A, \bar{b}$ are integral (in $A\bar{x}=\bar{b}$ or $A\bar{x}\le\bar{b}$).

Def Let $A \in \mathbb{Z}^{m\times n}$ with full row rank ($\text{rank}(A)=m\le n$).
A is **unimodular** if each basis of A has determinant ± 1.
$\hookrightarrow$ $B_{m\times m}$ submatrix of A with $\text{rank}(B)=m$.

$A=[B\ N]$, $B\in\mathbb{Z}^{m\times m}$, $\text{rank}(B)=m$, $\det(B)=\pm1 \Rightarrow B^{-1}\in\mathbb{Z}^{m\times m}$.

For $\bar{b}\in\mathbb{Z}^m$, $A\bar{x}=\bar{b}$ has all integer solutions.

Recall: basic feasible solutions (bfs's) for $\max\{\bar{c}^T\bar{x} \mid A\bar{x}=\bar{b}, \bar{x}\ge\bar{0}\}$ correspond to corner points (vertices) of $\{\bar{x}\mid A\bar{x}=\bar{b}, \bar{x}\ge\bar{0}\}$.

$A=[B\ N]$, $\bar{x}=\begin{bmatrix}\bar{x}_B\\ \bar{x}_N\end{bmatrix}$. Set $\bar{x}_N=\bar{0}$, solve for $\bar{x}_B$.

$$A\bar{x}=\bar{b} \Rightarrow B\bar{x}_B+N\overset{=\bar{0}}{\cancel{\bar{x}_N}}=\bar{b}.$$

We get $\bar{x}_B=B^{-1}\bar{b}$

$\bar{x}=\begin{bmatrix}B^{-1}\bar{b}\\ \bar{0}\end{bmatrix}$ is a basic solution.

If a basic solution $\bar{x}$ satisfies $\bar{x}\ge\bar{0}$, then it's feasible, and hence is a bfs. Each bfs corresponds to a vertex (or corner point) of P.

We can use the idea of bfs to give a correspondence between unimodularity of A and integrality of P.

Theorem 8 $A \in \mathbb{Z}^{m\times n}$, $\operatorname{rank}(A) = m$. Then $P = \{\bar{x} \mid A\bar{x} = \bar{b}, \underbrace{\bar{x} \geq \bar{0}}_{\text{ensures } P \text{ is pointed}}\}$ is integral for all $\bar{b} \in \mathbb{Z}^m$ iff A is unimodular.

$$A = [B\ N], \quad \bar{x} = \begin{bmatrix} \bar{x}_B \\ \bar{x}_N \end{bmatrix}, \quad \text{set } \bar{x}_N = 0 \Rightarrow \bar{x}_B = B^{-1}\bar{b} \in \mathbb{Z}^m.$$

If A is not unimodular, $\det(B) \neq \pm 1$ for some basis B of A, and hence the corresponding basic solution will not be integral for all $\bar{b} \in \mathbb{Z}^m$.

Note that $B^{-1}\bar{b}$ might be integral for some $\bar{b} \in \mathbb{Z}^m$ in this case, e.g., when $|\det(B)| = 2$, and $\bar{b} \in 2\mathbb{Z}^m$. But the result will not hold for all $\bar{b} \in \mathbb{Z}^m$.

We now define a stronger (tighter) property of A, which guarantees integrality for polyhedra defined in more general forms. In particular, we would like to relax the requirement that $\operatorname{rank}(A) = m$ (i.e., be able to consider more general "shapes" of A, e.g., more tall than wide, i.e., $m > n$).

Def A matrix A is **totally unimodular** (TU) if every square submatrix of A has determinant $-1, 0,$ or 1. In particular, $A_{ij} \in \{-1, 0, 1\}$ $\forall i, j$.

e.g., $A = \begin{bmatrix} 3 & 2 \\ 1 & 1 \end{bmatrix}$ is unimodular, but not TU.

$B = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}$ is TU (and unimodular here).

$A = \begin{bmatrix} \boxed{\begin{matrix} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 1 \end{matrix}} & \begin{matrix} 0 \\ 1 \\ 0 \end{matrix} \\ \begin{matrix} 1 & 1 & 0 \end{matrix} & 1 \end{bmatrix}$ is not TU, as $\det(A_{1:3,1:3}) = -2$.

Notice that we have to check **all** square submatrices in the worst case. But it turns out we could check whether a matrix is TU or not in polynomial time by Seymour's decomposition algorithm, which runs in $O(n^3)$ time. But no implementation is known. Another algorithm by Truemper runs in $O(n^5)$ time, but is implemented, though.

→ check out https://discopt.github.io/cmr/ [Combinatorial Matrix Recognition (CMR) library]

Here is a result that connects total unimodularity and integrality of polyhedra.

Theorem 9 [Hoffman & Kruskal, 1956]: Let $A \in \mathbb{Z}^{m\times n}$. Then $P = \{\bar{x} \mid A\bar{x} \le \bar{b}, \bar{x} \ge \bar{0}\}$ is integral $\forall \bar{b} \in \mathbb{Z}^m$ for which $P \ne \emptyset$ iff A is totally unimodular (TU).

Proof We need a proposition first.

Proposition The following statements are equivalent.

(i) A is TU.

(ii) A^T is TU. → determinant is preserved under transposes

(iii) $[A \; I_m]$ is unimodular ↳ full row rank now!

(iv) $\begin{bmatrix} A \\ -A \\ I_n \\ -I_n \end{bmatrix}$ is TU.

Back to proof of Theorem 9.

$P = \{\bar{x} \mid A\bar{x} \le \bar{b}, \bar{x} \ge \bar{0}\}$ is integral $\Longleftrightarrow$

$\text{Proj}_{\bar{x}}(P^z)$ is integral, where $P_z = \{\bar{z} \mid [A \; I]\bar{z} = \bar{b}, \bar{z} \ge \bar{0}\}$

is integral, where $\bar{z} = \begin{bmatrix} \bar{x} \\ \bar{s} \end{bmatrix}$. → slack variables

Now apply Theorem 8, which gives that P_z is integral iff $[A \; I]$ is unimodular, which is true iff A is TU, by the proposition above. $\square$

Here is another characterization of TU and integral polyhedra.

Theorem 10 Let $A \in \mathbb{Z}^{m\times n}$. A is TU iff $P = \{\bar{x} \mid A\bar{x} \leq \bar{b}\}$ is integral $\forall\, \bar{b} \in \mathbb{Z}^m$ for which $P \neq \phi$.

$\bar{x}$ is urs (unrestricted in sign) here. We can replace $\bar{x}$ by $\bar{x}^+ - \bar{x}^-$, where $\bar{x}^+, \bar{x}^- \geqslant \bar{0}$, and use Theorem 9.

The upshot is that as long as the constraint matrix of the LP is TU, we're in good shape. The form of the LP—general or standard—does not matter.

Operations that preserve total unimodularity

1. Swap two rows (or columns).
2. Taking transpose.
3. Scaling a row/column by -1.
4. Pivoting, i.e., converting a column to a unit vector using EROs.
5. Adding a zero row/column, or a singleton row/column with the single nonzero entry being ± 1.
6. Repeating a row/column.

⋮

MATH 567: Lecture 12 (02/18/2025)

Today: * sufficient conditions for TU
* min-cost flow
* LP duality, TDI

Some details on the operations that preserve TU...

Example of pivoting:

$$A = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 1 \end{bmatrix} \xrightarrow{R_2 - R_3} \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & -1 & 0 & 1 \\ 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 1 \end{bmatrix}$$

det $= -2$

this was the example for a non-TU matrix introduced in Lecture 11...

Equivalently, replacement EROs of the form

$$R_i \leftarrow R_i \pm R_j \quad \text{preserve TU.}$$

By "preserve", we mean that (when $\tilde{A}$ is obtained by performing the operation on A)

$$A \text{ is TU} \Leftrightarrow \tilde{A} \text{ is TU, and}$$

$$A \text{ is not TU} \Leftrightarrow \tilde{A} \text{ is not TU.}$$

Seymour's decomposition theorem uses these and a few other operations that preserve TU (k-sum, for $k=1,2,3$). It decomposes the task of checking for TU of A into doing the same for several small submatrices obtained by these TU-preserving operations. The TU of these small matrices can be checked immediately (in constant time).

Sufficient Conditions for TU

Theorem 11 Let $A \in \{-1,0,1\}^{m\times n}$, with each column having at most one $+1$ and one -1. Then A is TU.

Proof We prove the result using induction on k for $k\times k$ submatrix B of A.

$k=1$. $A_{ij} \in \{-1,0,1\}$. ✓

Induction for $k \geq 2$ (going from k to $k+1$)

If B has a row/column of all zeros, $\det(B)=0$. ✓

If B has a row/column with one nonzero (± 1), we can expand along that row/column, and using the induction assumption, we get $\det(B) \in \{-1,0,1\}$.

If every column of B has exactly two nonzeros, then adding all rows of B gives the zero vector. Hence $\det(B)=0$.

as every column has one $+1$ and -1.

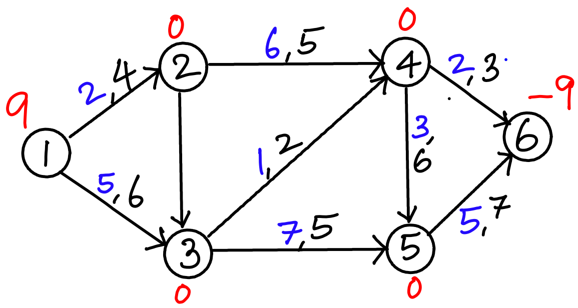
$B\bar{1} = \bar{0}$, where $\bar{1} = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}$ is a non-trivial solution to $B\bar{x}=\bar{0} \Rightarrow \det(B)=0$.

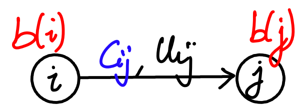
□

Min-Cost Flow (MCF) on a directed Network

Network matrices satisfy the above sufficient conditions. The node-arc incidence matrix of a directed network (or graph) in the context of the min-cost flow problem is an example.

$G = (V, E)$





c_{ij} : unit cost on (i,j)

u_{ij} : capacity (upper bound) of flow on (i,j)

Assume: total supply = total demand.

Each node i has supply/demand $b(i)$. If $b(i) > 0$, i is a supply node, and if $b(i) < 0$, i is a demand node. If $b(i) = 0$ then i is a transshipment. The goal is to satisfy demand using the supply by transporting the good through the arcs at the least total cost while honoring arc capacities.

Here is the LP: x_{ij} = flow in arc (i,j).

$$\min \sum_{(i,j)\in A} c_{ij} x_{ij}$$

$$\text{s.t.} \quad \underbrace{\sum_{j:(i,j)\in A} x_{ij}}_{\text{outflow}} - \underbrace{\sum_{j:(j,i)\in A} x_{ji}}_{\text{inflow}} = \underbrace{b(i)}_{\text{supply/demand}} \quad \forall i \in V$$

$$0 \le x_{ij} \le u_{ij} \quad \forall (i,j) \in E.$$

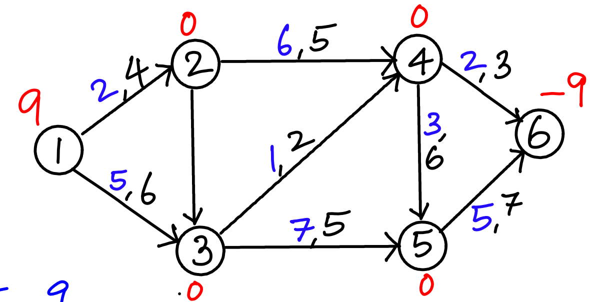
we assume lower bounds are all zero

With $\bar{x} = \begin{bmatrix} \vdots \\ x_{ij} \\ \vdots \end{bmatrix}$, the LP can be written as

$$\begin{aligned} \min \quad & \bar{c}^T \bar{x} \\ \text{s.t.} \quad & A\bar{x} = \bar{b} \\ & I\bar{x} \leq \bar{u} \\ & \bar{x} \geq \bar{0} \end{aligned} \qquad \bar{b} = \begin{bmatrix} \vdots \\ b(i) \\ \vdots \end{bmatrix}$$

$$\begin{bmatrix} A \\ I \end{bmatrix} \bar{x} \begin{pmatrix} = \\ \leq \end{pmatrix} \begin{bmatrix} \bar{b} \\ \bar{u} \end{bmatrix}$$

where A is the node-arc incidence matrix of G, which is guaranteed to be TU as it satisfies the sufficient condition for TU in Theorem 11.



$$A = \begin{array}{c} \\ \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \end{array} \begin{array}{c} \begin{array}{ccccccccc} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 \\ (1,2) & (1,3) & (2,3) & (2,4) & (3,4) & (3,5) & (4,5) & (4,6) & (5,6) \end{array} \\ \begin{bmatrix} 1 & 1 & & & & & & & \\ -1 & & 1 & 1 & & & & & \\ & -1 & -1 & & 1 & 1 & & & \\ & & & -1 & -1 & & 1 & 1 & \\ & & & & & -1 & -1 & & 1 \\ & & & & & & & -1 & -1 \end{bmatrix} \end{array}$$

$$\begin{array}{c} \\ i \\ \\ j \end{array} \begin{array}{c} (i,j) \\ \begin{bmatrix} +1 \\ \\ -1 \end{bmatrix} \end{array}$$

A is TU. From A we get the constraint matrix $\begin{bmatrix} A \\ I \end{bmatrix}$ by adding singleton rows (one for each $(i,j) \in E$), which all preserve TU.

Hence, if $\bar{b}$ and $\bar{u}$ are integral, then the min-cost-flow problem is guaranteed to have integer optimal solutions.

This result does not necessarily hold for undirected graphs.

The same result holds for other problems on directed networks, e.g., shortest path, max flow, transportation, etc. problems. But there are efficient algorithms for each problem — which are faster than solving them as LPs.

We now introduce the concept of total dual integrality, which is a more general concept than TU.

We first do a quick review of LP duality.

Review of LP Duality

For every linear program (LP), there is another associated LP called its dual LP. Solving the original (primal) LP is equivalent to solving its dual LP, and there are many results relating the two LPs and their interplay.

Here is an example:

(P) primal LP

$$\max\ z = 2x_1 + 3x_2$$
s.t.
$$x_1 + 4x_2 \le 5 \quad y_1 \ge 0$$
$$-2x_1 + 3x_2 = 4 \quad y_2 \text{ urs}$$
$$5x_2 \ge 7 \quad y_3 \le 0$$
$$x_1 \le 0,\ x_2 \ge 0$$
$$\le \qquad \ge$$

(D) dual LP

$$\min\ w = 5y_1 + 4y_2 + 7y_3$$
s.t.
$$y_1 - 2y_2 \le 2$$
$$4y_1 + 3y_2 + 5y_3 \ge 3$$
$$y_1 \ge 0,\ y_2 \text{ urs},\ y_3 \le 0$$

Normal vars and normal constraints

max-LP: $\le$ is normal

"maximize revenue s.t. upper bound on raw materials."

min-LP: $\ge$ is normal

"minimize cost s.t. meeting demand, i.e., produce at least a lower bound # units"

≥ 0 vars are always normal.

(opposite to) normal vars correspond to (opposite to) normal constraints in the dual LP. And urs vars correspond to $=$ constraints.

Table of Primal-Dual relationships

	Primal $\longleftrightarrow$	Dual	
	min	max	
variables	≥ 0	$\leq$	$\rightarrow$ normal
	≤ 0	$\geq$	$\rightarrow$ opposite to normal
	urs	$=$	
constraints	$\geq$	≥ 0	
	$\leq$	≤ 0	
	$=$	urs	

LP duality in matrix form:

$$(P) \quad \begin{array}{ll} \max & z = \bar{c}^T \bar{x} \\ \text{s.t.} & A\bar{x} \leq \bar{b} \quad \bar{y} \geq \bar{0} \end{array} \qquad \begin{array}{ll} \min & w = \bar{b}^T \bar{y} \\ \text{s.t.} & A^T \bar{y} = \bar{c} \\ & \bar{y} \geq \bar{0} \end{array} \quad (D)$$

One could imagine pushing z up, and pulling w down. Every value of z (i.e., for each feasible solution) lies below every value of w. When they are equal, we have optimality for both primal and dual LPs.

$\downarrow w$

$w^* \quad z^*$

$\uparrow z$

Results on LP duality

1. Weak duality: $z = \bar{c}^T \bar{x} \leq \bar{b}^T \bar{y} = w$ for any feasible $\bar{x}, \bar{y}$ for (P) and (D), respectively.

2. Strong duality: $\bar{c}^T \bar{x} = \bar{b}^T \bar{y} \iff \bar{x}$ and $\bar{y}$ are optimal for (P) and (D), respectively.

The default simplex method tries to push z up to optimality by working on (P). There is an equivalent dual simplex method that pushes w down by working on (D). There are also primal-dual methods which work on both ends, trying to push both z and w to optimality simultaneously.

Total Dual Integrality (TDI)

LP duality: $\max \{ \bar{c}^T \bar{x} \mid A\bar{x} \le \bar{b} \} = \min \{ \bar{b}^T \bar{y} \mid A^T \bar{y} = \bar{c}, \bar{y} \ge \bar{0} \}$ —— (*)

Def A system $A\bar{x} \le \bar{b}$ is **totally dual integral** (TDI) if the minimum in (*) is achieved by an integral $\bar{y}$ for each integral $\bar{c}$ for which the optimum exists.

MATH 567: Lecture 13 (02/20/2025)

Today: * Total Dual Integrality (TDI)
* AMPL

Total Dual Integrality (TDI) (Recall...)

LP duality: $\max\{\bar{c}^T\bar{x} \mid A\bar{x} \le \bar{b}\} = \min\{\bar{b}^T\bar{y} \mid A^T\bar{y} = \bar{c}, \bar{y} \ge \bar{0}\}$ —— (*)

Def A system $A\bar{x} \le \bar{b}$ is **totally dual integral** (TDI) if the minimum in (*) is achieved by an integral $\bar{y}$ for each integral $\bar{c}$ for which the optimum exists.

We present the first result connecting TDI systems and integral polyhedra — it's implication goes only one way, i.e., it is not an "if-and-only-if" result.

Theorem 12 [Hoffman, 1974] Let $A\bar{x} \le \bar{b}$ be a TDI system such that $P = \{\bar{x} \mid A\bar{x} \le \bar{b}\}$ is a rational polytope and $\bar{b}$ is integral. Then P is an integral polytope.

Proof As $\bar{b}$ is integral, and $A\bar{x} \le \bar{b}$ is TDI, $\max\{\bar{c}^T\bar{x} \mid A\bar{x} \le \bar{b}\}$ is integral for all integral $\bar{c}$. Then use Theorem 7.

Note that: TDI is the property of a specific system of inequalities used to describe a polyhedron, and not of the polyhedron itself. So, the same polyhedron could be described by both a TDI system and another system which is not TDI!

Example 1

$$\text{(P)} \quad \begin{array}{ll} \max & c_1x_1 + c_2x_2 \\ \text{s.t.} & x_1 + x_2 \le b_1 \quad y_1 \ge 0 \\ & \phantom{x_1 +{}} x_2 \le b_2 \quad y_2 \ge 0 \end{array}$$

$$\text{(D)} \quad \begin{array}{ll} \min & b_1y_1 + b_2y_2 \\ \text{s.t.} & y_1 \phantom{{}+y_2} = c_1 \\ & y_1 + y_2 = c_2 \\ & y_1, y_2 \ge 0 \end{array}$$

Let $b_1, b_2 \in \mathbb{Z}_{\ge 0}$. For $c_1, c_2 \in \mathbb{Z}$, we solve system in (D) to get

$$\left.\begin{array}{l} y_1 = c_1 \quad \in \mathbb{Z} \\ y_2 = c_2 - c_1 \in \mathbb{Z} \end{array}\right\} \Rightarrow$$ Solution to (D) is integral, when it exists, i.e., when $c_1 \ge 0$, $c_2 \ge c_1$.

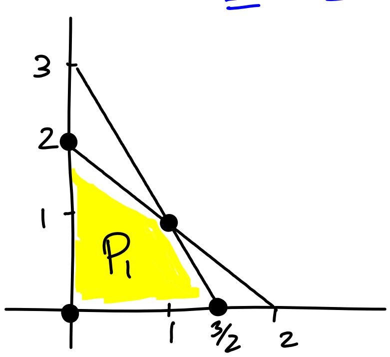
else (D) is infeasible

$\Rightarrow$ The system $\left\{\begin{array}{l} x_1 + x_2 \le b_1 \\ x_2 \le b_2 \end{array}\right\}$ is TDI.

Example 2

$$(P_1) \quad \begin{array}{ll} \max & z = c_1x_1 + c_2x_2 \\ \text{s.t.} & x_1 + x_2 \le 2 \quad y_1 \ge 0 \\ & 2x_1 + x_2 \le 3 \quad y_2 \ge 0 \\ & -x_1 \le 0 \quad y_3 \ge 0 \\ & -x_2 \le 0 \quad y_4 \ge 0 \end{array}$$

$$\text{(D)} \quad \begin{array}{ll} \min & w = 2y_1 + 3y_2 \\ \text{s.t.} & y_1 + 2y_2 - y_3 = c_1 \\ & y_1 + y_2 - y_4 = c_2 \\ & y_i \ge 0 \;\forall i \end{array}$$



$$\left[\begin{array}{cccc|c} 1 & 2 & -1 & 0 & c_1 \\ 1 & 1 & 0 & -1 & c_2 \end{array}\right] \xrightarrow{R_2 - R_1} \left[\begin{array}{cccc|c} 1 & 2 & -1 & 0 & c_1 \\ 0 & -1 & 1 & -1 & c_2 - c_1 \end{array}\right]$$

$$\xrightarrow[\text{then } -R_2]{R_1 + 2R_2} \left[\begin{array}{cccc|c} 1 & 0 & 1 & -2 & 2c_2 - c_1 \\ 0 & 1 & -1 & 1 & c_1 - c_2 \end{array}\right]$$ gives

$$\left.\begin{array}{l} y_1 = 2c_2 - c_1 - y_3 + 2y_4 \\ y_2 = c_1 - c_2 + y_3 - y_4 \end{array}\right\}$$ does not help much!

But, for $c_1 = 1, c_2 = 0$, (D) has a unique optimal solution @ $y_2 = y_4 = \frac{1}{2}$, $w^* = \frac{3}{2}$.

Note that $\max\{x_1 \mid \bar{x} \in P_1\} = 3/2$

P_1 is not integral!

So, the system describing (P_1) is not TDI!

We get this result also as a contrapositive result to Theorem 12.

It may not be surprising that the polyhedron (P_1) is non-integral and the system describing (P_1) is not TDI. But we could have the reverse case as well — the polyhedron is integral but the system is still not TDI!

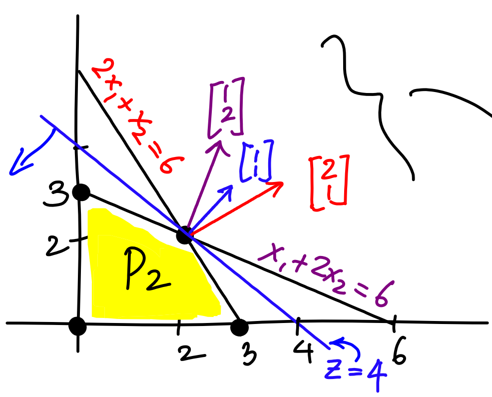
Example 3

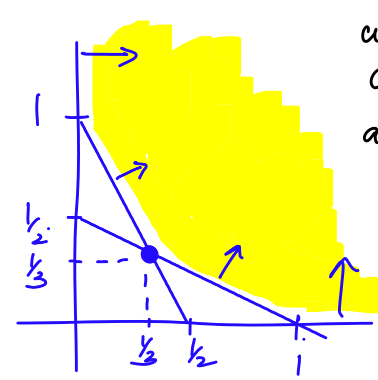
$$\max\ z = x_1 + x_2$$
$$(P_2)\quad \text{s.t.} \begin{cases} x_1 + 2x_2 \le 6 & y_1 \ge 0 \\ 2x_1 + x_2 \le 6 & y_2 \ge 0 \\ x_1, x_2 \ge 0 \\ \ge \quad \ge \end{cases}$$

$z^* = 4$ at $\begin{bmatrix} 2 \\ 2 \end{bmatrix}$

$$\min\ w = 6y_1 + 6y_2$$
$$\text{s.t.}\quad y_1 + 2y_2 \ge 1 \quad (D)$$
$$2y_1 + y_2 \ge 1$$
$$y_1, y_2 \ge 0$$

$w^* = 4$ at $\begin{bmatrix} 1/3 \\ 1/3 \end{bmatrix}$





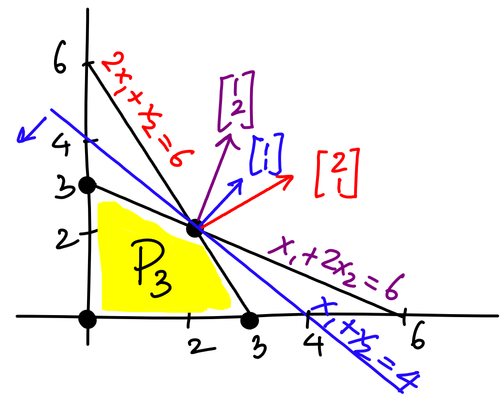
We could treat $x_i \ge 0$ as regular inequalities, use y_3, y_4 for them, and still get $y_1 = y_2 = \frac{1}{3}$ as the unique optimal solution!

Normal vectors of the constraints and $z = x_1 + x_2$.

We should be able to express $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$ as an integer linear combination of $\begin{bmatrix} 1 \\ 2 \end{bmatrix}$ and $\begin{bmatrix} 2 \\ 1 \end{bmatrix}$, for an integer (optimal) solution to exist. Hence (P_2) is not TDI.

So, (P_2) is not TDI, even though polytope is integral.

But we can describe (P_2) (the polytope) by another system of inequalities (P_3), which is indeed TDI.



$$\max \; z = x_1 + x_2$$

$$\text{s.t.} \quad (P_3) \left\{ \begin{array}{r} x_1 + 2x_2 \leq 6 \\ 2x_1 + x_2 \leq 6 \\ x_1 + x_2 \leq 4 \\ x_1, x_2 \geq 0 \end{array} \right\} y_3$$

$y_3 = 1$, $y_1 = y_2 = 0$ is an integral optimal solution to (D), showing is TDI.

Now, $\begin{bmatrix}1\\1\end{bmatrix}$ can indeed be expressed as an integer linear combination of $\begin{bmatrix}1\\2\end{bmatrix}$, $\begin{bmatrix}2\\1\end{bmatrix}$, and $\begin{bmatrix}1\\1\end{bmatrix}$.

The power of TDI lies oftentimes more on the mathematical side than on the computational/practical side. Knowing that a polyhedron can be described by a TDI system could be useful in proving certain related results.

<u>Theorem 8.13 (Bertsimas-Weismantel)</u>

Every rational polyhedron P can be described as a TDI system of the form $A\bar{x} \leq \bar{b}$ with A integral.

<u>Corollary</u> A rational polyhedron P is integral iff there exists a TDI system describing P of the form $A\bar{x} \leq \bar{b}$ with $A, \bar{b}$ integral.

AMPL

See AMPL handout posted on the course web page.

For the Farmer Jones LP (used as the first example), one could use n for the # crops in place of a set of crops. See the course web page for AMPL files using # crops.

Integer programming example

Knapsack feasibility problem: $\beta' \leq \bar{a}^T \bar{x} \leq \beta$

$\bar{x} \in \{0,1\}^n$

$a_1 x_1 + \cdots + a_n x_n$

goal is to check feasibility: $\overset{?}{\exists}$ $\bar{x} \in \{0,1\}^n$ satisfying the knapsack inequalities?

There is no objective function (or, one could use a dummy objective function). The goal is to find an integer feasible point $\bar{x}$ satisfying the knapsack bounds, or prove there are no integer feasible solutions. Indeed, the latter case represents the worst case instances for most IP algorithms.

For the instance illustrated in class, we had $n=50$, and all the numbers (50 a_i's, β', and β) were available in a text file. The data could be read into ampl using the **read** command.

MATH 567: Lecture 14 (02/25/2025)

Today: * Branch-and-Bound (B&B)

Branch-and-Bound (B&B)

We describe a generic branch-and-bound algorithm for the problem of finding $z(S) = \max\{\bar{c}^T\bar{x} \mid \bar{x} \in S\}$. S here need not be a polyhedron, or disjoint collections of polyhedra, or even polyhedra intersected with $\mathbb{Z}^n$. It could be quite general.

We assume that

* we can divide a subproblem $T \subseteq S$, and
* we can compute lower and upper bounds

$$z_\ell(T) \le z(T) \le z_u(T)$$

for $z(T) = \max\{\bar{c}^T\bar{x} \mid \bar{x} \in T\}$.

We should be able to compute these bounds easily, i.e., in polynomial time. For MIP/IP, we usually solve LP relaxations, i.e., the problems without integrality restrictions.

We will describe how to maintain and update these bounds so as to arrive at the final answer.

Here is the generic algorithm (for $z = \max\{\bar{c}^T\bar{x} \mid \bar{x} \in S\}$)

Step 0 Let $\mathcal{L} = \{S\}$. (the list of (sub) problems).
compute $z_\ell(S), z_u(S)$.

Step r (i) Remove a subproblem $T \in \mathcal{L}$. $(\mathcal{L} \leftarrow \mathcal{L}/\{T\})$

(ii) Divide T as $T = T_1 \cup \dots \cup T_k$;
compute $z_\ell(T_i)$, $z_u(T_i)$, $i = 1, \dots, k$.
set $\mathcal{L} = \mathcal{L} \cup \{T_1, \dots, T_k\}$.

(iii) Let $z_\ell(S) = \max\{z_\ell(S), \max\{z_\ell(T) \mid T \in \mathcal{L}\}\}$

save the solution $\bar{x}$ here
integer feasible

(iv) Prune all $T \in \mathcal{L}$ with
$$z_u(T) \leq z_\ell(S);$$

throw away; i.e., remove from $\mathcal{L}$

(v) if $\mathcal{L} = \phi$ STOP;
else
set $z_u(S) = \max\{z_u(T) \mid T \in \mathcal{L}\}$;
end

Correctness of the generic B&B algorithm

Claim 1 At any time

$$\{\bar{x} \in S' \mid \bar{c}^T\bar{x} > z_\ell(S)\} \subseteq \mathcal{L}.$$

* true in the beginning
* maintained in Step (iv), where we prune (remove) a problem from $\mathcal{L}$.

Claim 2 Update in Step (v) is correct.

Case 1: $z(S) > z_\ell(S)$

If $\bar{x}^*$ has $\bar{c}^T\bar{x}^* = z(S)$, then by Claim 1, $\bar{x}^* \in T$ for $T \in \mathcal{L}$. Then $z_u(T) \geq \bar{c}^T\bar{x}^* = z(S)$.

Case 2: $z(S) = z_\ell(S)$.

Since we are already past Step (iv), we must have

$$z_u(T) > z_\ell(S) = z(S) \quad \forall\, T \in \mathcal{L}.$$

□

Let's compare the updates of z_ℓ, z_u:

consider current best value, and those from all children

$$z_\ell(S) = \max\{z_\ell(S), \max\{z_\ell(T) \mid T \in \mathcal{L}\}\}.$$

$$z_u(S) = \max\{z_u(T) \mid T \in \mathcal{L}\}.$$ → consider values only from the children

<u>More specific details for $k=2$</u> (we create two subproblems: $S = S_1 \cup S_2$)

1. Partition S: let $x_i \in \mathbb{Z}$ in S, but $x_i = k + \delta$ in the LP solution for S, where $k \in \mathbb{Z}$, $0 < \delta < 1$. Then we can set $S_1 = S \cap \{\bar{x} \mid x_i \leq k\}$ and $S_2 = S \cap \{\bar{x} \mid x_i \geq k+1\}$.

2. Find z_{uj}, $j=1,2$ by solving the LP relaxations of $\max\{\bar{c}^T\bar{x} \mid \bar{x} \in S_j\}_{j=1,2}$. If infeasible, set $z_{uj} = -\infty$.

3. Find z_{lj}, $j=1,2$. Try to find any integer feasible solution $\bar{x}^j \in S_j$, $j=1,2$. If we cannot find an integer solution $\bar{x}^j$, set $z_{lj} = -\infty$.

We will have

$$\max_j \{z_j\} = z \qquad \text{——— (1)}$$

$$\max_j \{z_{lj}\} \leq z \leq \max_j \{z_{uj}\} \qquad \text{——— (2)}$$

We keep updating the lower and upper bounds by taking the max in each case.

In general, z_{lj} comes from an integer feasible solution, and z_{uj} comes from a **relaxation**. The typical relaxation involves relaxing, i.e., ignoring the integrality constraints. But one could ignore any subset of constraints.

<u>Another example of a relaxation:</u>

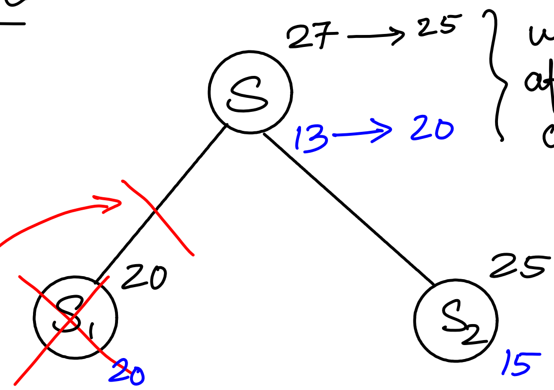
$S = \{\bar{x} \mid \bar{x}$ is the incidence vector of a TSP tour$\}$.

To get a relaxation of S, throw away the subtour constraints.

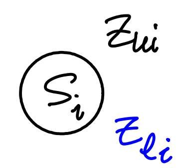
How do we use (2): Update of bounds

Three examples

1.



update bounds after handling child nodes

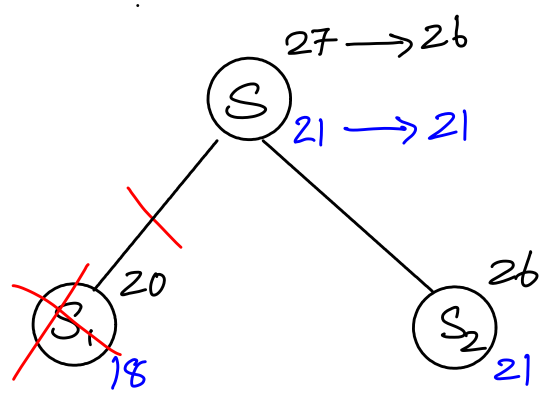


Notation for pruning: X or

prune S_1 by **optimality**.

We have equality of the bounds in S_1. We cannot improve the solution any more, so can prune it. Also, there is no need to branch any more.

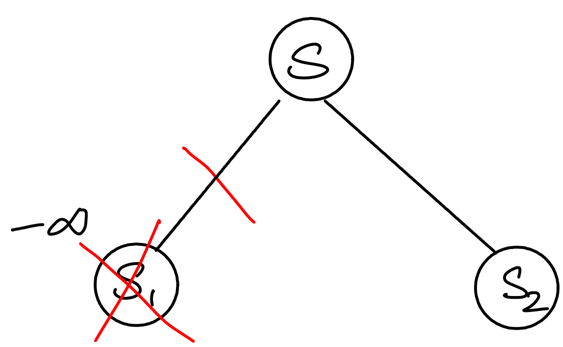
2.



prune S_1 by **bound**.

$z_{u1} = 20 < z_l = 21$. We cannot possibly find a better solution by branching on S_1 any more. So we prune it.

3.



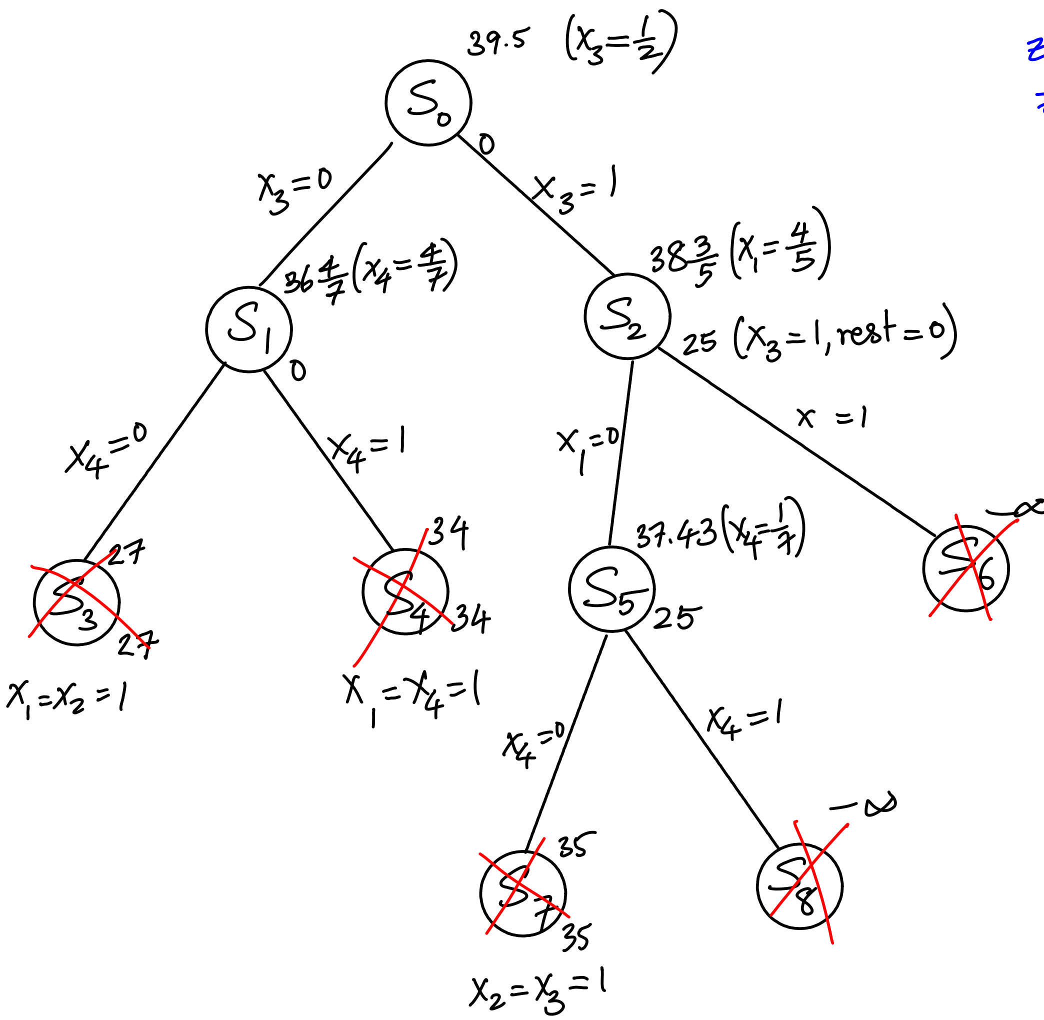
prune S_1 by **infeasibility**.

S_1 is not feasible even as an LP – no point considering it any further.

Illustration of B&B on $n=4$ knapsack problem

Prob 3, Chap 7 of Wolsey, Integer programming

$$\max \; z = 17x_1 + 10x_2 + 25x_3 + 17x_4$$
$$\text{s.t.} \quad 5x_1 + 3x_2 + 8x_3 + 7x_4 \le 12$$
$$\bar{x} \in \{0,1\}^4$$



$z_u = 39.5$
$z_\ell = 0$

$z_u = 38.6$
$z_\ell = 25$

$z_u = 37.43$
$z_\ell = 34$

$z_u = 35$
$z_\ell = 35$

S_3, S_4, S_7 are pruned by optimality, while S_6 and S_8 are pruned by infeasibility. No nodes are pruned by bound here. See the AMPL session for details.

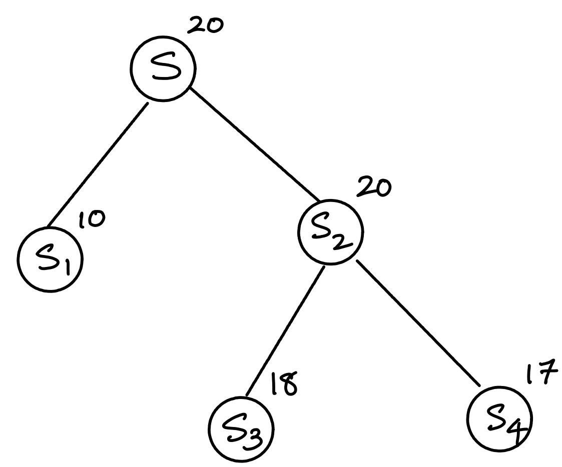
MATH 567: Lecture 15 (02/27/2025)

Today:
* B&B strategies
* reduced cost fixing in B&B
* types of branching

Node selection Strategies

How do we select a subproblem from $\mathcal{L}$?

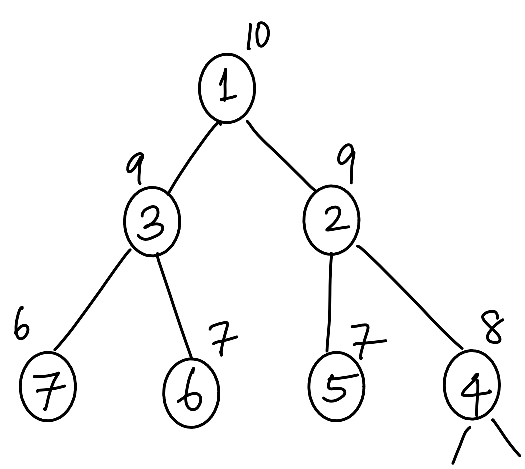
Consider this example:



If we subdivide S_1, z_u will remain at 20. If $z^*=15$ (optimal objective function value) and we knew it, we would not subdivide S_1. On the other hand, subdividing S_2 decreases z_u to 18.

This example seems to suggest that choosing a node with a high z_u may be a good idea. This strategy is called **best node first** (BNF) strategy. (pick subproblem from $\mathcal{L}$ with largest z_u).

Another typical BNF B&B tree



nodes are numbered in the order they are examined here

Advantages of BNF Strategy

* Rapidly decreases z_u — global upper bound

* Never subdivides a node T_k with $z_u(T_k) < z^*$ (optimal z-value), can prune many nodes, and hence the # nodes to prove optimality is relatively small.

↳ assuming you already identified the optimal solution — you still have to prove it is indeed optimal.

Disadvantages of BNF strategy

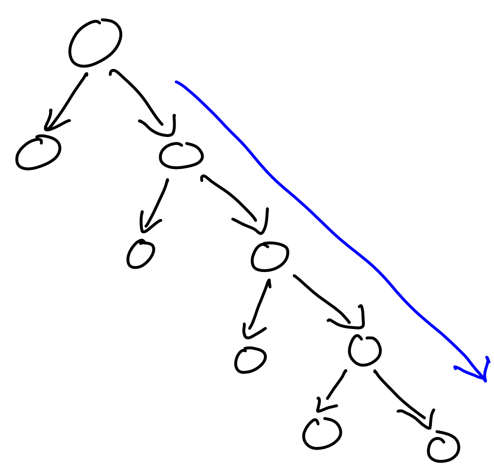
* The B&B tree is widespread, and memory needed to store the list of subproblems $\mathcal{L}$ may be huge.

* May take a long time to find an integer feasible solution (i.e., a node T_k with $z_u(T_k) = z_\ell(T_k)$).

Depth-First Search (DFS) B&B Strategy

Exact opposite to BNF $\longrightarrow$ always select the problem that was added to $\mathcal{L}$ the last (LIFO order).

A typical DFS B&B tree:



Advantages of DFS B&B Strategy

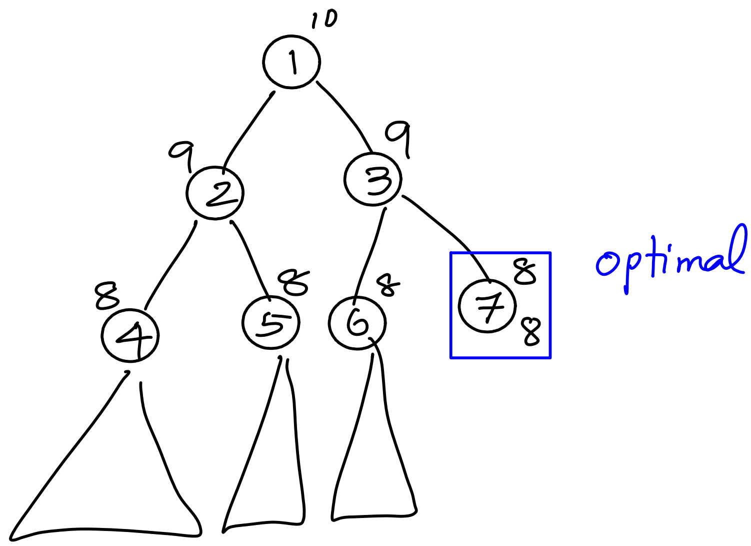
* Maximum depth of B&B tree is n; at any point, DFS stores at most $2n$ subproblems in $\mathcal{L}$.
* Since it gets down deep quickly in the B&B tree, DFS find integer feasible solutions relatively quickly.

Disadvantages of DFS

* If it hits a "wrong" subtree, it may not find a feasible solution, or even change the bounds for a long time.
* It may take a long time to prove optimality.

Let's consider a sample B&B tree, and how both strategies (BNF and DFS) perform on the same. We will consider both "good" and "bad" extremes for their performances — "lucky" or "unlucky"!

An Example



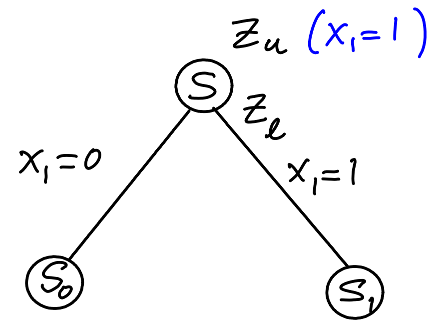
Strategy	# nodes until finding optimal solution	# nodes until finishing (proving optimality)
BNF lucky	4 (1-2-3-7)	7 (1-2-3-7-4-5-6)
BNF unlucky	7 (1-2-3-4-5-6-7)	7 (1-2-3-4-5-6-7)
DFS lucky	3 (1-3-7)	7 (1-3-7-6-2-5-4)
DFS unlucky	M	M

So, DFS is a gambler, while BNF is conservative.

In practice, we combine the two strategies, along with other "intelligent" strategies specific to the problem in hand.

Reduced Cost fixing in B&B

Consider a 0-1 IP.



Say we solve the LP relaxation at S (to get $z_u(S)$), and in the optimal solution $\bar{x}$, we have $x_1=1$. Can we conclude that

$z_u(S_0) =$ LP optimum at $S_0 \le z_\ell$?

If yes, we can fix $x_1=1$ (in the optimal solution of IP).

LP relaxation at S

$$z_u(S) = \left\{ \begin{array}{ll} \max & \bar{c}^T\bar{x} \\ \text{s.t.} & A\bar{x} \le \bar{b} \rightarrow \bar{y} \ge \bar{0} \\ & \bar{x} \le \bar{1} \rightarrow \bar{u} \ge \bar{0} \\ & -\bar{x} \le \bar{0} \rightarrow \bar{v} \ge \bar{0} \end{array} \right. \quad (P)$$

$=$

$\uparrow$ primal LP

Dual

$$\left. \begin{array}{ll} \min & \bar{b}^T\bar{y} + \bar{1}^T\bar{u} \\ \text{s.t.} & A^T\bar{y} + \bar{u} - \bar{v} = \bar{c} \\ & \bar{y}, \bar{u}, \bar{v} \ge \bar{0} \end{array} \right\} (D)$$

$\uparrow$ dual LP

Theorem 13 Suppose the optimal solution to (P) and (D) be $(\bar{x}, \bar{y}, \bar{u}, \bar{v})$ with

1. $x_1 = 1$, and
2. $u_1 \ge z_u(S) - z_\ell$

also = opt(D), the optimal obj. fn of dual (D)

Then $z_u(S_0) \le z_\ell$. So we can fix $x_1 = 1$.

Recall complementary slackness conditions — if a constraint in (P) is satisfied as a strict inequality, i.e., it's nonbinding, the corresponding dual variable will be zero in the optimal solution. So, $v_1 = 0$ here (as $-x_1 \le 0$ is not binding).

Proof

Consider the dual LP at S_0. $(D)\wedge(x_1=0)$ is the same as (D), but with v_1 free (urs). v_1 appears in (D) only in $(A^T\bar{y})_1 + u_1 - v_1 = c_1$. Hence a feasible solution to $(D)\wedge(x_1=0)$ (i.e., (D) at S_0) is given by $(\bar{y}', \bar{u}', \bar{v}')$, where

$$\bar{y}' = \bar{y}, \quad \bar{u}' = \bar{u}, \quad \bar{v}' = \bar{v} \text{ except for } u_1' = 0,\ v_1' = -u_1.$$

$\Rightarrow$ The optimal obj. fn. value at $(D)\wedge(x_1=0) \leq z_u(S) - u_1$.
$$\leq z_\ell \text{ by (2)}.$$

Hence we can prune S_0, i.e., fix $x_1 = 1$. $\square$

In practice, reduced cost fixing and other similar strategies are all implemented as part of B&B (for example, in CPLEX). In fact, packages such as CPLEX do much more than simple B&B. Still, there are some pathological instances of certain IPs, which are bad for CPLEX even at moderate dimensions (≤ 100!).

Example

$$(P)\quad \begin{cases} \max & 2x_1 + x_2 \\ \text{s.t.} & x_1 + 2x_2 \leq 2 \quad y \\ & x_1 \leq 1 \quad u_1 \\ & x_2 \leq 1 \quad u_2 \\ & -x_1 \leq 0 \quad v_1 \\ & -x_2 \leq 0 \quad v_2 \end{cases}$$

$$(D)\quad \begin{aligned} \min\ & 2y + u_1 + u_2 \\ \text{s.t.}\ & y + u_1 - v_1 = 2 \\ & 2y + u_2 - v_2 = 1 \\ & y, u_1, u_2, v_1, v_2 \geq 0 \end{aligned}$$

$z_\ell = z^* = 2$ with $\bar{x}^* = \begin{bmatrix}1\\0\end{bmatrix}$.

$z_u = 5/2$ with $\bar{x} = \begin{bmatrix}1\\1/2\end{bmatrix}$.

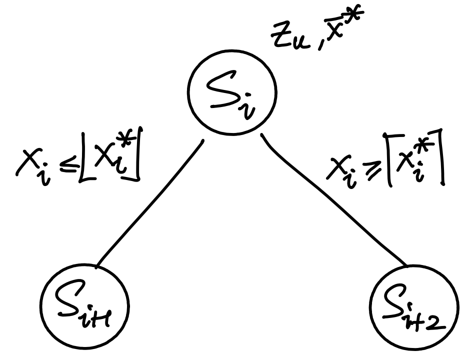
For (D), opt. solution is $y = \frac{1}{2}$, $u_1 = 3/2$.

$u_1 \geq z_u - z_\ell = \frac{5}{2} - 2 = \frac{1}{2}$.

So, fix $x_1 = 1$ by Theorem 13.

Types of Branching

① Binary branching

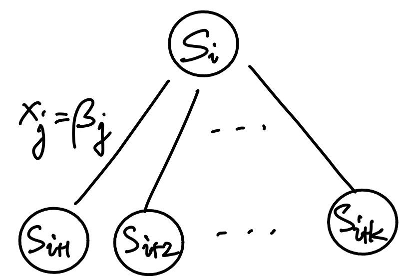


Solve LP relaxation at S_i.
Let the optimal solution to this LP relaxation be $\bar{x}^*$ with x_i^* non-integral, where $x_i \in \mathbb{Z}$ is required. Create two branches by adding $x_i \le \lfloor x_i^* \rfloor$ and $x_i \ge \lceil x_i^* \rceil$.

Example: $x_5 = 13.6$ (in $\bar{x}^*$). Create the branches $x_5 \le 13$ and $x_5 \ge 14$.

Binary variables are indeed covered in this case.

② Integer branching



Choose a variable x_j that needs to be integral, find

$$\delta_{ij} = \min \{ x_j \mid \bar{x} \in \text{LP relaxation at } S_i \},$$
$$\gamma_{ij} = \max \{ x_j \mid \bar{x} \in \text{LP relaxation at } S_i \}.$$

$k = \lfloor \gamma_{ij} \rfloor - \lceil \delta_{ij} \rceil + 1$

Create branches by adding constraints

$$x_j = \beta_j \quad \text{where} \quad \beta_j \in \{ \lceil \delta_{ij} \rceil, \lceil \delta_{ij} \rceil + 1, \ldots, \lfloor \gamma_{ij} \rfloor \}.$$

So, create $\lfloor \gamma_{ij} \rfloor - \lceil \delta_{ij} \rceil + 1$ nodes.

e.g., $\delta_{ij} = 13.64$, $\gamma_{ij} = 16.39$ for $\delta_{ij} \le x_j \le \gamma_{ij}$; we create 3 branches with $x_j = 14, 15, 16$.

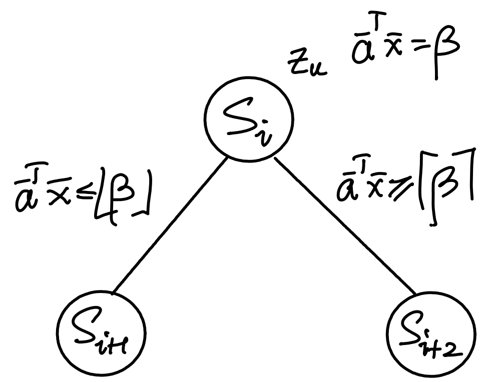
MATH 567: Lecture 16 (03/04/2025)

Today:
* branching on constraint
* Jeroslow's IP
* cutting planes

Types of Branching (continued..)

③ Binary branching on a constraint:

Assume IP, i.e., $\bar{x} \in \mathbb{Z}^n$ is required.
Let $\bar{a}^T\bar{x} = \beta$ is valid for the LP relaxation at S_i, where β is non-integral, but $\bar{a} \in \mathbb{Z}^n$. We then create two nodes by adding $\bar{a}^T\bar{x} \leq \lfloor \beta \rfloor$ and $\bar{a}^T\bar{x} \geq \lceil \beta \rceil$.



<u>Example</u> Let $2x_1 + 3x_2 + 5x_3 = 7.43$ hold for LP at S_i, where $x_1, x_2, x_3 \in \mathbb{Z}$. Create two branches by adding $2x_1 + 3x_2 + 5x_3 \leq 7$ and $2x_1 + 3x_2 + 5x_3 \geq 8$.

④ Integer branching on a constraint:

Similar to ②, but for a constraint $\bar{a}^T\bar{x}$, $\bar{a} \in \mathbb{Z}^n$.

<u>Example</u> Let $6.71 \leq 3x_1 + 5x_3 - x_4 + 2x_5 \leq 11.99$ be valid, where $x_1, x_3, x_4, x_5 \in \mathbb{Z}$ is required. We create five branches by adding $3x_1 + 5x_3 - x_4 + 2x_5 = \beta$ for $\beta = 7, 8, 9, 10, 11$ $\left(7 = \lceil 6.71 \rceil,\ 11 = \lfloor 11.99 \rfloor\right)$.

Jeroslow's IP (1974)

$$\begin{aligned} \min\ & x_{n+1} \\ \text{s.t. } & 2x_1 + 2x_2 + \cdots + 2x_n + x_{n+1} = n \quad \text{for **odd** } n \\ & x_j \in \{0,1\},\ j = 1,2,\ldots,n+1. \end{aligned}$$

The optimal solution must set $x_{n+1} = 1$. But binary branching on variables (option 1) will take an exponential number (in n) of nodes to solve it!

Feasibility version of Jeroslow's IP

We will prove the above result for this simpler version.

$n = 2k+1$ (odd). Consider the following feasibility binary IP:

$$2x_1 + 2x_2 + \cdots + 2x_n = 2k+1$$
$$x_j \in \{0,1\},\ j = 1,2,\ldots,n.$$

The goal here is to **prove** that the above IP is integer infeasible using B&B.

Say, $x_1, \ldots, x_j$ for $j < k$ are fixed already (WLOG). Also, assume $x_r = 1$ for $r = 1, \ldots, i$ for $i < j$, and $x_r = 0$ for $r = i+1, \ldots, j$.

The LP feasibility problem at the current node is

$$2x_{j+1} + \cdots + 2x_{2k+1} = 2k+1-2i.$$
$$0 \le x_r \le 1,\ r = j+1, \ldots, 2k+1.$$

$$\Rightarrow \qquad \underbrace{x_{j+1} + \cdots + x_{2k+1}}_{2k+1-j} = \frac{2k+1-2i}{2} = k - i + \frac{1}{2}$$

$$0 \leq x_r \leq 1, \quad r = j+1, \ldots, 2k+1.$$

As long as $j < k$, $2k+1-j > k+1$. So we can always find an LP-feasible solution (non-integral) to this subproblem. Hence we cannot prune this node! In fact, there may be many LP-feasible solutions.

$\Rightarrow$ We have to fix at least $k = \lfloor \frac{n}{2} \rfloor$ of the x_i's before we can prune a node. Hence the B&B tree has at least $2^k = 2^{\lfloor n/2 \rfloor}$ nodes.

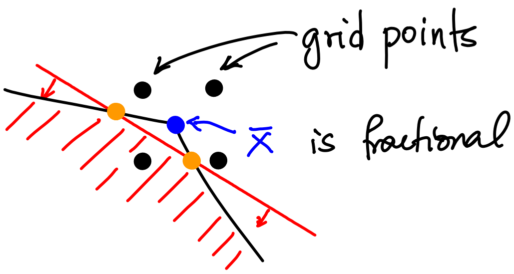
But we could prove integer infeasibility at the root node itself by branching on the constraint $x_1 + x_2 + \cdots + x_n$!

$$\begin{aligned} \max/\min \quad & \sum_{j=1}^{n} x_j \\ \text{s.t.} \quad & 2\sum_{j=1}^{n} x_j = 2k+1 \\ & 0 \leq x_j \leq 1, \; j = 1, 2, \ldots, 2k+1. \end{aligned}$$

$\delta(\min) = \gamma(\max) = k + \frac{1}{2}$, and hence $\lceil \delta \rceil > \lfloor \gamma \rfloor$.

So we create zero nodes!

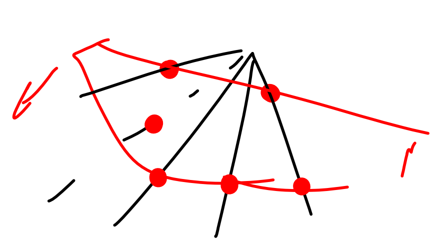
Cutting Planes



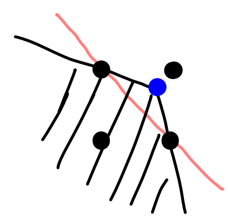
A cutting plane cuts off a non-integral corner point (in the feasible region of the LP relaxation).

As illustrated here, cutting a fractional corner point might add more (new) fractional vertices.

In higher dimensions, it could add many more new nonintegral vertices!



But it could happen that we do not add any new non-integal vertices by adding the cut. Indeed, such cuts are the tightest ones you could add.



It may not be possible to always add a tightest cut — we still benefit from cutting off fractional corner points, so we study cutting planes in general...

Recall: $\bar{a}^T\bar{x} \le \beta$ is valid for $P \subseteq \mathbb{R}^n$ if $\bar{a}^T\bar{x} \le \beta \ \forall \bar{x} \in P$.

Chvátal-Gromory (CG) Cuts

Vásek Chvátal ("Vashek HoTal").

Most other classes of cuts could be derived by applying the CG cut procedure repeatedly.

Pure integer case

(1) $Y = \{\bar{x} \in \mathbb{Z}^n \mid A\bar{x} \leq \bar{b}\}$.

$\bar{u} \geq \bar{0} \implies (\bar{u}^T A)\bar{x} \leq \bar{u}^T\bar{b}$ is valid for Y.

If $\bar{u}^T A$ is integral, then

$(\bar{u}^T A)\bar{x} \leq \lfloor \bar{u}^T \bar{b} \rfloor$ is valid for Y.

(2) $P = \{\bar{x} \in \mathbb{R}^n \mid A\bar{x} \leq \bar{b}, \bar{x} \geq \bar{0}\}$.

$\bar{u} \geq \bar{0} \implies (\bar{u}^T A)\bar{x} \leq \bar{u}^T\bar{b}$ is valid for P. (1)

$\implies \lfloor(\bar{u}^T A)\rfloor\bar{x} \leq \bar{u}^T\bar{b}$ is valid for P (2)

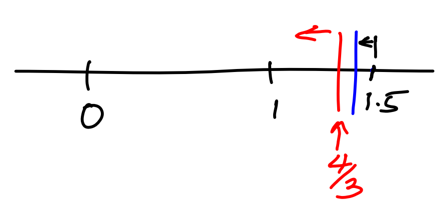
Since $\bar{x} \geq \bar{0}$, (2) weakens (1).

Hence $\lfloor \bar{u}^T A \rfloor \bar{x} \leq \lfloor \bar{u}^T \bar{b} \rfloor$ is valid for $Y = P \cap \mathbb{Z}^n$.

Example $\lfloor 3.3 \rfloor x \leq 4.5$ is valid for P

$\implies 3x \leq \lfloor 4.5 \rfloor$ is valid for P

$3x \leq 4$ is valid for $P \cap \mathbb{Z}$.



Mixed Integer Case (of the CG cut)

Mixed integer rounding (MIR)

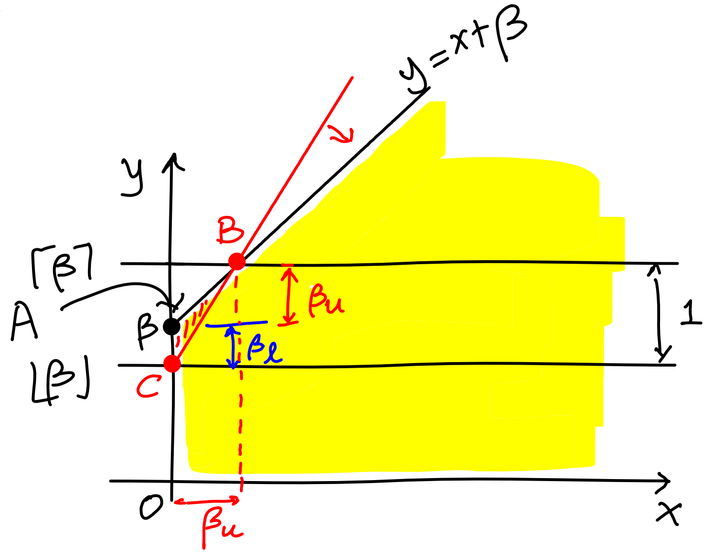
$X = \{(x,y) \in \mathbb{R}_{\geq 0} \times \mathbb{Z} \mid y \leq x + \beta\}.$

interesting case: β is non-integral.

$X = \{(x,y) \in \mathbb{R}_{\geq 0} \times \mathbb{Z} \mid y \leq x+\beta\}$

β is non-integral.

$A(0,\beta)$ needs to be cut off.



Notation

$\beta_l = \beta - \lfloor \beta \rfloor$
$\beta_u = \lceil \beta \rceil - \beta$ } lower and upper fractional parts.

e.g., $\beta = 13.3$,
$\beta_l = 0.3$, $\beta_u = 0.7$.

Hence we get that

$$y \leq \frac{1}{\beta_u} x + \lfloor \beta \rfloor$$

is valid for X.

$x \geq 0$ is needed to get the fractional corner point $A(0,\beta)$ in the first place.

At B, $y = \lceil \beta \rceil = \beta + \beta_u$. With $y = x + \beta$, we get

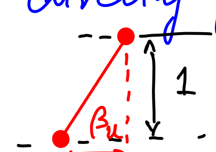
$\beta + \beta_u = x + \beta \Rightarrow x = \beta_u$.

The cut is $y = mx + \lfloor \beta \rfloor$, and at $B(\beta_u, \lceil \beta \rceil)$, we get

$$\lceil \beta \rceil = \lfloor \beta \rfloor + 1 = m\beta_u + \lfloor \beta \rfloor$$

$$\Longrightarrow \quad m = \frac{1}{\beta_u}.$$

Alternatively, $m = \frac{1}{\beta_u}$ directly from the figure



MATH 567 : Lecture 17 (03/06/2025)

Today : * MIG cuts
* Knapsack cuts
* cover inequalities

Mixed-integer Gomory Cut (MIG cut)

Extension of MIR to higher dimensions. Let

$$X = \{(\bar{x},\bar{y}) \in \mathbb{R}^m_{\geq 0} \times \mathbb{Z}^n_{\geq 0} \mid \sum_{j \in N} a_j y_j + \sum_{j \in M} a_j x_j = \beta\}$$

where $N = \{1,2,\dots,n\}$ and $M = \{1,2,\dots,m\}+n$.
→ N, M are index sets for $\bar{y}, \bar{x}$, resp.

IDEA: Derive a valid inequality of the form $y \leq x + \beta$ from the equation defining X, and apply MIR.

$$\sum_{j \in N} a_j y_j + \sum_{j \in M} a_j x_j = \beta$$

we ignore terms with $a_j \geq 0$ ($x_j \geq 0 \ \forall j$)

$$\Rightarrow \sum_{j: a_{j_\ell} \leq \beta_\ell} \lfloor a_j \rfloor y_j + \sum_{j: a_{j_\ell} > \beta_\ell} \underbrace{a_j}_{\lceil a_j \rceil - a_{j_u}} y_j + \sum_{a_j < 0} a_j x_j \leq \beta$$

$$\Rightarrow \underbrace{\left(\sum_{j: a_{j_\ell} \leq \beta_\ell} \lfloor a_j \rfloor y_j + \sum_{j: a_{j_\ell} > \beta_\ell} \lceil a_j \rceil y_j\right)}_{y} \leq \beta + \underbrace{\left(\sum_{j: a_{j_\ell} > \beta_\ell} a_{j_u} y_j - \sum_{a_j < 0} a_j x_j\right)}_{x}$$

We now apply MIR to get $y \leq \frac{1}{\beta_u} x + \lfloor \beta \rfloor$.

$$\Rightarrow \left(\sum_{a_{j_\ell}\le\beta_\ell}{}' \lfloor a_j\rfloor y_j + \sum_{a_{j_\ell}>\beta_\ell}{}' \underbrace{\lceil a_j\rceil}_{\lfloor a_j\rfloor+1} y_j\right) \le \lfloor\beta\rfloor + \left(\sum_{a_{j_\ell}>\beta_\ell}{}' \frac{a_{ju}}{\beta_u} y_j - \sum_{a_j<0}{}' \frac{a_j}{\beta_u} x_j\right)$$

$$\Rightarrow \sum_{a_{j_\ell}\le\beta_\ell}{}' \lfloor a_j\rfloor y_j + \sum_{a_{j_\ell}>\beta_\ell}{}' \left(\lfloor a_j\rfloor + \left(\frac{\beta_u - a_{ju}}{\beta_u}\right)\right) y_j + \frac{1}{\beta_u}\sum_{a_j<0}{}' a_j x_j \le \lfloor\beta\rfloor$$

is the MIG cut.

<u>Note</u>: If $|M|=0$, i.e., there are no x_j's, the usual CG cut

$$\sum_{j\in N}{}' \lfloor a_j\rfloor y_j \le \lfloor\beta\rfloor.$$

But the MIG cut gives

$$\sum_{a_{j_\ell}\le\beta_\ell}{}' \lfloor a_j\rfloor y_j + \sum_{a_{j_\ell}>\beta_\ell}{}' \left(\lfloor a_j\rfloor + \underbrace{\left(\frac{\beta_u - a_{ju}}{\beta_u}\right)}_{\ge 0}\right) y_j \le \lfloor\beta\rfloor,$$

which is stronger than the CG cut.

Wolsey (Integer Programming) calls the MIR cut as the "basic mixed integer inequality", and the special case of MIG cut with $|M|=1$, $|N|=2$ as the "MIR inequality".

Example

$$X = \left\{ (\bar{x}, \bar{y}) \in \mathbb{R}^2_{\geq 0} \times \mathbb{Z}^3_{\geq 0} \;\middle|\; \underbrace{2}_{a_4} x_1 - \underbrace{x_2}_{a_5} + \underbrace{\tfrac{10}{3}}_{a_1} y_1 + \underbrace{y_2}_{a_2} + \underbrace{\tfrac{11}{4}}_{a_3} y_3 = \underbrace{\tfrac{21}{2}}_{\beta} \right\}.$$

$$a_{1_\ell} = \tfrac{1}{3},\; a_{1_u} = \tfrac{2}{3},\; a_{3_\ell} = \tfrac{3}{4},\; a_{3_u} = \tfrac{1}{4},\; \beta_\ell = \beta_u = \tfrac{1}{2}.$$

$\Rightarrow \frac{10}{3} y_1 + y_2 + \frac{11}{4} y_4 - x_2 \leq \frac{21}{2}$ is valid for X.

Note that we have removed the $2x_1$ term from lhs.

$$\Rightarrow \left\lfloor \tfrac{10}{3} \right\rfloor y_1 + y_2 + \left(\left\lfloor \tfrac{11}{4} \right\rfloor + \frac{\left(\frac{1}{2} - \frac{1}{4}\right)}{1/2} \right) y_3 - \frac{1}{1/2} x_2 \leq \left\lfloor \tfrac{21}{2} \right\rfloor$$

is valid for X.

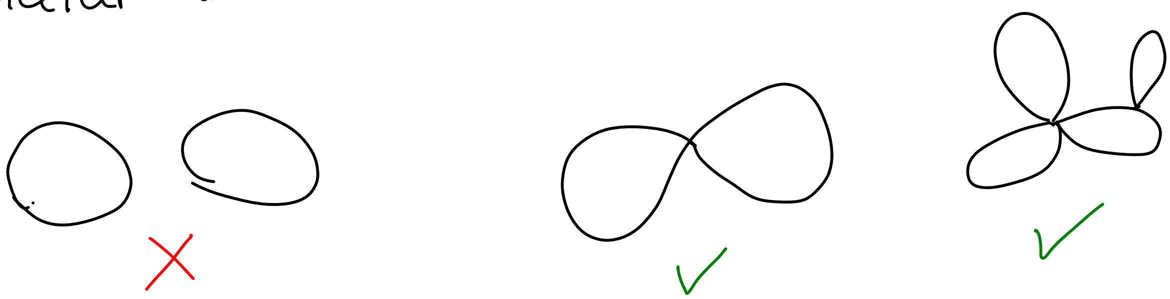
$\Rightarrow 3y_1 + y_2 + \frac{5}{2} y_3 - 2x_2 \leq 10$ is valid for X.

Project 1: Hiker's tour problem (HTP)

$G = (V, E)$ directed graph

Find a circuit (closed walk) with following properties:

* start and end at a given vertex;
* do not have to visit every $v \in V$;
* could visit a node more than once;
* subtours are allowed as long as they are connected at vertices.



* $\sum_{(i,j) \in W} c_{ij} \geq L$ ← data

Come up with formulations similar to the MTZ and subtour formulations for TSP.

Knapsack Cuts for pure 0-1 Programs

IDEA:

Given $\left\{ \begin{array}{ll} \max & \bar{c}^T\bar{x} \\ \text{s.t.} & A\bar{x} \le \bar{b} \\ & \bar{x} \in \{0,1\}^n \end{array} \right\}$, pick $\bar{a}^T\bar{x} \le \beta$ from $A\bar{x} \le \bar{b}$,

generate cuts for $Y = \{\bar{x} \in \{0,1\}^n \mid \bar{a}^T\bar{x} \le \beta\}$, and add these cuts to the original IP.

Assume $a_i, \beta \in \mathbb{Z}$. WLOG, assume $a_i \ge 0 \; \forall i$ (in $\bar{a}$). If $a_1 < 0$, we could replace x_1 with $(1-x_1)$ and a_1 with $-a_1$ to get another inequality, for instance.

We define covers that capture the subsets of a_i that add to values larger than β (and hence "cover" it). If their sum is $> \beta$, we cannot have all the corresponding $x_j = 1$, which is the cut we are seeking.

Def $C \subseteq \{1,2,\dots,n\} = N$ is a **cover** if $\bar{a}(C) > \beta$, where $\bar{a}(C) = \sum_{i \in C} a_i$. Further, we say that C is a **minimal cover** if C is a cover, but $C \setminus \{i\}$ is not a cover $\forall i \in C$.

Example

Let $Y = \{\bar{x} \in \{0,1\}^7 \mid \underline{11x_1 + 6x_2 + 6x_3 + 5x_4 + 5x_5 + 4x_6 + x_7} \le 19\}$ (*)

$C_1 = \{1,4,5\}$ is a minimal cover.

$C_2 = \{3,4,5,6\}$ is a minimal cover.

$C_3 = \{3,4,5,6,7\}$ is a cover, but is not minimal.

Note that $a_3 + a_4 + a_5 + a_6 + a_7 = 21 > \beta = 19$. But so is $a_3 + a_4 + a_5 + a_6 (= 20)$.

Claim C is a cover $\Longrightarrow$ $\bar{x}(C) \le |C| - 1$ is valid for Y.

Here, $\bar{x}(C) = \sum_{j \in C} x_j$.

C_1: $\underbrace{x_1 + x_4 + x_5 \le 2 \text{ is valid for } Y.}_{(1)}$

C_2: $\underbrace{x_3 + x_4 + x_5 + x_6 \le 3 \text{ is valid for } Y}_{(2)}$

C_3: $\underbrace{x_3 + x_4 + x_5 + x_6 + x_7 \le 4 \text{ is valid for } Y,}_{(3)}$.

But (3) is weaker than (2), e.g., $x_3 + x_4 + x_5 + x_6 = 3.5$ satisfies (3), but violates (2).

Notice we added an extra variable (x_7) to the lhs of the $\le$ inequality with $x_7 \ge 0$, but also increased the rhs by 1. If we could add more nonnegative terms to the lhs while not changing the rhs, then we will strengthen the cut.

Def The **extension** of a cover C is

$$E(C) = \{ j \notin C, j \in N \mid a_j \geq \max_{i \in C} \{a_i\} \} \cup C.$$

e.g., $E(\{3,4,5,6\}) = \{1,2,3,4,5,6\}$.

Claim $\bar{x}(E(C)) \leq |C|-1$ is valid for Y.

So, $x_3+x_4+x_5+x_6 \leq 3$ —— (2) can be strengthened

to $x_1+x_2+x_3+x_4+x_5+x_6 \leq 3$ —— (4).

Since $\bar{a}(C) > \beta$, and the added to C to obtain $E(C)$ are such that $a_j \geq \max_{i \in C}(a_i)$, the validity of the new cut follows.

MATH 567: Lecture 18 (03/18/2025)

Today: * lifted cover inequalities
* separation problem

Recall definitions on knapsack cover inequalities:

Def $C \subseteq \{1,2,\dots,n\} = N$ is a **cover** if $\bar{a}(C) > \beta$, where $\bar{a}(C) = \sum_{i \in C} a_i$. Further, we say that C is a **minimal cover** if C is a cover, but $C \setminus \{i\}$ is not a cover $\forall i \in C$.

Let $Y = \{\bar{x} \in \{0,1\}^7 \mid 11x_1 + 6x_2 + 6x_3 + 5x_4 + 5x_5 + 4x_6 + x_7 \leq 19\}$ (*)

$C_1 = \{1,4,5\}$ is a minimal cover.

$C_2 = \{3,4,5,6\}$ is a minimal cover.

$C_3 = \{3,4,5,6,7\}$ is a cover, but is not minimal.

Claim C is a cover $\Rightarrow$ $\bar{x}(C) \leq |C| - 1$ is valid for Y.

Here, $\bar{x}(C) = \sum_{j \in C} x_j$.

C_1: $x_1 + x_4 + x_5 \leq 2$ is valid for Y. (1)

C_2: $x_3 + x_4 + x_5 + x_6 \leq 3$ is valid for Y (2)

C_3: $x_3 + x_4 + x_5 + x_6 + x_7 \leq 4$ is valid for Y, (3)

Def The **extension** of a cover C is

$$E(C) = \{j \notin C, j \in N \mid a_j \geq \max_{i \in C} \{a_i\}\} \cup C.$$

e.g., $E(\{3,4,5,6\}) = \{1,2,3,4,5,6\}$.

Claim $\bar{x}(E(C)) \leq |C| - 1$ is valid for Y.

So, $x_3+x_4+x_5+x_6 \leq 3$ — (2) can be strengthened to

$$x_1+x_2+x_3+x_4+x_5+x_6 \leq 3 \quad \text{—— (4).}$$

This is an extended cover cut/inequality.

But, $\underbrace{2x_1+x_2+x_3+x_4+x_5+x_6 \leq 3}_{(5)}$ is also valid for Y.

Recall, $Y = \{\bar{x} \in \{0,1\}^7 \mid 11x_1+6x_2+6x_3+5x_4+5x_5+4x_6+x_7 \leq 19\}$ (*)

(5) holds, as $x_1 = 1 \Rightarrow (x_2+\cdots+x_6) \leq 1$ $(19-11=8)$.

Note that (5) is stronger than (4).

How did we get (5)? By **lifting** coefficient(s)!

We lifted the coefficient of x_1 from 1 to 2.

In a more general setting, we could lift the coefficient of some x_j from 0 to the largest possible value. Also, the idea of lifting could be applied to other classes of inequalities as well, and not just for covers.

Given a cover C_1 with $1 \notin C_1$, we know $\bar{x}(C) \leq |C|-1$ is a valid inequality for $(\bar{a}^T\bar{x})(C_1) \leq \beta$, where $(\bar{a}^T\bar{x})(C_1) = \sum_{j \in C_1} a_j x_j$. We want α_1 such that

$\alpha_1 x_1 + \bar{x}(C_1) \leq |C|-1$ is valid for $a_1x_1 + (\bar{a}^T\bar{x})(C_1) \leq \beta$.

If $x_1 = 0$, α_1 can be any valid value ($\alpha_1 \geq 0$).

If $x_1 = 1$, $\alpha_1 + \bar{x}(C) \leq |C| - 1$ should hold for all $\bar{x} \in \{0,1\}^n$ such that $a_1 + (\bar{a}^T \bar{x})(C_1) \leq \beta$.

$$\text{let } z = \left\{ \begin{array}{ll} \max & \bar{x}(C_1) \\ \text{s.t.} & (\bar{a}^T \bar{x})(C_1) \leq \beta - a_1 \\ & \bar{x} \in \{0,1\}^n \end{array} \right\} \quad \text{(KP)}$$

Then we have $z \leq |C_1| - 1 - \alpha_1 \implies \boldsymbol{\alpha_1 \leq |C| - 1 - z}$, an upper bound on α_1. The best α_1 is $|C| - 1 - z$, but by choosing $z = z_u$, the LP-relaxation objective function value of (KP), we still get a good value for α_1.

In general, we do not want to solve a subproblem as an IP — always solve only LPs as subproblems.

So, we set $\alpha_1 = |C| - 1 - z_u$.

Example

$$Y = \{\bar{x} \in \{0,1\}^7 \mid 11x_1 + 6x_2 + 6x_3 + 5x_4 + 5x_5 + 4x_6 + x_7 \leq 19\} \quad (*)$$

Consider $C_2 = \{3,4,5,6\} \not\ni 1$.

$$\text{(KP) here is } z = \left\{ \begin{array}{ll} \max & x_3 + x_4 + x_5 + x_6 \\ \text{s.t.} & 6x_3 + 5x_4 + 5x_5 + 4x_6 \leq 19 - 11 = 8 \\ & x_3, x_4, x_5, x_6 \in \{0,1\} \end{array} \right\}.$$

$z = 1$ here ($x_j = 1$ for any one $j \in C_2$). $\implies \alpha_1 = |C_2| - 1 - z$
$= 4 - 1 - 1 = 2$.

Solving the LP relaxation of (KP), we get

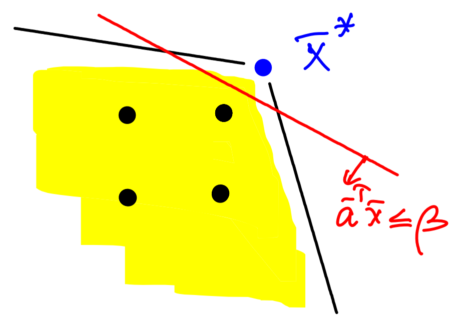
$z_u = 1.8$ ($x_6 = 1$, and $x_5 = 0.8$ or $x_4 = 0.8$) $\Rightarrow \alpha_1 = |C_2| - 1 - z_u = 1.2$, (which is still better than 1). So, the new lifted cover inequality is $1.2x_1 + x_3 + x_4 + x_5 + x_6 \leq 3$.

How did I get $z_u = 1.8$? Essentially using a "greedy" approach to solve the knapsack problem.

$$\begin{aligned} \max \quad & c_1x_1 + \cdots + c_nx_n \qquad c_j, a_j \geq 0 \\ \text{s.t.} \quad & a_1x_1 + \cdots + a_nx_n \leq \beta \\ & 0 \leq x_j \leq u_j \end{aligned}$$

Sort the x_j's in the decreasing order of $\frac{c_j}{a_j}$, and set x_j's to $\min\{u_j, \beta'/a_j\}$, where β' is the "updated" β, i.e, $\beta \leftarrow \beta - a_ix_i$ after setting x_i in the previous step.

Separation Problem



In general, for any combinatorial optimization problem (COP): $\max = \{\bar{c}^T\bar{x} \mid \bar{x} \in X \subseteq \mathbb{R}^n\}$, and given $\bar{x}^* \in \mathbb{R}^n$, is $\bar{x}^* \in \text{conv}(X)$? If YES, prove it. If NO, find an inequality $\bar{a}^T\bar{x} \leq \beta$ satisfied by all $\bar{x} \in X$, but is violated by $\bar{x}^*$, i.e, $\bar{a}^T\bar{x}^* > \beta$.

The inequality with $(\bar{a}^T\bar{x}^* - \beta)$ largest is the "most violated" separating inequality.

We consider the separation problem in the context of knapsack cover inequalities.

Let $Y = \{\bar{x} \in \{0,1\}^n \mid \bar{a}^T\bar{x} \le \beta\}$, $a_i, \beta \in \mathbb{Z}_{\geq 0}$, and let $\bar{x}^* \in \mathbb{R}^n$, but $\bar{x}^* \notin \{0,1\}^n$, i.e., $0 < x_j^* < 1$ for at least one $j \in N$. We want to separate $\bar{x}^*$ using a cover inequality, i.e., find a cover C such that $(\bar{a}^T\bar{x}^*)(C) > \beta$ and $\bar{x}^*(C) > |C|-1$.

Define $\bar{y} \in \{0,1\}^n$ as the incidence vector of C. We need

$$\left\{ \begin{array}{c} \sum_{j=1}^{n} x_j^* y_j > \sum_{j=1}^{n} y_j - 1 \\ \sum_{j=1}^{n} a_j y_j > \beta \\ y_j \in \{0,1\} \ \forall j \end{array} \right\}$$

$$\Longleftrightarrow \left\{ \begin{array}{c} 1 > \sum_{j=1}^{n} (1-x_j^*) y_j \\ \sum_{j=1}^{n} a_j y_j \geq \beta + 1 \\ y_j \in \{0,1\} \ \forall j \end{array} \right\}$$

$\rightarrow$ as $a_j, \beta \in \mathbb{Z}_{\geq 0}$

So, we can find

$$z = \left\{ \begin{array}{ll} \min & \sum_{j=1}^{n} (1-x_j^*) y_j \\ \text{s.t.} & \sum_{j=1}^{n} a_j y_j \geq \beta+1 \\ & y_j \in \{0,1\} \ \forall j \end{array} \right\}.$$

If $z<1$, the cover we seek exists, and its incidence vector is given by $\bar{y}$. Hence $\bar{x}^*$ violates the cover inequality $\bar{x}(C) \leq |C|-1$.

Example

$$Y = \{\bar{x} \in \{0,1\}^7 \mid 11x_1 + 6x_2 + 6x_3 + 5x_4 + 5x_5 + 4x_6 + x_7 \leq 19\} \quad (*)$$

Let $\bar{x}^* = [\overset{1}{0}, \overset{2}{0}, \overset{3}{1}, \overset{4}{1}, \overset{5}{1}, \overset{6}{\tfrac{3}{4}}, \overset{7}{0}]^T$. Find a separating cover for $\bar{x}^*$.

We solve

$$\min \quad z = y_1 + y_2 + \tfrac{1}{4} y_6 + y_7$$
$$\text{s.t.} \quad 11y_1 + 6y_2 + 6y_3 + 5y_4 + 5y_5 + 4y_6 + y_7 \geq 20$$
$$y_j \in \{0,1\}, \ j = 1, \dots, 7.$$

Optimal solution: $\bar{y} = [0,0,1,1,1,1,0]$, $z^* = \frac{1}{4}$.

Hence $\bar{x}^*$ violates $x_3 + x_4 + x_5 + x_6 \leq 3$.

Indeed, $\bar{x}^*(C) = 3\frac{3}{4} \nleq 3$.

Note that a greedy approach gives the optimal integer solution for this knapsack problem!

MATH 567: Lecture 19 (03/20/2025)

Today: * disjunctive cuts

Disjunctive Cuts (for 0-1 IPs)

IDEA: Derive cuts by first creating a non-linear system then linearizing the same by going to higher dimensions, and then projecting back.

If $x_j \in \{0,1\} \;\forall j$, $\quad x_j^2 \longleftarrow x_j$, $\quad x_i x_j \longleftarrow y_{ij} \in \{0,1\}$.

Let $P_i = \{\bar{x} \mid A_i \bar{x} \le \bar{b}^i\}$, $i = 1,2$, $P_i \neq \emptyset$.

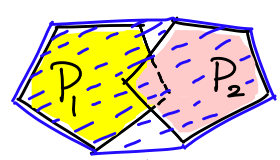
Assume $\operatorname{rec}(P_1) = \operatorname{rec}(P_2)$. Thus the sharp representation for $P_1 \cup P_2$ is

$$\left.\begin{aligned} A_1 \bar{x}^1 &\le \bar{b}^1 y_1 \\ A_2 \bar{x}^2 &\le \bar{b}^2 y_2 \\ \bar{x} &= \bar{x}^1 + \bar{x}^2 \\ y_1 + y_2 &= 1 \\ y_1, y_2 &\in \{0,1\} \end{aligned}\right\} \text{— } *\text{-sharp}$$

Recall ① $\bar{x} \in P_1 \cup P_2 \iff \exists\, (\bar{x}^1, \bar{x}^2, y_1, y_2)$ such that $(\bar{x}, \bar{x}^1, \bar{x}^2, y_1, y_2)$ satisfies $*$-sharp.

② $\operatorname{Proj}_{\bar{x}}$ (LP-relaxation of $*$-sharp) $= \operatorname{conv}(P_1 \cup P_2)$.

if you project out $\bar{x}^1, \bar{x}^2, y_1, y_2$



$\operatorname{conv}(P_1 \cup P_2)$

Idea: we create a non linear system from the original system, then linearize by adding more variables, and finally project back to the original space to derive valid inequalities.

Lovász-Schrijver (LS) Procedure (for 0-1 IPs)

$X = \{\bar{x} \in \mathbb{Z}^n \mid A\bar{x} \le \bar{b}\}$ → includes $0 \le x_j \le 1$

$K = \{\bar{x} \in \mathbb{R}^n \mid A\bar{x} \le \bar{b}\}$

1. Select $j \in \{1, 2, \ldots, n\}$.

2. Create the non-linear system

$$\left.\begin{aligned} (A\bar{x} - \bar{b})\,x_j &\le \bar{0} \\ (A\bar{x} - \bar{b})(1 - x_j) &\le \bar{0} \\ x_j(1 - x_j) &= 0 \end{aligned}\right\} M_j^{NL}(K)$$

holds, as $x_j \in \{0,1\}$

non linear, as there are quadratic terms $x_i x_j$

3. Linearize the system by replacing x_j^2 by x_j, and $x_i x_j$ for $j \neq i$ by y_i (where y_i is supposed to be binary). The polyhedron thus obtained is $M_j(K)$.

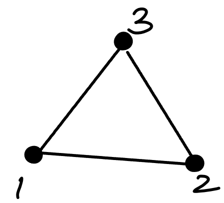
4. Let $P_j(K) = \mathrm{Proj}_{\bar{x}}(M_j(K))$. → has the cut(s) we seek

The LS and other similar procedures have many theoretical and computational applications. A standard question is whether we could get the required cut by a small (i.e., polynomial) number of applications (repeatedly) of the LS procedure.

<u>Example</u> Vertex packing problem (also called the maximal independent set problem — select the largest subset of vertices so that no two of the vertices are joined by an edge).

e.g.,

$$X\left\{\begin{array}{l} \left.\begin{array}{l} x_1+x_2\le 1\\ x_2+x_3\le 1\\ x_1+x_3\le 1\\ 0\le x_i\le 1,\ i=1,2,3 \end{array}\right\} K \\ \quad x_i\in\mathbb{Z} \end{array}\right.$$



Want to derive
$x_1+x_2+x_3\le 1$

Apply LS procedure with $j=1$:

$$x_1^2+x_1x_2\le x_1 \quad , \text{ replace } x_1^2 \text{ by } x_1$$

$$\Rightarrow x_1x_2\le 0$$

But from $-x_2\le 0$, we get $-x_1x_2\le 0 \Rightarrow x_1x_2\ge 0$.

$$\Rightarrow x_1x_2=0.$$

Similarly, $x_1x_3=0$.

Consider $(x_2+x_3\le 1)(1-x_1)$:

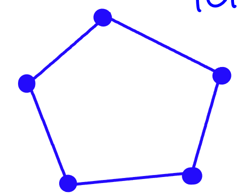
$$x_2+x_3-\underbrace{x_1\cancel{x_2}}_{=0}-\underbrace{x_1\cancel{x_3}}_{=0}\le 1-x_1$$

$$\Rightarrow \boxed{x_1+x_2+x_3\le 1}$$

This is an instance of "odd-hole" inequality.

Def An **odd hole** is $C \subseteq V$ with $|C|$ odd, with edges connecting the vertices making a simple cycle, i.e., a "hole".

$|C|=5$



We can pick at most $\frac{|C|-1}{2}$ nodes, i.e.,

$$\bar{x}(C) \leq \frac{|C|-1}{2}$$ is valid, and is

derivable by the LS procedure using $M_j(C)$ for any $j \in C$.

$\sum_{(i,j)\in C} x_j \leq 2$ here.

We could also derive this inequality by adding $x_i + x_j \leq 1$ over C, which gives

$$2\,\bar{x}(C) \leq |C|,$$ which we can

divided by 2, and round down (CG procedure) to get

$$\bar{x}(C) \leq \left\lfloor \frac{|C|}{2} \right\rfloor = \frac{|C|-1}{2}.$$

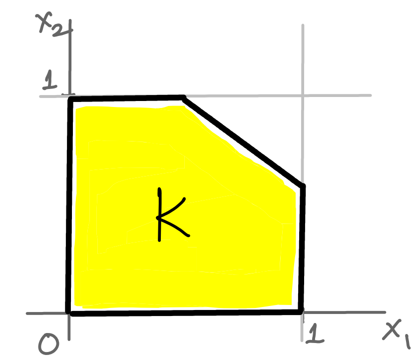
But there are other problem instances where the LS procedure gives inequalities which cannot be derived by other procedures.

Theorem 14 If $Q_j(K) = \text{conv}\left([K \cap (x_j=0)] \cup [K \cap (x_j=1)]\right)$

then $P_j(K) = Q_j(K)$.

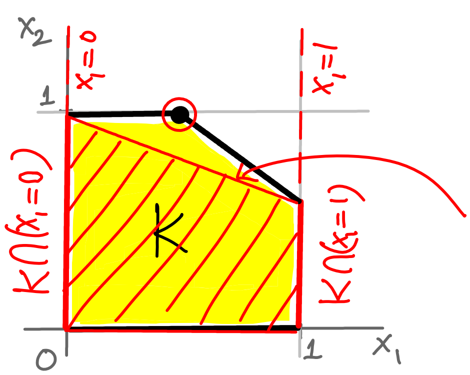
Theorem 13 was on reduced cost fixing in lecture 15!

Before presenting the proof, we illustrate the concept in 2D. Consider a non-trivial polytope in the unit square.



Consider $Q_1(K) = \text{conv}\left([K \cap (x_1=0)] \cup [K \cap (x_1=1)]\right)$.

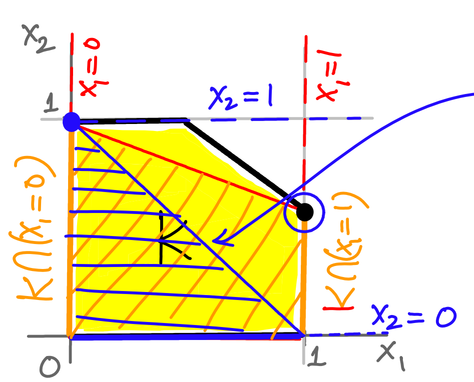
Note: the polytope need not be "symmetric" —  or  show the same behavior



$Q_1(K) = \text{conv}\left([K \cap (x_1=0)] \cup [K \cap (x_1=1)]\right)$

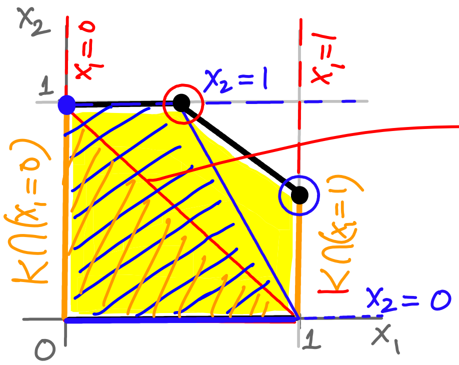
Notice how the fractional point ⊙ is cut off.

We could now apply the same procedure again using $j=2$ to get the tightest polytope. In detail, we consider $Q_2(Q_1(K))$.



$Q_2(Q_1(K))$

Notice that the other fractional corner point ⊙ is also cutoff now.



$$Q_1(Q_2(K)) = Q_2(Q_1(K))$$

the order does not matter!

Recall Theorem 14: $P_j(K) = \underset{j}{Q}(K) := \operatorname{conv}\left([K\cap(x_j=0)] \cup [K\cap(x_j=1)]\right)$.

<u>Proof</u> $(\Longleftarrow)$ $\quad P_j(K) \supseteq Q_j(K)$

We try to show $K\cap(x_j=0) \subseteq P_j(K)$

and $K\cap(x_j=1) \subseteq P_j(K)$.

If $\bar{x}'\in K$ and x_j' is either 0 or 1, then

$$\left.\begin{array}{l} A\bar{x}' \leq \bar{b} \\ x_j' \geq 0,\ 1-x_j' \geq 0 \\ x_j'(1-x_j') = 0 \end{array}\right\} \text{ all hold.}$$

So, we can indeed form the system $M_j^{N2}(K)$

$$\left\{\begin{array}{l} (A\bar{x}-\bar{b})x_j' \leq \bar{0} \\ (A\bar{x}-\bar{b})(1-x_j') \leq \bar{0} \\ x_j'(1-x_j') = 0 \end{array}\right\},$$

eliminate nonlinear terms, linearize, and project to get $P_j(K)$.

$$\Longrightarrow \quad Q_j(K) \subseteq P_j(K).$$

$(\Longrightarrow)\quad P_j(K) \subseteq Q_j(K)$.

We show that $P_j(K)$ contains the sharp formulation of union of polyhedra, whose convex hull is $Q_j(K)$.

$$M_j(K) \text{ has } \left\{ \begin{array}{c} (A\bar{x}-\bar{b})x_j \leq \bar{0} \\ (A\bar{x}-\bar{b})(1-x_j) \leq \bar{0} \\ x_j(1-x_j)=0 \end{array} \right\} \qquad \begin{array}{c} A\overbrace{\bar{x}x_j}^{\bar{x}^1} - \bar{b}\overbrace{x_j}^{y_1} \leq \bar{0} \\ A\overbrace{\bar{x}(1-x_j)}^{\bar{x}^2} - b\underbrace{(1-x_j)}_{y_2} \leq \bar{0} \\ [\bar{x}(1-x_j)]_j = 0 \end{array}$$

Write $\bar{x}x_j$ as $\bar{x}^1$, $\bar{x}(1-x_j)$ as $\bar{x}^2$, $x_j \leftarrow y_1$, $(1-x_j) \leftarrow y_2$

$$\Longrightarrow \quad \begin{array}{l} A\bar{x}^1 \leq \bar{b}y_1 \\ A\bar{x}^2 \leq \bar{b}y_2 \end{array}$$

$$\bar{x} - \bar{x}x_j - \bar{x}(1-x_j) = \bar{0} \Longrightarrow \bar{x} = \bar{x}^1 + \bar{x}^2$$

$$x_j + (1-x_j) = 1 \Longrightarrow y_1 + y_2 = 1$$

$$x_j^2 - x_j = 0 \Longrightarrow (\bar{x}^1)_j = y_1 \equiv \underbrace{\bar{e}_j^T}_{j\text{th unit vector}} \bar{x}^1 = y_1$$

$$[\bar{x}(1-x_j)]_j = 0 \Longrightarrow \bar{x}^2_j = 0 \equiv \bar{e}_j^T \bar{x}^2 = 0 = 0\cdot y_2$$

$$\boxed{\begin{array}{l} A\bar{x}^1 \leq \bar{b}y_1 \\ \bar{e}_j^T\bar{x}^1 = y_1 \\ A\bar{x}^2 \leq \bar{b}y_2 \\ \bar{e}_j^T\bar{x}^2 = 0\cdot y_2 \\ \bar{x} = \bar{x}^1 + \bar{x}^2 \\ y_1 + y_2 = 1 \end{array}}$$

$\to$ polyhedron of the sharp formulation of $P_1 \cup P_2$

where $P_1 = \{\bar{x} \mid A\bar{x} \leq \bar{b},\ \underbrace{\bar{e}_j^T\bar{x} = 1}_{x_j=1}\}$ and $P_2 = \{\bar{x} \mid A\bar{x} \leq \bar{b},\ \underbrace{\bar{e}_j^T\bar{x} = 0}_{x_j=0}\}$.

$$\Longrightarrow \quad P_j(K) \subseteq Q_j(K).$$

$\square$

MATH 567: Lecture 20 (03/25/2025)

Today: * A different proof for $P_j(K) \subseteq Q_j(K)$
* Disjunctive programming

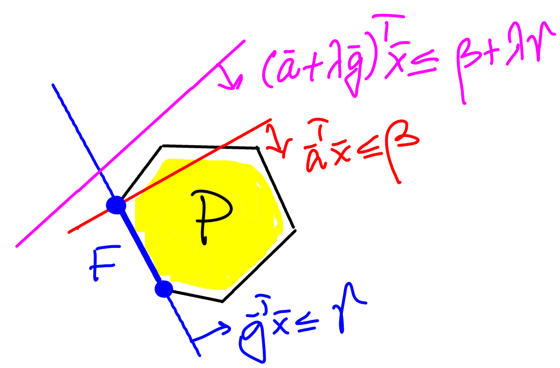
Recall $Q_j(K) = \operatorname{conv}\left([K \cap (x_j=0)] \cup [K \cap (x_j = 1)]\right)$; **Theorem 14** $P_j(K) = Q_j(K)$.

A different proof We first state and prove a lemma.

Lemma 15 Let $P = \{\bar{x} \in \mathbb{R}^n \mid A\bar{x} \le \bar{b},\ \bar{g}^T\bar{x} \le \gamma\}$ and
$F = P \cap \{\bar{x} \in \mathbb{R}^n \mid \bar{g}^T\bar{x} = \gamma\}$, i.e.,
F is a face of P. Suppose $\bar{a}^T\bar{x} \le \beta$ is valid for F but not valid for P. Then there exists $\lambda \geq 0$ such that
$(\bar{a} + \lambda\bar{g})^T\bar{x} \le \beta + \lambda\gamma$ is valid for P.

Proof (Farkas' lemma)

$$F \left\{ \begin{array}{ll} \left.\begin{array}{l} A\bar{x} \le \bar{b} \\ \bar{g}^T\bar{x} \le \gamma \end{array}\right\} P & \begin{array}{l} \bar{u} \geq \bar{0} \\ v_1 \geq 0 \end{array} \\ -\bar{g}^T\bar{x} \le -\gamma & \quad v_2 \geq 0 \end{array} \right.$$



Can derive $\bar{a}^T\bar{x} \le \beta$ from F:

$$\Rightarrow \left.\begin{array}{l} \bar{u}^TA + v_1\bar{g}^T - v_2\bar{g}^T = \bar{a}^T \\ \bar{u}^T\bar{b} + v_1\gamma - v_2\gamma \le \beta \end{array}\right\} \quad \begin{array}{l} \bar{u}^TA + v_1\bar{g}^T = \bar{a}^T + v_2\bar{g}^T \\ \bar{u}^T\bar{b} + v_1\gamma \le \beta + v_2\gamma \end{array}$$

Another inequality can be derived using multipliers $(\bar{u}, v_1)$ from P:

$\Rightarrow (\bar{a} + v_2\bar{g})^T\bar{x} \le \beta + v_2\gamma$ is valid for P.

$\lambda = v_2$ works for the lemma. $\square$

Proof for $P_j(K) \subseteq Q_j(K)$

Suppose $\bar{a}^T\bar{x} \leq \beta$ is valid for both $K \cap (x_j = 0)$ and $K \cap (x_j = 1)$, two faces of K.

$-x_j \leq 0$ $\qquad$ $x_j \leq 1$ or $-(1-x_j) \leq 0$

We use Lemma 15 to simultaneously lift this inequality so that it is valid for all of K.

$\Rightarrow$ Find $\lambda \geq 0$ and $\mu \geq 0$ such that

$$\bar{a}^T\bar{x} - \lambda x_j \leq \beta \text{ is valid for } K, \qquad (1)$$

and

$$\bar{a}^T\bar{x} - \mu(1-x_j) \leq \beta \text{ is valid for } K. \qquad (2)$$

WLOG, (1) and (2) are already part of $A\bar{x} \leq \bar{b}$. Else, we could derive them from $A\bar{x} \leq \bar{b}$ using nonnegative multipliers.

Consider the following scaled inequalities in $M_j^{NL}(K)$

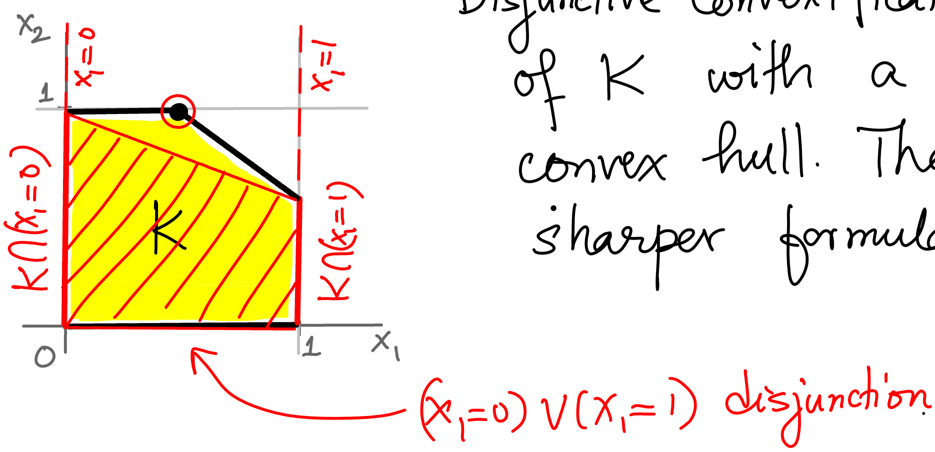
$$\left.\begin{array}{c} (1-x_j)(\bar{a}^T\bar{x} - \lambda x_j) \leq (1-x_j)\beta \\ x_j(\bar{a}^T\bar{x} - \mu(1-x_j)) \leq x_j\beta \\ x_j(1-x_j) = 0 \end{array}\right\} \text{parts of } M_j^{NL}(K).$$

Adding them gives $\bar{a}^T\bar{x} - (\lambda+\mu)\underbrace{(\cancel{x_j}(1-x_j))}_{=0} \leq \beta$.

$\Rightarrow$ $\bar{a}^T\bar{x} \leq \beta$ is valid for $M_j^{NL}(K)$, and hence for $P_j(K)$.

$\square$

Disjunctive Programming (DP) and Disjunctive Convexification



Disjunctive Convexification: take intersection of K with a disjunction, and take convex hull. The idea is to obtain a sharper formulation in the process.

A **disjunctive program** (DP) is an optimization problem of the following form:

$$\left\{ \begin{array}{ll} \max & \bar{c}^T \bar{x} \\ \text{s.t.} & \bar{x} \in K \\ & \bar{x} \in D_1 \cap D_2 \cdots \cap D_p \end{array} \right\} \text{(DP)}$$

where $K = \{\bar{x} \in \mathbb{R}^n \mid A\bar{x} \leq \bar{b}\}$ and

$$D_i = D_{i_1} \cup D_{i_2} \cdots \cup D_{i_{k_i}}, \quad i = 1, \ldots, p, \quad \text{i.e., the}$$

i^{th} disjunction has k_i alternatives.

The set K is the LP-relaxation of (DP).

D_{i_ℓ} are polyhedra $(\ell = 1, \ldots, k_i)$, and are called the terms in the i^{th} disjunction.

Examples

1. $k_i = 2\ \forall i$, $D_{i_1} = \{\bar{x} \in \mathbb{R}^n \mid x_i = 0\}$ and $D_{i_2} = \{\bar{x} \in \mathbb{R}^n \mid x_i = 1\}$.
   $K = \{\bar{x} \in \mathbb{R}^n \mid A\bar{x} \le \bar{b}\}$ includes the bounds $0 \le x_i \le 1$ for $i = 1, \dots, p$, $p \le n$.
   Then (DP) is the usual 0-1 (M)IP. if $p < n$, we get MIP.

2. $k_i = 2\ \forall i$, $D_{i_1} = \{\bar{x} \in \mathbb{R}^n \mid x_{\ell_1} = 0\}$ and $D_{i_2} = \{\bar{x} \in \mathbb{R}^n \mid x_{\ell_2} = 0\}$, while K contains bounds $x_\ell \geq 0\ \forall \ell$. Here (DP) is a linear program with complementarity constraints of the form $x_{\ell_1} x_{\ell_2} = 0$.

We can solve DP "easily" if we have all inequalities for $\operatorname{conv}[K \cap (D_1 \cap \dots \cap D_p)]$. But when do we get efficient representations?

Notation $\quad A \cap_c B = \operatorname{conv}(A \cap B)$.

Assuming we know the sharp representation of $K \cap D_i\ \forall i$, we can devise a theoretical cutting plane algorithm for DP.

Theoretical Cutting Plane Algorithm

Step 0 $\quad K_0 = K = \{\bar{x} \mid A\bar{x} \le \bar{b}\}$.

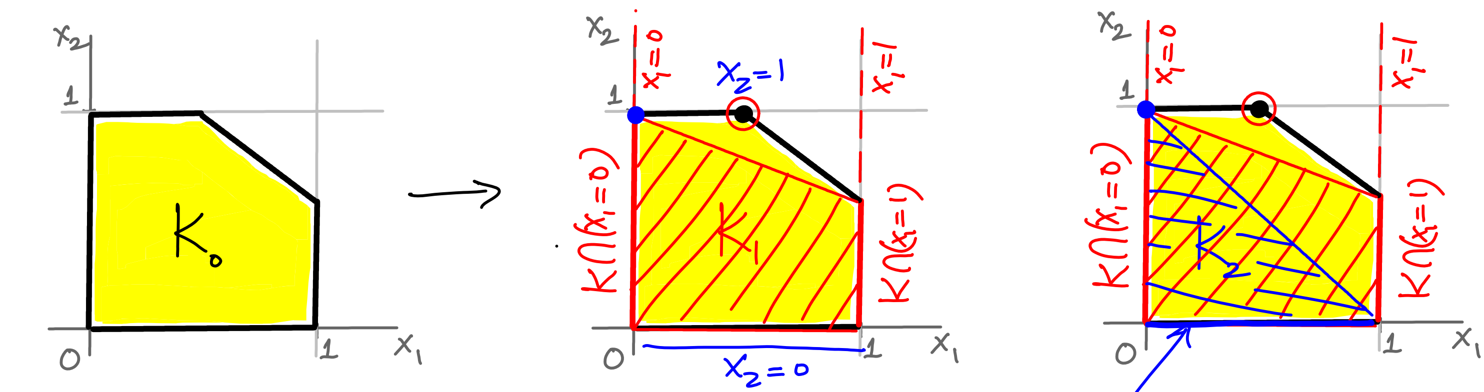
Step i $\quad (1 \le i \le p)$

if $K_{i-1} = \{\bar{x} \mid A_{i-1}\bar{x} \le \bar{b}^{i-1}\}$

set $K_i = K_{i-1} \cap_c D_i = \operatorname{conv}[K_{i-1} \cap D_i]$; generate all inequalities for $K_{i-1} \cap_c D_i$

$i \leftarrow i+1$;

Example $D_1 = \{x_1 = 0 \vee x_1 = 1\}$, $D_2 = \{x_2 = 0 \vee x_2 = 1\}$.



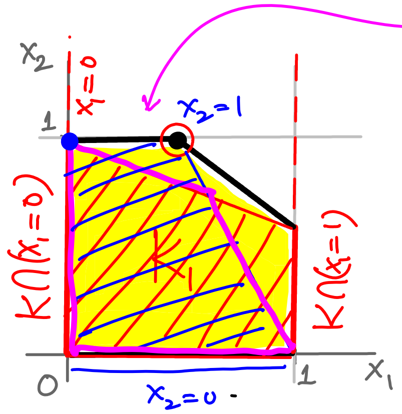
convex hull of the three vertices (0,0), (1,0) and (0,1), which is the triangle.

Here, $K_2 = \text{conv}[K \cap D_1 \cap D_2] = K \cap_c (D_1 \cap D_2)$.

Hence, this is a "good instance".

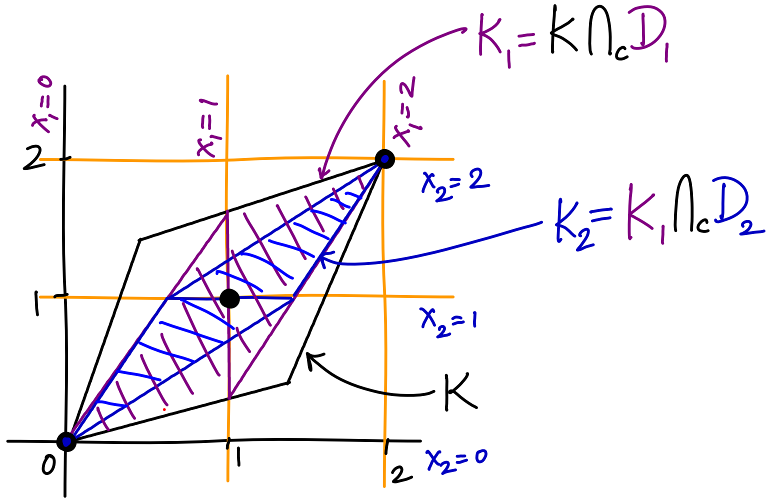
Remark $\text{conv}[K \cap D_1] \cap \text{conv}[K \cap D_2] \neq \text{conv}[K \cap D_1 \cap D_2]$!

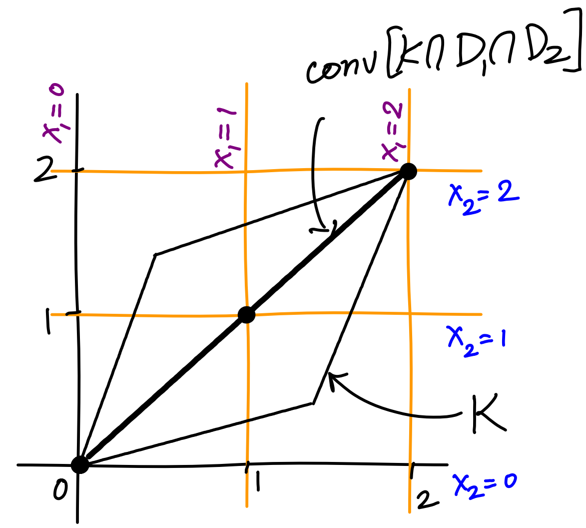
(typically)



A "bad" instance $\quad p=2,\ k_i=3,\ i=1,2$

$$D_i = (x_i=0) \vee (x_i=1) \vee (x_i=2), \quad i=1,2.$$





Here, $K_2 \neq \text{conv}[K \cap D_1 \cap D_2]$.

Q: When is $K_p = K \cap_c (D_1 \cap \cdots \cap D_p)$, where

$$K_p = (\cdots((K \cap_c D_1) \cap_c D_2) \cdots \cap_c D_p)\ ?$$

In general '=' does not hold above.

Notice that in Example 1, the disjunctions $(x_1=0) \vee (x_1=1)$ and $(x_2=0) \vee (x_2=1)$ both defined faces of K, while this was not the case in Example 2 ($x_1=1$ and $x_2=1$ both did not define faces of K). It turns out that if all terms in each disjunction defines a face of K, things are nice!

MATH 567: Lecture 21 (03/27/2025)

* facial disjunctions
* practical algorithm
* rank of cuts
* semidefinite relaxation

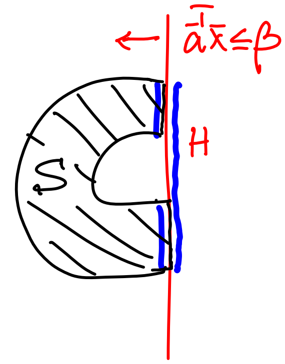
Def D_i is a **facial disjunction** w.r.t. K if D_{ij} are faces of K for $j=1,\dots,k_i$, i.e., $D_{ij} = \{\bar{x} \mid (\bar{a}^{ij})^T\bar{x} = \beta_{ij}\}$ where $(\bar{a}^{ij})^T\bar{x} \le \beta$ is a supporting hyperplane of K.

Theorem 16 If $D_1,\dots,D_p$ are facial disjunctions, then

$$K_p = K \cap_c (D_1 \cap \dots \cap D_p)$$

in the theoretical algorithm.

Proposition 17 Let S be any set (possibly nonconvex), and $H = \{\bar{x} \mid \bar{a}^T\bar{x} = \beta\}$ is a hyperplane such that $\bar{a}^T\bar{x} \le \beta \;\forall \bar{x} \in S$. Then $H \cap \text{conv}(S) = \text{conv}(H \cap S)$.



Proof (Theorem 16)

We show the result for $p=2, k_i=2, i=1,2$.

We need to show

$$(K \cap_c D_i) \cap_c D_j = K \cap_c (D_i \cap D_j)$$

$$(K \cap_c D_i) \cap_c D_j = \text{conv}\left[\text{conv}(K \cap D_i) \cap D_j\right] \qquad D_j = D_{j_1} \cup D_{j_2}$$

$$= \text{conv}\left[\left(\text{conv}(K \cap D_i) \cap D_{j_1}\right) \cup \left(\text{conv}(K \cap D_i) \cap D_{j_2}\right)\right]$$

$$= \text{conv}\left[\text{conv}(K \cap D_i \cap D_{j_1}) \cup \text{conv}(K \cap D_i \cap D_{j_2})\right]$$

by Proposition 17.

$$= \operatorname{conv}\left[(K \cap D_i \cap D_{j_1}) \cup (K \cap D_i \cap D_{j_2})\right]$$

$$= \operatorname{conv}\left[K \cap D_i \cap D_j\right] = K \cap_c (D_i \cap D_j). \quad \square$$

The theoretical algorithm might not work well in practice. Getting efficient descriptions of the convex hulls in each step might be difficult.

A practical Algorithm

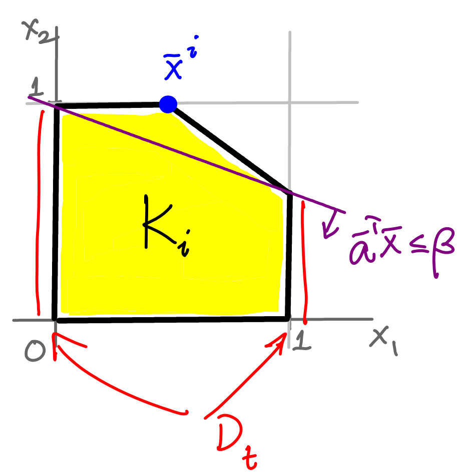
<u>Step 0</u>: $K_0 = K = \{\bar{x} \mid A\bar{x} \le \bar{b}\}$

<u>Step i</u> $(i \ge 1)$: K_i : current relaxation, and
$\bar{x}^i$: optimal solution over K_i

Find $\bar{a}^T\bar{x} \le \beta$ such that

1. $\bar{a}^T\bar{x} \le \beta$ is valid for $K_i \cap D_t$ for some $t > i$.
2. $\bar{a}^T\bar{x} \le \beta$ is violated by $\bar{x}^i$ (i.e., $\bar{a}^T\bar{x}^i > \beta$).

Set $K_{i+1} \leftarrow$ LP relaxation of $K_i \cap D_t \cap \{\bar{x} \mid \bar{a}^T\bar{x} \le \beta\}$.



How do we find $(\bar{a}, \beta)$?

Solve an LP with $\bar{a}, \beta$ as variables.

$$\max \quad \beta - \bar{a}^T \bar{x}^i \quad \text{is given}$$

$$\text{s.t.} \quad \left(\begin{array}{l} \bar{a}^T \bar{x} \leq \beta \text{ is derivable from } K_i \cap D_t \\ \text{by Farkas' Lemma} \end{array} \right) \qquad (1)$$

normalization constraint : e.g.,

$$\sum_{i=1}^{n} |a_i| + |\beta| \leq 1. \longrightarrow \text{we can linearize this constraint}$$

Without the normalization, the LP could be unbounded. If $(\beta, \bar{a}^T)$ works, then $100\beta - 100\bar{a}^T\bar{x}^i$ gives a bigger separation. And so does $10000\beta - 10000\,\bar{a}^T\bar{x}^i$.

For (1), we will use variables representing the multipliers for deriving the constraint $\bar{a}^T\bar{x}^i \leq \beta$ from $K_i \cap D_t$.

Q. How good is any such cutting plane algorithm? First, we define rank of cuts.

Rank of cuts

$K = \{\bar{x} \mid A\bar{x} \leq \bar{b}\}$: All inequalities in $A\bar{x} \leq \bar{b}$, or derivable from $A\bar{x} \leq \bar{b}$ are **rank 0 cuts** (or inequalities).

Let $\bar{a}^T\bar{x} \leq \beta$ be valid for K. Then the CG cut $\lfloor \bar{a}^T \rfloor \bar{x} \leq \lfloor \beta \rfloor$ is a **rank 1 CG cut**.

Combining some (or all) rank-1 CG cuts and applying the CG procedure again gives me a **rank 2 CG cut**.

Similar notion of rank can be defined for the LS-procedure, MIG cuts, etc.

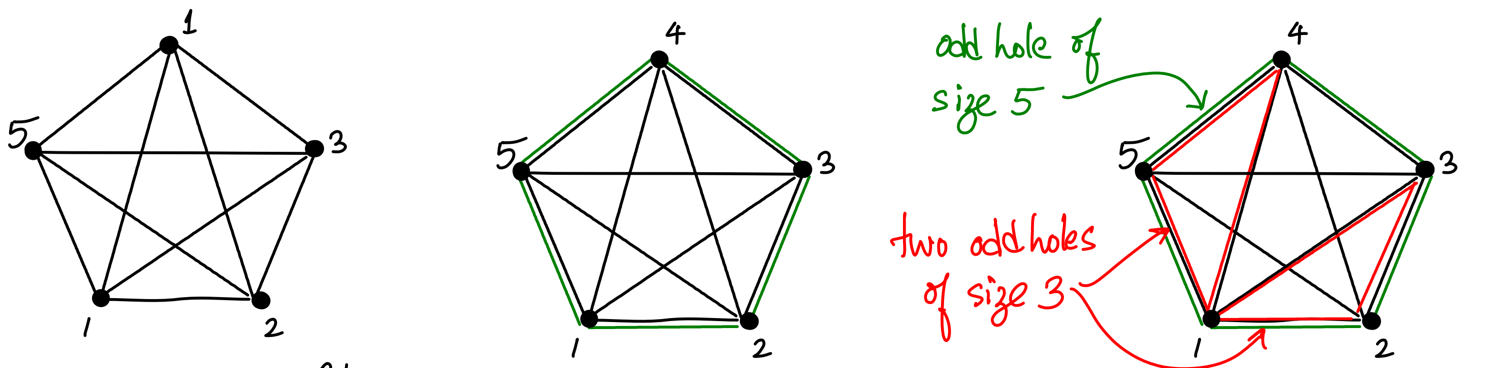
Ideally, we want to derive inequalities with small rank, so that we do not have to apply the cut-procedure too many times.

Back to LS Procedure

Q: How many steps to generate a good inequality?

Example: node packing on complete graph with 5 nodes.

$$K = \left\{ \begin{array}{l} x_i + x_j \le 1 \ \forall (i,j) \\ 0 \le x_i \le 1 \ \forall i \end{array} \right\}$$



complete graph

Node packing problem:

A good inequality is $x_1 + x_2 + x_3 + x_4 + x_5 \le 1$ —— $(*)$

We can pick at most one node.

Recall the definitions of $M_j^{NL}(K)$, $M_j(K)$, and $P_j(K)$. We have

$M_1^{NL}(K)$ specified as
$$\left\{ \begin{array}{c} (A\bar{x} - \bar{b})x_1 \le 0 \\ (A\bar{x} - \bar{b})(1 - x_1) \le 0 \\ x_1(1 - x_1) = 0 \end{array} \right\}.$$

We get odd hole inequalities of size 3:

$$x_1 + x_2 + x_3 \leq 1$$
$$x_1 + x_2 + x_4 \leq 1$$
$$\vdots$$

and $x_1 + x_2 + x_3 + x_4 + x_5 \leq 2$, odd-hole inequality of size 5.

We do not get $\circledast$.

In $P_2(P_1(K))$, we get $x_1 + x_2 + x_3 + x_4 \leq 1$ ——— (2)

To see (2) is valid for $P_2(P_1(K))$, we verify that (2) is valid for $P_1(K) \cap (x_2 = 0 \vee x_2 = 1)$.

$P_1(K) \cap (x_2 = 0)$ gives $x_1 + x_3 + x_4 \leq 1$, which is there in $P_1(K)$.

$P_1(K) \cap (x_2 = 1)$ gives $x_1 + x_3 + x_4 \leq 0$, which is also valid for $P_1(K)$, since we originally (in K itself) have $x_i + x_j \leq 1 \;\forall (i,j)$. Hence $x_2 = 1$ immediately forces $x_j = 0 \;\forall j \neq 2$.

But we still do not get $\circledast$ in $P_2(P_1(K))$.

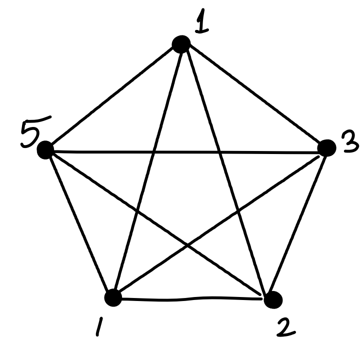
$P_3(P_2(P_1(K)))$ gives $x_1 + \cdots + x_5 \leq 1$ ——— $\circledast$!

$\Rightarrow$ LS-rank of $\circledast$ is 3.

In general, LS rank of $x_1 + \cdots + x_k \leq 1$ is $\leq k-2$, and is often $= k-2$.

Q. Could we derive $x_1+x_2+x_3+x_4+x_5 \le 1$ — ⊛
in one step? As a rank-1 cut.

YES!



Semidefinite Relaxation

Recall:

$$M_j^{NL}(K) \equiv \left\{ \begin{array}{c} (A\bar{x}-\bar{b})x_j \le \bar{0} \\ (A\bar{x}-\bar{b})(1-x_j) \le \bar{0} \\ x_j(1-x_j) = 0 \end{array} \right\}, \quad j=1,\dots,n.$$

We linearize $M_j^{NL}(K)$ $(x_j^2 \leftarrow x_j,\ x_i x_j \leftarrow y_i)$ to $M_j(K)$.

Define $M^{NL}(K) = \bigcap_{j=1}^{n} M_j^{NL}(K)$, and $M(K) = \bigcap_{j=1}^{n} M_j(K)$

We could linearize all systems, and then take their intersection. Equivalently, we could take the intersection of the nonlinear systems, and then linearize.

Let $M_+(K) \equiv M(K) \cap \left\{ \bar{x} \;\middle|\; \underline{(a_0+\bar{a}^T\bar{x})^2 \ge 0} \ \ \forall \begin{bmatrix} a_0 \\ \bar{a} \end{bmatrix} \in \mathbb{R}^{n+1} \right\}$.

$\begin{bmatrix} 1 & \bar{x}^T \\ \bar{x} & \bar{x}\bar{x}^T \end{bmatrix}$ is positive semidefinite

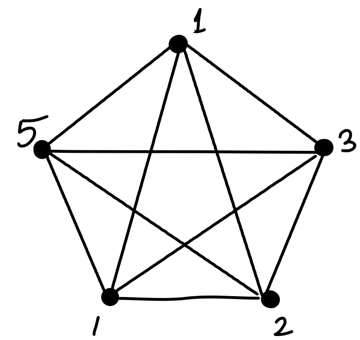
You would think this restriction is always satisfied! But imposing it explicitly makes the difference — see Notes to follow...

$M_+(K)$ is the **semidefinite relaxation** of the problem.

Def $A \in \mathbb{R}^{n\times n}$ is **positive semidefinite** (PSD) if $\bar{x}^T A \bar{x} \geq 0 \;\; \forall \bar{x} \in \mathbb{R}^n$. We write $A \succeq 0$

If A is PSD, all its eigenvalues are nonnegative.

Back to example on vertex packing



$$M_+(K) \text{ has } (1-x_1-x_2\cdots x_5)^2 \geq 0$$

$$\Rightarrow 1 - 2\sum_{i=1}^{5} x_i + \sum_{i=1}^{5} \underbrace{x_i^2}_{x_i} + 2\sum_{i\neq j} \underbrace{x_i x_j}_{=0} \geq 0$$

$$\Rightarrow \quad 1 - \sum_{i=1}^{5} x_i \geq 0, \quad \text{which is } (*)!$$

$M(K)$ has $(x_i + x_j \leq 1)\, x_i \Rightarrow x_i x_j \leq 0$ as $x_i^2 = x_i$

$M(K)$ also has $(-x_j \leq 0)\, x_i \Rightarrow x_i x_j \geq 0$

$\Rightarrow x_i x_j = 0.$

Hence the semidefinite relaxation rank of $(*)$ is 1!

Notes

① $M^{NL}(K)$ contains inequalities for

$$X = \begin{pmatrix} 1 & \bar{x}^T \\ \bar{x} & \bar{x}\bar{x}^T \end{pmatrix} = \left[\begin{array}{c|cccc} 1 & x_1 & x_2 & \cdots & x_n \\ \hline x_1 & x_1^2 & & & \\ x_2 & & x_2^2 & & x_i x_j \\ \vdots & & & \ddots & \\ x_n & & x_j x_i & & x_n^2 \end{array}\right].$$

Inequalities for X can be written as

$$B \bullet X \geq 0, \text{ where } A \bullet B = \operatorname{trace}(A^T B)$$

② To get $M(K)$ from $M^{NL}(K)$, we replace x_i^2 by x_i and $x_i x_j$ by y_{ij}. Hence inequalities of $M(K)$ can be written as

$$C \bullet \begin{pmatrix} 1 & \bar{x}^T \\ \bar{x} & Y \end{pmatrix} \geq 0, \text{ where } \operatorname{diag}(Y) = \bar{x}.$$

③ $(a_0 + \bar{a}^T\bar{x})^2 \geq 0$ can be written equivalently as

$$[a_0\ \bar{a}^T]\begin{bmatrix} 1 & \bar{x}^T \\ \bar{x} & \bar{x}\bar{x}^T \end{bmatrix}\begin{bmatrix} a_0 \\ \bar{a} \end{bmatrix} \geq 0 \Rightarrow [a_0\ \bar{a}^T]\begin{bmatrix} a_0 + \bar{a}^T\bar{x} \\ a_0\bar{x} + (\bar{x}\bar{x}^T)\bar{a} \end{bmatrix} = [a_0\ \bar{a}^T]\begin{bmatrix} (a_0 + \bar{a}^T\bar{x}) \\ (a_0 + \bar{a}^T\bar{x})\bar{x} \end{bmatrix}$$

$$= (a_0 + \bar{a}^T\bar{x})(a_0 + \bar{a}^T\bar{x}) \geq 0.$$

In other words, $M_+(K)$ has $\begin{bmatrix} 1 & \bar{x}^T \\ \bar{x} & Y \end{bmatrix} \succeq 0$ as added constraints.

MATH 567: Lecture 22 (04/01/2025)

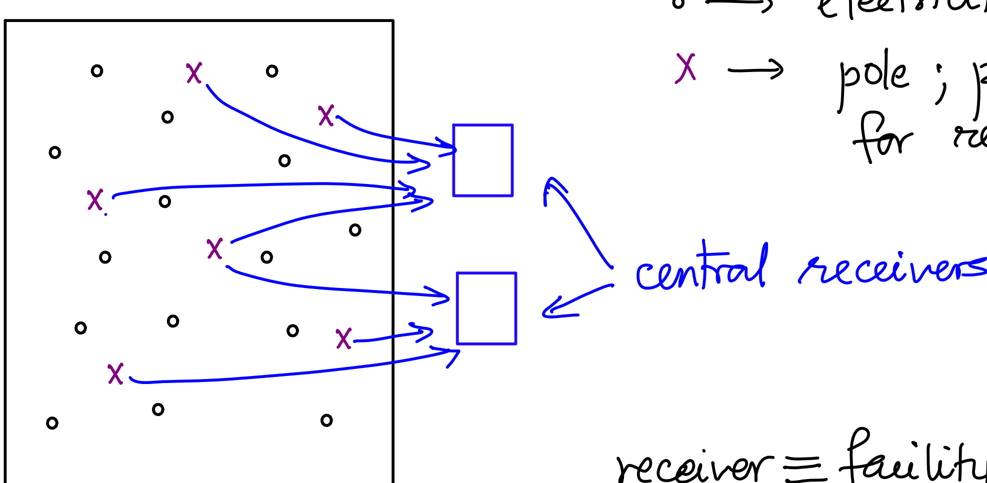
Today: * set covering problem (heuristics)

Solving Large sized Integer Programs: Set Covering Problem

Given:
1) n customer locations
2) m candidate facility locations
3) for each candidate facility location, the subset of customers that can be covered.

Assume no limits on # customers a facility can serve — hence we could look at it as an instance of uncapacitated facility location (UFL) problem.

Application Receiver location problem for reading electricity/gas meters.



o → electricity meter

x → pole; potential locations for receivers/amplifier

receiver ≡ facility   meter ≡ customer

The meters transmit readings to (at least one) receiver, which amplifies it before transmitting to a central receiver.

Goal: Identify which poles to locate receivers on, so that we minimize the total # recievers (i.e., facilities) used such that every meter (i.e., customer) can transmit to at least one receiver.

Such problems are often quite big, and hence cannot be handled easily as (M)IPs. We consider heuristics.
→ algorithms that are not guaranteed to find the optimal solution.

Also, we do not get any measures of the quality of the solutions found.

But, they often work well in practice!

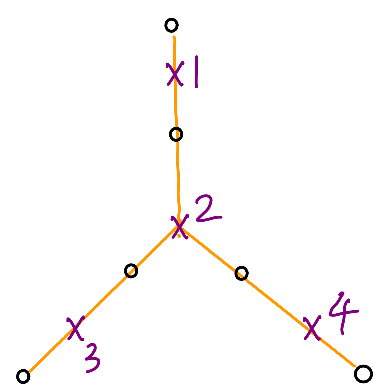
Heuristics

1. Greedy algorithm: In each step, pick the pole that covers the **largest number of uncovered meters**.

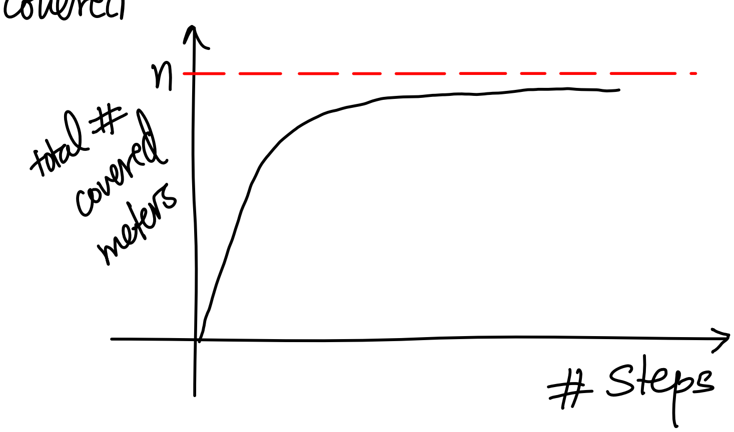
   Break ties arbitrarily.

   In general, will not give optimal solution.

   Here, greedy gives $\{2,1,3,4\}$, while optimal solution is $\{1,3,4\}$.



As the heuristic runs, the #-covered meters "plateaus" out.

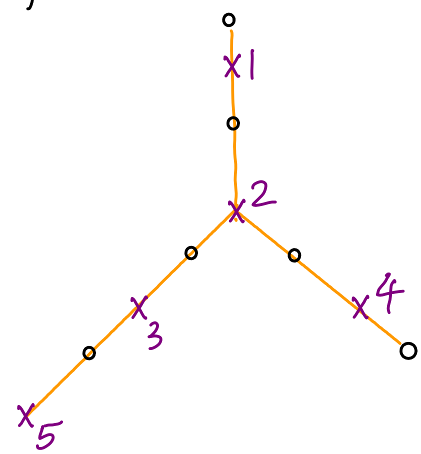


Cleaning up the solution

If removing the i^{th} pole from the set of selected poles leaves all meters covered (as covered up to now), then remove that pole. Repeat for $i=1,\dots,p$ after p-steps, for all p (or, say, repeat after every 10^{th} pole).

Clean up gives optimal solution in the previous example.

But in this example, if greedy gives $\{2,1,4,5\}$, clean up will do nothing.

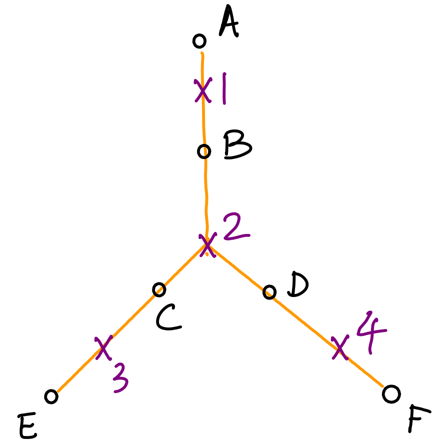


(2) **Modified Greedy algorithm** (Balas and Ho)

- Uses more foresight than greedy
- IDEA: Define a scoring function, and in each step, pick the pole with the largest value.

Def A meter is called **hard to cover** if the number of poles that cover it is minimal.

Here, A, E, F are hard-to-cover.



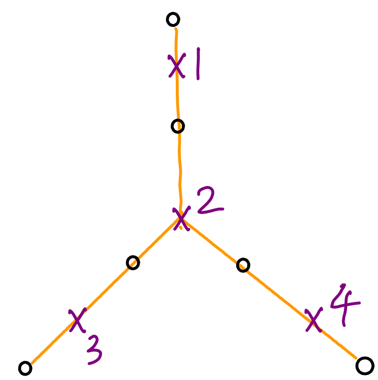
For pole j, define

$$\text{Score}_1(j) = \begin{cases} \text{total \# meters covered by pole } j \text{ if it covers at least one hard-to-cover meter} \\ 0, \quad \text{otherwise.} \end{cases}$$

and

$$\text{Score}_2(j) = (\text{\# meters covered by pole } j) \times (\text{\# hard-to-cover meters covered by pole } j).$$

Modified greedy works in this example. $\text{Score}_1(2) = 0$ and $\text{Score}_1(j) = 2$ for $j = 1, 3, 4$, at start, and do not change as the algorithm proceeds. Hence, we select $\{1,3,4\}$.



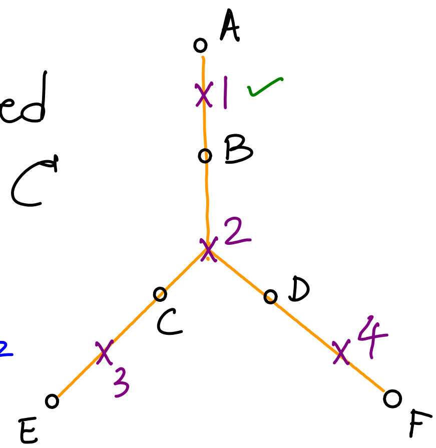
A Generalized Scoring Function

Def Suppose modified greedy at some intermediate step has selected a subset $P' \subseteq P$ of the poles. Let $m_{P'}$ be the minimum # poles that can cover a meter (not yet covered). For $t \in \mathbb{Z}_{>0}$, an uncovered meter is **t-hard to cover** if the # poles that can cover it is $\leq m_{P'} + t$.

So, 1-hard to cover $(t=1) \equiv$ hard-to-cover as previously defined.

Example Let $P' = \{1\}$. Then $m_{p'} = 1$ (for E and F). Meter C is covered by both poles 2 and 3. Hence, C is 2-hard to cover, as $2 < 1 + 2$.

t=2   poles 2,3 $m_{p'}$ t=2



E, F are 1-hard to cover ($t=1$).

C, D are <u>also</u> t-hard to cover for all $t \geq 3$.

Let $s(j,t)$ = # t-hard to cover meters covered by pole j.

We define

$$\text{Score}_g(j) = s(j,\infty) \prod_{t=1}^{k} [s(j,t)]^{1/t}$$

weighs 1-hard-to-cover meters
> 2-hard-to-cover meters
> 3-hard-to-cover
⋮

general

total # uncoverd meters coverd by j

where $k \geq 1$ is a fixed positive integer.

<u>Note</u>

1. $\text{Score}_g(j) = \text{Score}_2(j)$ when $k=1$.

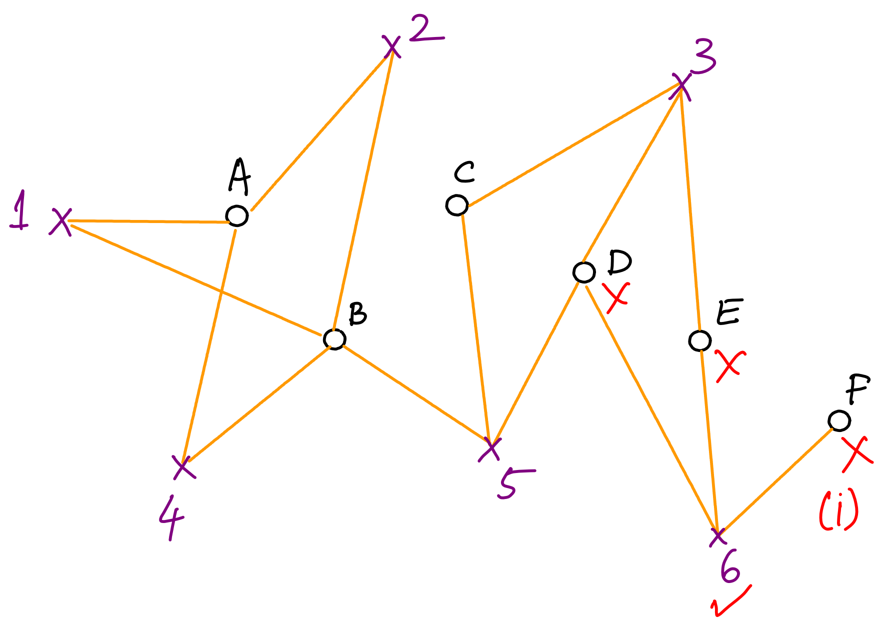
2. $\text{Score}_g(j) = \text{Score}_1(j)$ if there is a unique meter covered by pole j that is 1-hard to cover

3. higher $k \Rightarrow$ more foresight

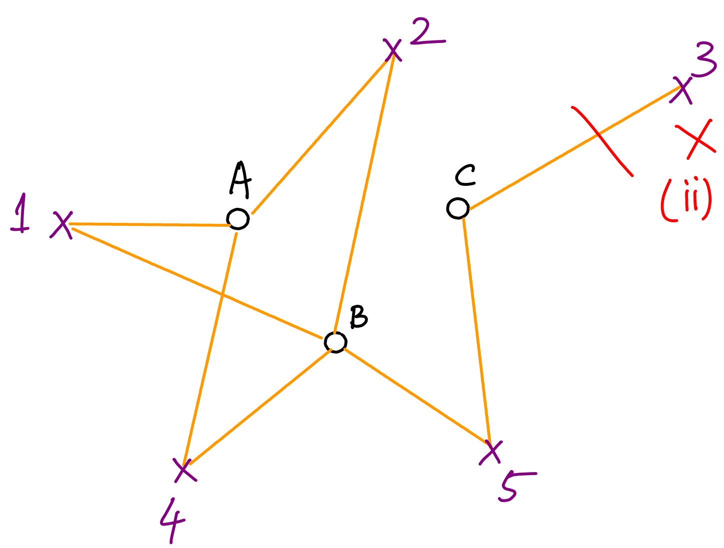
(3) Preprocessing

Reduces the size of the problem, but does not typically give an optimal solution (except in trivial cases).

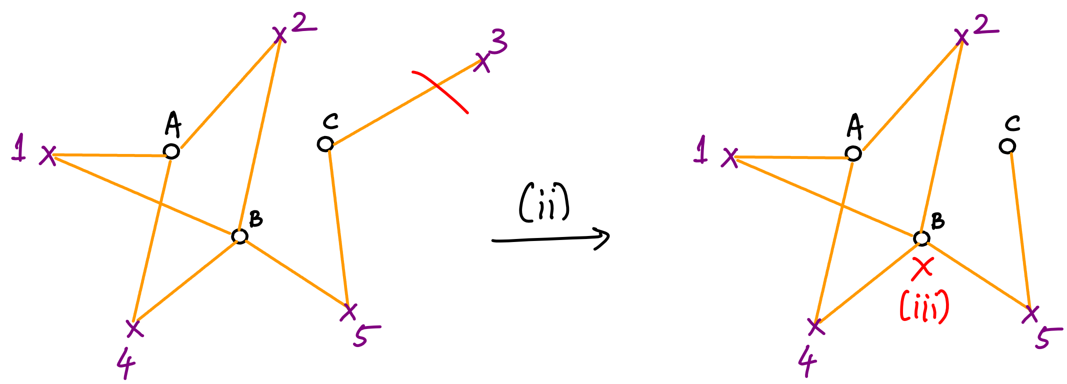
We illustrate the main steps on an example.



(i) Only 6 covers F $\Longrightarrow$ Choose 6, delete D, E, F
(as pole 6 covers D, E, F).

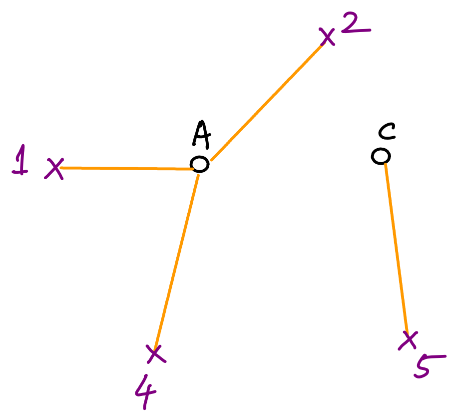


(ii) Now pole 5 covers all meters that pole 3 covers $\Rightarrow$ delete pole 3.



(iii) $\{1,2,4,5\}$ and $\{A,B,C\}$ are left. Now,

poles covering A also cover B $\Longrightarrow$ delete B.



another application of step (i) here!

(iv) Left with $\{1,2,4,5\}$ and $\{A,C\}$.
Optimal solution: pick 5 (as only 5 covers C), and pick one out of 1,2,4, say, 1 $\Longrightarrow$ $\{1,5\}$.

(On larger instances, we run greedy/modified greedy on this smaller instance).

(v) Extend (optimal) solution in Step (iv) to an (optimal) solution to the whole problem by adding pole 6 chosen in Step (i) $\Longrightarrow$ Solution is $\{1,5,6\}$.