

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.

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

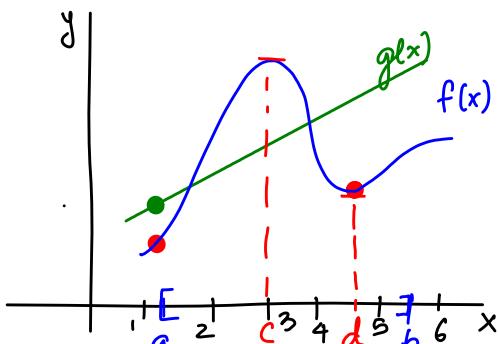
Optimization in Calculus

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

$$f'(x) = 0 \rightarrow \text{critical points}$$

$$f''(x) > 0 \rightarrow \text{minima}$$

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: $\min f(x)$ → insist on finding integer optimal solutions
 in 1D $x \in [a, b]$
 $x \in \mathbb{Z}$ → set of integers

A standard linear program (LP)

$$\begin{array}{ll} \max & \bar{c}^T \bar{x} \\ \text{s.t.} & \bar{A} \bar{x} \leq \bar{b} \\ & \bar{x} \in \mathbb{R}_{\geq 0}^n \end{array}$$

$\bar{c}, \bar{x} \rightarrow$ vectors (lower-case letters w/ bar)
 ↳ my notation in these notes!
 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):

$$x_i = \# \text{ acres of crop } i, \quad i=1, 2 \quad (1=\text{corn}, \quad 2=\text{wheat})$$

maximize $Z = 3 \cdot 10 \cdot x_1 + 4 \cdot 25 \cdot x_2 \quad (\text{total revenue})$

s.t.

subject to

$$x_1 + x_2 \leq 7 \quad (\text{total land})$$

$$4x_1 + 10x_2 \leq 40 \quad (\text{total labor hrs})$$

$$10x_1 \geq 30 \quad (\text{min corn})$$

$$x_1, x_2 \geq 0 \quad (\text{non-neg})$$

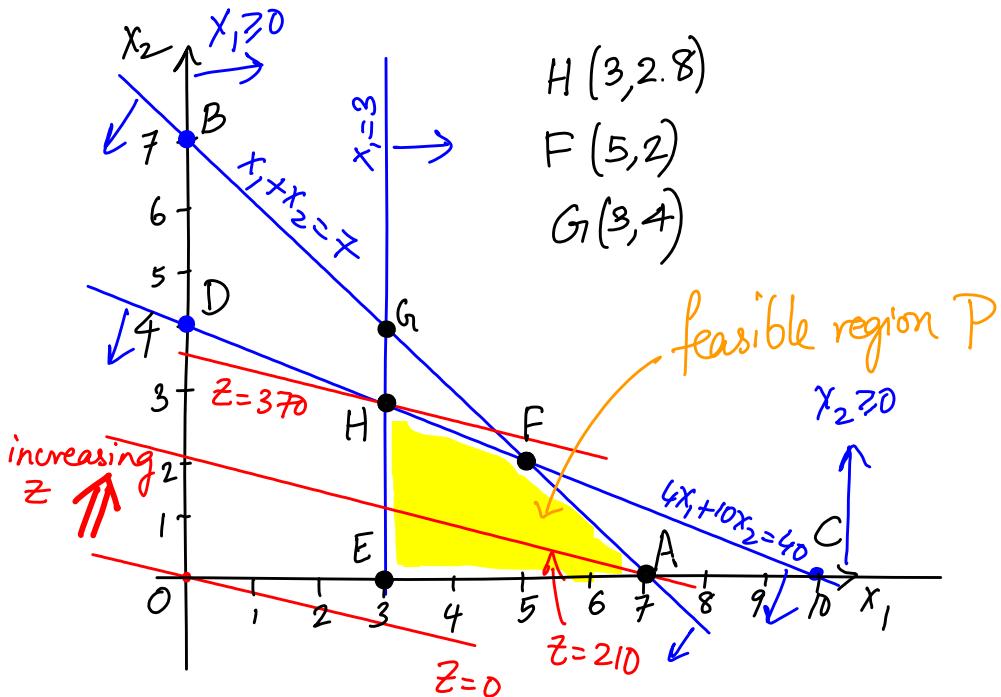
linear program (LP)

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

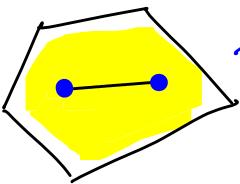
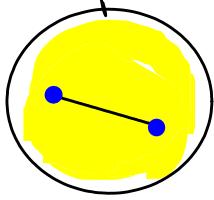
The first result depends on the fact that P is convex — indeed, we will strive hard to utilize convexity whenever possible!

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

$$\lambda \bar{x}_1 + (1-\lambda) \bar{x}_2 \in P.$$

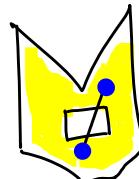
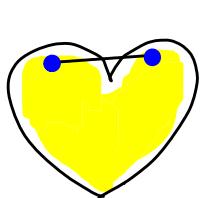
In words, the line segment connecting \bar{x}_1 and \bar{x}_2 lies in P .

Examples of convex regions:



We will talk a lot about polytopes and polyhedra

not convex:

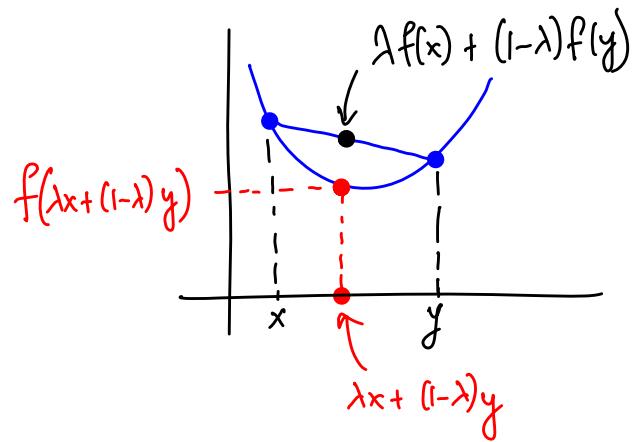


Convex function

$f: \mathbb{R}^n \rightarrow \mathbb{R}$ is convex if

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

$$\begin{aligned} f(\lambda \bar{x} + (1-\lambda) \bar{y}) &\leq \lambda f(\bar{x}) + (1-\lambda) f(\bar{y}) \\ &\geq \text{Concave} \end{aligned}$$



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 $f_1, \dots, f_m: \mathbb{R}^n \rightarrow \mathbb{R}$ 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 $\bar{x}, \bar{y} \in \mathbb{R}^n$, $\lambda \in [0, 1]$.

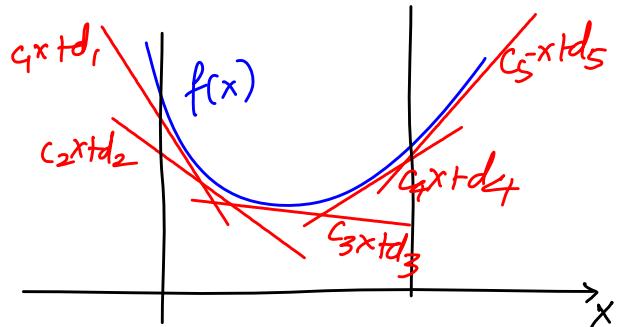
$$\begin{aligned} f(\lambda \bar{x} + (1-\lambda) \bar{y}) &= \max_{1 \leq i \leq m} f_i(\lambda \bar{x} + (1-\lambda) \bar{y}) \\ &\leq \max_{1 \leq i \leq m} \lambda f_i(\bar{x}) + (1-\lambda) f_i(\bar{y}) \quad \text{as each } f_i \text{ is convex} \\ &\leq \underbrace{\lambda \left[\max_{1 \leq i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

□

Def $f(\bar{x}) = \max_{1 \leq i \leq m} (\bar{c}_i^T \bar{x} + d_i)$, $\bar{c}_i \in \mathbb{R}^n$, $d_i \in \mathbb{R}$ 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:

$$\begin{array}{ll} \min & \max_{1 \leq i \leq m} (\bar{c}_i^T \bar{x} + d_i) \\ \text{s.t.} & A\bar{x} \leq \bar{b} \\ & \bar{x} \geq \bar{0} \end{array} \quad \left. \begin{array}{l} \text{not an LP as written} \\ \text{(as the objective is not } \bar{c}^T \bar{x}) \end{array} \right\}$$

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

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

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

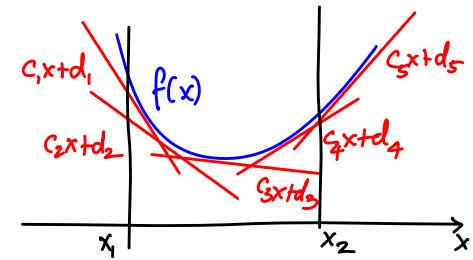
What if it were a min-min or a max-max one?

We will have to use integer variables!
this LP is unbounded! $\left. \begin{array}{l} \max z \\ z \geq \bar{c}_i^T \bar{x} + d_i \\ A\bar{x} \leq \bar{b} \\ \bar{x} \geq \bar{0} \end{array} \right\}$

Analogy:

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

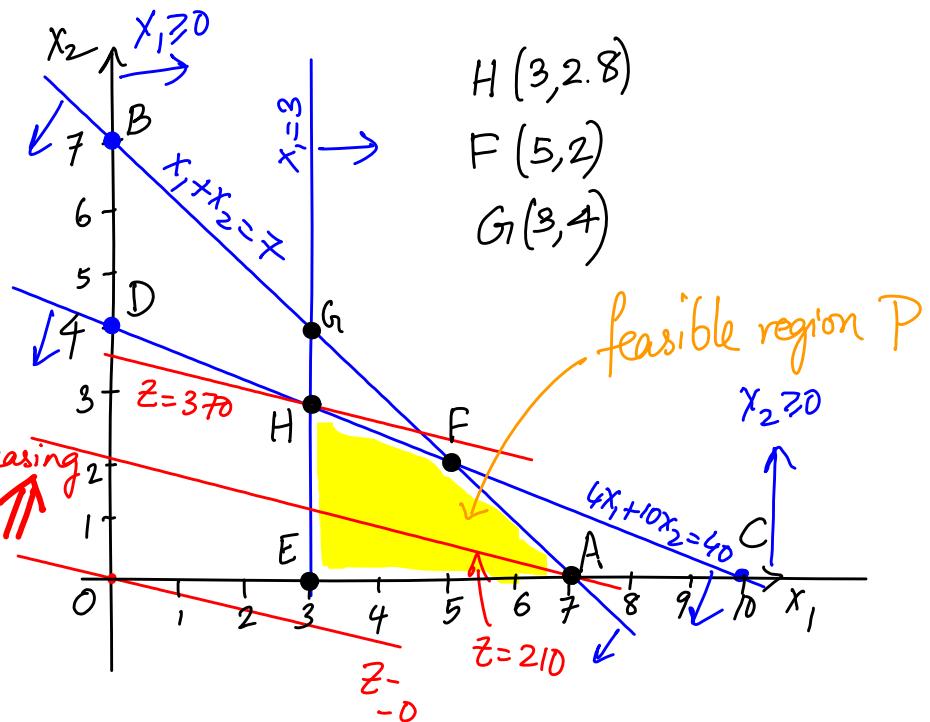


The first instinct on given an IP is to drop the integer restrictions and solve the underlying LP. May be then we can "round" the LP solution to a nearest integral solution to get a solution for the IP. But this idea fails in many cases.

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!
 $\rightarrow (3, 3) \notin P$



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

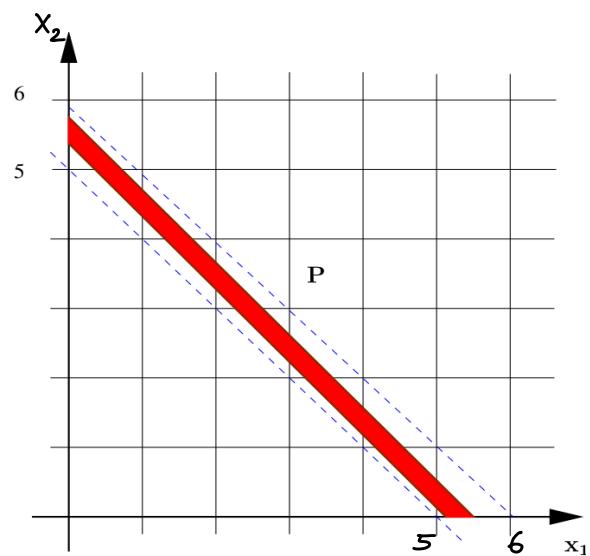
MATH 567: Lecture 2 (01/14/2025)

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.

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



As is evident from the figure, $P \cap \mathbb{Z}^2 = \emptyset$!

The idea of rounding for any IP defined on P is most here.)

for any objective function

We will return to such examples later on.

General Forms of integer (linear) Programs

Mixed integer Program (MIP)

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

Pure integer program (IP)

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

Special case of IP: Binary IP (BIP)

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

Q When do we insist $x_i \in \mathbb{Z}$? ↗ fractional value does not make sense

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

How many rooms should we build?

$y = 385.6$ ↗ 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 $x_{ij} = \begin{cases} 1 & \text{if person } i \text{ does job } j, \\ 0 & \text{o.w.} \end{cases}$ \rightarrow "otherwise" n^2 vars.

Step 2: Constraints

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

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

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

Step 3 Objective function

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

In Summary

$$\min Z = \sum_i \sum_j c_{ij} x_{ij} \quad (\text{total cost})$$

s.t.

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

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

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

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 $x_j = 1$ if project j is selected, 0 o.w.

constraints

$$\sum_{j=1}^n a_j x_j \leq b \quad (\text{budget})$$

$$x_j \in \{0, 1\} \forall j \quad (\text{binary vars}).$$

objective function

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

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

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

In feasibility knapsack, we want to find $x_j \in \{0, 1\}$

$$\text{s.t. } \sum a_j x_j = b. \quad (\text{or, more generally, } \left\{ \begin{array}{l} b' \leq \bar{a}^T \bar{x} \leq b \\ \sum a_j x_j \end{array} \right\})$$

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."

2. Can choose exactly 2 out of projects 1,3,6,7.
 Must at most
 Must at least

$$x_1 + x_3 + x_6 + x_7 \stackrel{\leq}{\geq} 2$$

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.

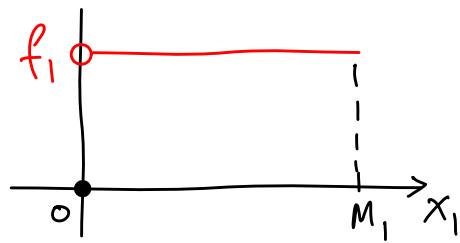
3. Fixed Charge (continued...)

$$\min f(x_1) + c_2 x_2 + \dots + c_n x_n$$

$$A\bar{x} \leq \bar{b}$$

$$0 \leq x_1 \leq M_1$$

$$f(x_1) = \begin{cases} 0, & x_1 = 0 \\ f_1, & x_1 > 0 \end{cases} \quad (f_1 > 0).$$



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

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

We want

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

$$\begin{aligned} \min \quad & f_1 y_1 + c_2 x_2 + \dots + c_n x_n \\ \text{s.t.} \quad & A\bar{x} \leq \bar{b} \\ & 0 \leq x_1 \leq M_1 y_1 \\ & y_1 \in \{0, 1\} \end{aligned}$$

If $x_1 > 0$, y_1 is forced to 1. Else, $x_1 \leq M_1 y_1$ will not hold (with $y_1=0$).

If $x_1=0$, $x_1 \leq M_1 y_1$ can hold with $y_1=0$ or $y_1=1$. But the term $f_1 y_1$ 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 $0 \leq x_1 \leq M_1$, $f_{12} \geq f_1 > 0$, $f_{12} \geq f_2 > 0$,

$0 \leq x_2 \leq M_2$, $f_{12} \neq f_1 + f_2$

need not hold as equality; indeed

$f_{12} \stackrel{>}{\leq} f_1 + f_2$ 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 — may be 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.

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

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

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

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

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 : $\min f_1 y_1 + \dots$ ($f_i > 0$)
 s.t. ...

$$x_i \leq M_i y_i \quad y_i \in \{0, 1\}$$

We will see another problem class where fixed charge shows up. Later, we will see how to force the relation between x_i and y_i , without relying on the $\min f_i y_i$ 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:

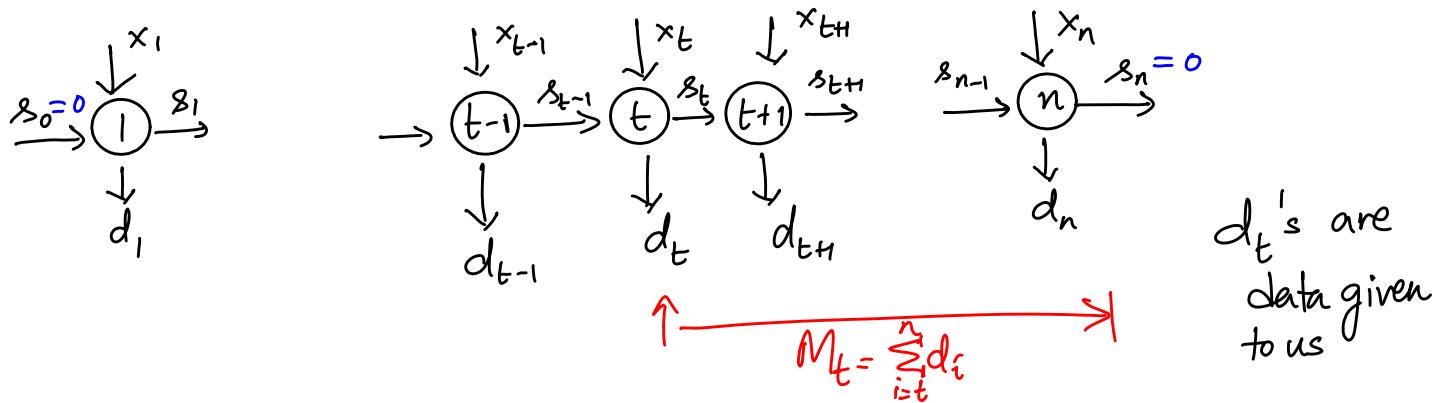
x_t = # units produced in period t , $t=1, \dots, n$ (≥ 0 , continuous)

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:



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

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

s.t. $s_0 = 0, s_n = 0$ (no start/end inventory)

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

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

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

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.

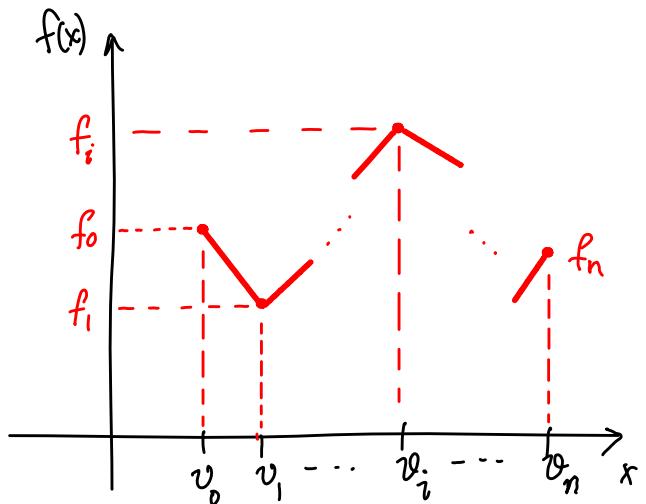
6. (General) Piecewise linear function (not convex in the interesting case)

x : scalar

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

If $x = \lambda_i v_i + \lambda_{i+1} v_{i+1}$
 $\lambda_i, \lambda_{i+1} \geq 0, \lambda_i + \lambda_{i+1} = 1$, then
 $f(x) = \lambda_i f_i + \lambda_{i+1} f_{i+1}$

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



$$s_i = \frac{f_i - f_{i-1}}{s_i}, \quad i=1, \dots, n \quad (\text{slopes, can be } \geq 0 \text{ or } \leq 0).$$

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

If we

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

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

$$0 \leq x_i \leq s_i,$$

2. somehow enforce

"if $x_{i+1} > 0$ then $x_i \geq s_i$ ", 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 $\underline{x_i \geq s_i}$ "

$$-x_i + s_i \leq 0$$

$$\begin{aligned} A \Rightarrow B &= \\ \neg A \text{ or } B & \\ \text{"not"} & \end{aligned}$$

let y_i and z_i are 0-1 variables

$x_{i+1} \leq s_{i+1} y_i$	if $x_{i+1} > 0$ then $y_i = 1$ $\Rightarrow z_i = 0$
$-x_i + s_i \leq s_i z_i$	$\forall i=1, \dots, n-1$
$y_i + z_i = 1$	assuming XOR "exclusive OR" A or B, but not both
$y_i, z_i \in \{0, 1\}$	

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

Can simplify :

$$\begin{aligned} x_{i+1} &\leq s_{i+1} y_i && \rightarrow \text{as } y_i + z_i = 1 \\ -x_i + s_i &\leq s_i (1 - y_i) \\ \hookrightarrow x_i &\geq s_i y_i \end{aligned}$$

$$\text{i.e., } s_i y_i \leq x_i \leq s_i y_{i-1}, \quad i=1, \dots, n-1$$

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

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(y),
 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 (and $\leq M$)
 (≥ 0)

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

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

1. Modeling with only 0-1 variables

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

Notation

$$L_i \equiv (x_i = 1)$$

$$\vee \equiv \text{OR}, \wedge \equiv \text{AND}$$

$$\Rightarrow \equiv \text{"implies"}, \Leftrightarrow \equiv \text{"equivalent"}$$

$$\neg \equiv \text{NOT} \quad (\text{negation})$$

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.

ExamplesStatement

$$1. L_1 \vee L_2 \vee \dots \vee L_n$$

model (constraints)

$$x_1 + x_2 + \dots + x_n \geq 1$$

$$2. L_1 \Rightarrow L_2$$

$$x_1 \leq x_2$$

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

i.e.,

$$\left\{ \begin{array}{l} L_1 \Rightarrow (L_2 \wedge L_3) \\ L_1 \Leftarrow (L_2 \wedge L_3) \end{array} \right.$$

$$x_1 \leq x_2, x_1 \leq x_3$$

think about it!

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.,

$$\left\{ \begin{array}{l} L_1 \Rightarrow (L_2 \wedge L_3) \\ L_1 \Leftarrow (L_2 \wedge L_3) \end{array} \right.$$

$x_1 \leq x_2, x_1 \leq x_3 \text{ OR } 2x_1 \leq x_2 + x_3$

$x_1 \geq \frac{x_2 + x_3}{2}$ will force $x_1 = 1$
when $x_2 = 1, x_3 = 0!$

$x_1 \geq x_2 + x_3$ nonlinear!
 $2x_1 = x_2 + x_3$ $x_2 = x_3 = 0$ 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., $\left\{ \begin{array}{l} x_1 + x_3 \geq 1 \\ (1-x_2) + x_3 + (1-x_5) \geq 1 \\ (1-x_3) + x_7 \geq 1 \end{array} \right\}$ 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.

Some Rules for doing transformations

$$\textcircled{1} \quad L_1 \wedge (L_2 \vee L_3) \equiv (L_1 \wedge L_2) \vee (L_1 \wedge L_3)$$

$$\textcircled{2} \quad L_1 \vee (L_2 \wedge L_3) \equiv (L_1 \vee L_2) \wedge (L_1 \vee L_3)$$

$$\textcircled{3} \quad \neg(L_1 \wedge L_2) \equiv \neg L_1 \vee \neg L_2$$

$$\textcircled{4} \quad \neg(L_1 \vee L_2) \equiv \neg L_1 \wedge \neg L_2$$

$$\textcircled{5} \quad L_1 \Rightarrow L_2 \stackrel{\text{def}}{\equiv} \neg L_1 \vee L_2$$

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

$$\begin{aligned}
 1. (L_2 \wedge \dots \wedge L_n) \Rightarrow L_1 &\equiv \neg(L_2 \wedge \dots \wedge L_n) \vee L_1 \\
 &\equiv (\neg L_2 \vee \neg L_3 \vee \dots \vee \neg L_n) \vee L_1 \\
 &\equiv \neg L_2 \vee \neg L_3 \vee \dots \vee \neg L_n \vee L_1
 \end{aligned}$$

which is in CNF.

$$\text{model: } (-x_2) + (-x_3) + \dots + (-x_n) + x_1 \geq 1$$

$$\begin{aligned}
 2. (L_1 \wedge L_2) \vee \underset{\cdot}{(L_3 \wedge \underset{+}{(L_4 \vee L_5)})} \\
 &\equiv ((L_1 \wedge L_2) \vee L_3) \wedge ((L_1 \wedge L_2) \vee \underset{+}{(L_4 \vee L_5)}) \\
 &\equiv ((L_1 \vee L_3) \wedge (L_2 \vee L_3)) \wedge [(L_1 \vee (L_4 \vee L_5)) \wedge (L_2 \vee (L_4 \vee L_5))] \\
 &\equiv (L_1 \vee L_3) \wedge (L_2 \vee L_3) \wedge (L_1 \vee L_4 \vee L_5) \wedge (L_2 \vee L_4 \vee L_5) \\
 &\quad \text{which is in CNF.}
 \end{aligned}$$

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

2. Modeling with 0-1 and continuous variables

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

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

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

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

3. Modeling arbitrary disjunctions

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

$$(A_1 \bar{x} \leq \bar{b}^1) \vee (A_2 \bar{x} \leq \bar{b}^2) \vee \dots \vee (A_k \bar{x} \leq \bar{b}^k) \quad \textcircled{\times}$$

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 $\textcircled{\times}$

In words, $\textcircled{\times}$ 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 $y_i \in \{0, 1\}$, $i = 1, \dots, k$. \rightarrow models whether the i^{th} disjunction holds

$$A_i \bar{x} \leq \bar{b}^i + \bar{u}^i(1-y_i), \quad i=1, \dots, k$$

$$y_1 + y_2 + \dots + y_k \geq 1$$

$$y_i \in \{0, 1\}, \quad i=1, \dots, k.$$

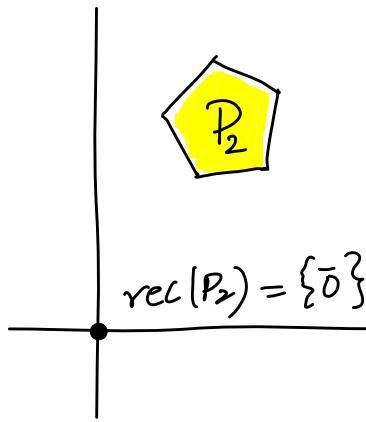
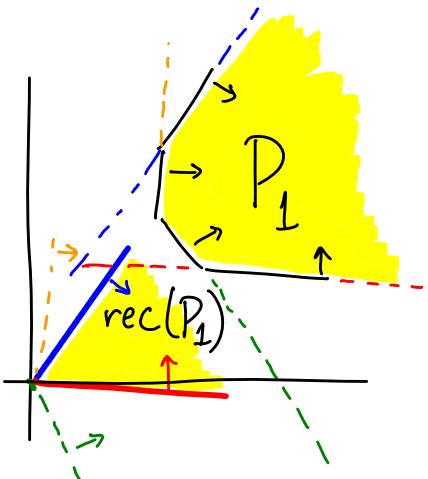
$\xrightarrow{\hspace{1cm}} (\text{x-big-M})$

Sharp formulation

Assumption 2 $\exists C$ such that

$$C = \{\bar{x} \mid A_i \bar{x} \leq \bar{0}\}, \quad i=1, \dots, k \text{ is independent of } i.$$

Def The recession cone of polyhedron $P = \{\bar{x} \mid A \bar{x} \leq \bar{b}\}$ is
 $\text{rec}(P) = \{\bar{x} \mid A \bar{x} \leq \bar{0}\}$.



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

$$\begin{aligned} A_1 \bar{x}' &\leq \bar{b}' y_1 \\ &\vdots \\ A_k \bar{x}^k &\leq \bar{b}^k y_k \\ \bar{x}' + \bar{x}^2 + \dots + \bar{x}^k &= \bar{x} \\ y_1 + y_2 + \dots + y_k &= 1 \\ y_i &\in \{0, 1\} \end{aligned}$$

$(\times\text{-sharp})$

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

We now prove the correctness of $(\times\text{-sharp})$.

Theorem 1 \bar{x} satisfies $\circledast \Leftrightarrow \exists (\bar{x}', \dots, \bar{x}^k, y_1, \dots, y_k)$ such that $(\bar{x}, \bar{x}', \dots, \bar{x}^k, y_1, \dots, y_k)$ satisfies $(\times\text{-sharp})$.

Proof (\Rightarrow) \bar{x} satisfies \circledast .

WLOG, let $A, \bar{x} \leq \bar{b}'$. We can choose

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

(\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 $\circledast \Leftrightarrow \exists (\bar{x}', \dots, \bar{x}^k, y_1, \dots, y_k)$ such that $(\bar{x}, \bar{x}', \dots, \bar{x}^k, y_1, \dots, y_k)$ satisfies $(\times\text{-sharp})$.

$$\begin{array}{l} A_1 \bar{x}' \leq \bar{b} y_1 \\ \vdots \\ A_k \bar{x}^k \leq \bar{b} y_k \\ \bar{x}' + \bar{x}^2 + \dots + \bar{x}^k = \bar{x} \\ y_1 + y_2 + \dots + y_k = 1 \\ y_i \in \{0, 1\} \end{array}$$

$\xrightarrow{\hspace{1cm}} (\times\text{-sharp})$

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

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

$$\Rightarrow A_1 \bar{x}' \leq \bar{b} \quad \text{and} \quad \bar{x}' + \dots + \bar{x}^k = \bar{x}$$

$$A_2 \bar{x}^2 \leq \bar{0}$$

$$\vdots$$

$$A_k \bar{x}^k \leq \bar{0}$$

from
Assumption 2

$$\Rightarrow A_1 \bar{x} = A_1(\bar{x}' + \dots + \bar{x}^k) = A_1 \bar{x}' + A_1 \bar{x}^2 + \dots + A_1 \bar{x}^k \leq \bar{b} + \underbrace{\bar{0} + \dots + \bar{0}}$$

$$\Rightarrow A_1 \bar{x} \leq \bar{b}, \text{ i.e., } \bar{x} \text{ satisfies } \circledast.$$

□

Representing Sets in general

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

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

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

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

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

Def $P = \left\{ \bar{x} \in \mathbb{R}^n \mid A\bar{x} \leq \bar{b} \right\}$ 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

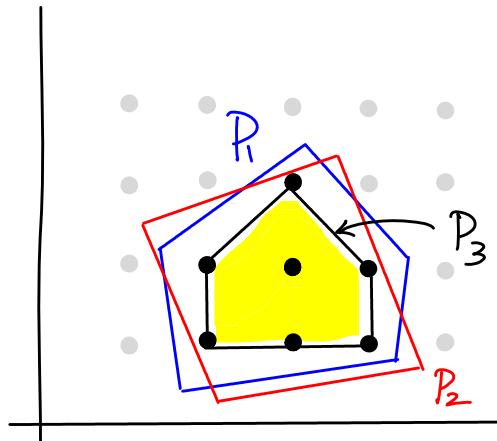
1. $S = \{ \bar{x} \in \{0,1\}^n \mid (x_1=1) \vee \dots \vee (x_n=1) \}$ has a formulation

$$P = \{ \bar{x} \in \mathbb{R}^n \mid 0 \leq x_i \leq 1 \forall i, x_1 + \dots + x_n \geq 1 \}.$$

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

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.

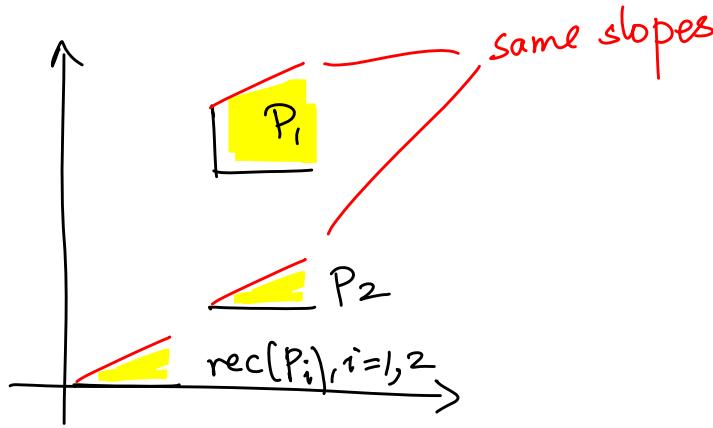


What kinds of sets S are b-MIP-r? Could we characterize them?

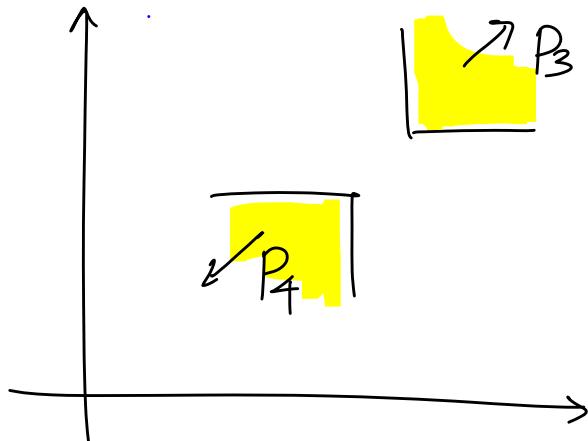
Theorem 2 (Jeraslow, Lowe): S is b-MIP-r iff

$S = P_1 \cup \dots \cup P_k$ for finite k , where P_i are polyhedra having the same recession cone i.e., $\text{rec}(P_i)$ is independent of i , $i=1,\dots,k$.

(Here are some examples.)



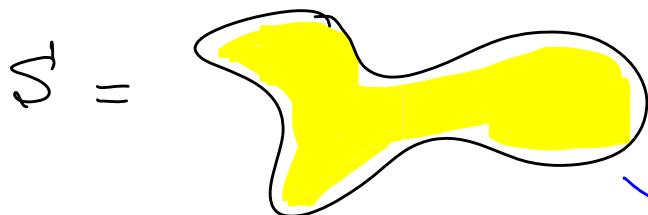
$P_1 \cup P_2$ is b-MIP-r.



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

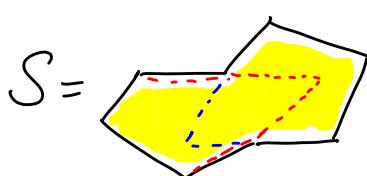


is okay as an MIP.
($\text{rec}(P_5) = \text{rec}(P_6) = \{\bar{0}\}$)



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.



→ o.k. as MIP! → union of two polytopes.

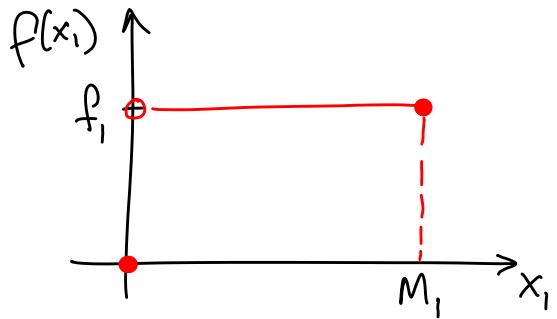
Can we use similar techniques to model functions, instead of sets?

Representing Sets v/s Functions

We already saw the case of fixed charge:

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

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

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

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

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

Notice that $\text{graph}(f)$, $\text{epi}(f)$, and $\text{hypo}(f)$ 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 $\left\{ \begin{array}{l} \min f(\bar{x}) \\ \text{s.t. } A\bar{x} \leq \bar{b} \end{array} \right\}$ where $\text{epi}(f)$ is b-MIPr.

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

Since $\text{epi}(f)$ is b-MIPr, we can write down an MIP representation of $\text{epi}(f)$, which completes the MIP model above.

Q. Why not require $\text{graph}(f)$ being b-MIPr?

Theorem 3 $\text{graph}(f)$ is b-MIPr iff both $\text{epi}(f)$ and $\text{hypo}(f)$ are b-MIPr.

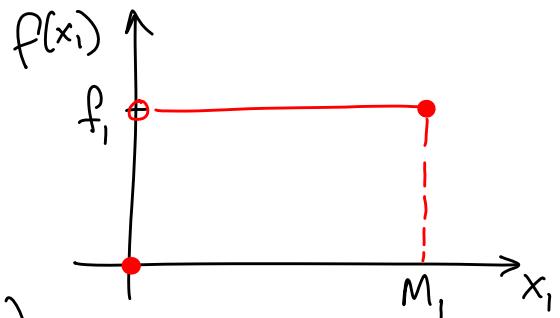
Example

The fixed charge function.

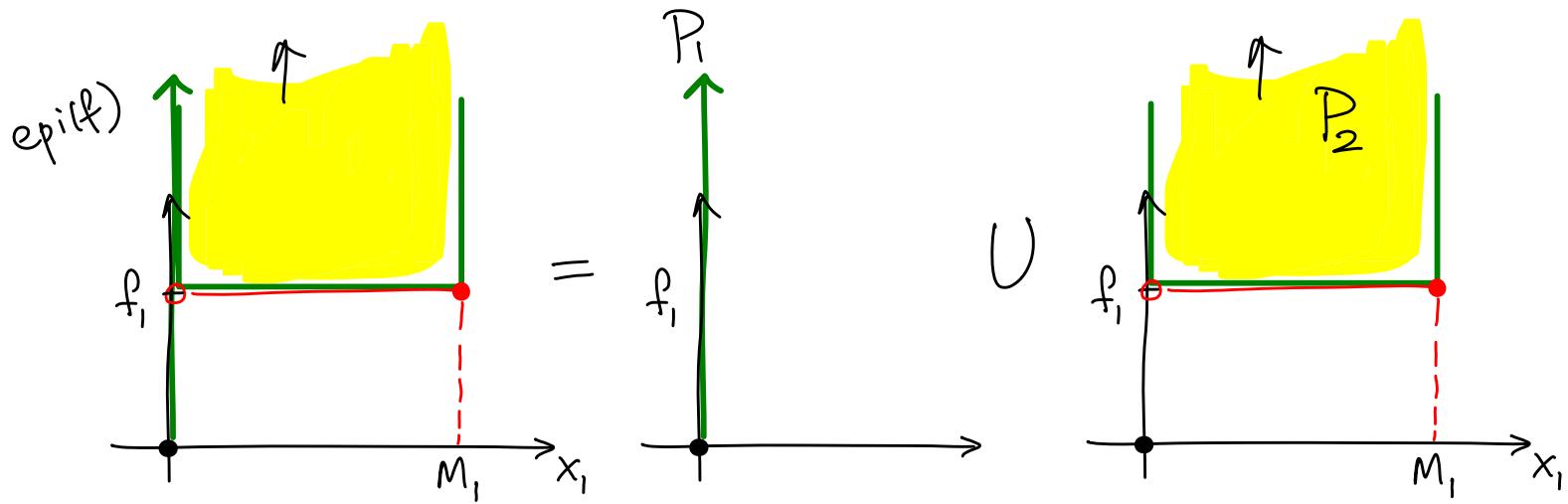
$\text{graph}(f)$, i.e., $f(x_i)$ as drawn, is not b-MIPr.

$\text{graph}(f)$ 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.

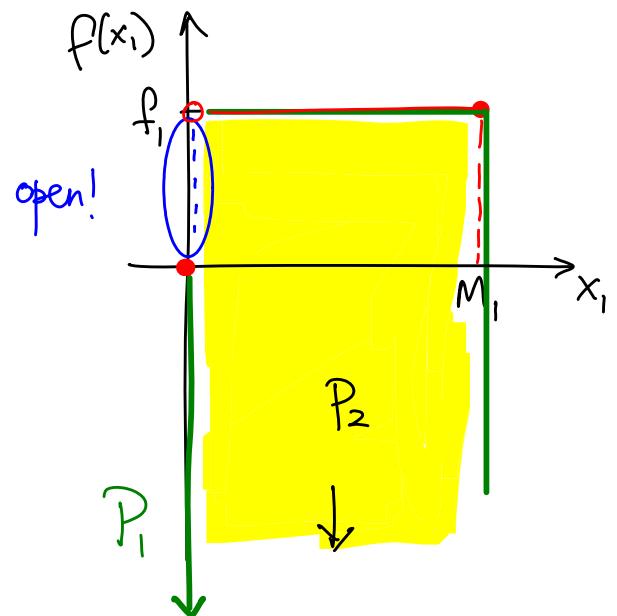


But $\text{epi}(f)$ turns out to be b-MIP-r here, and $\text{hypo}(f)$ is not b-MIP-r at the same time.



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

Here, $\text{hypo}(f)$ 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 $\text{graph}(f)$).

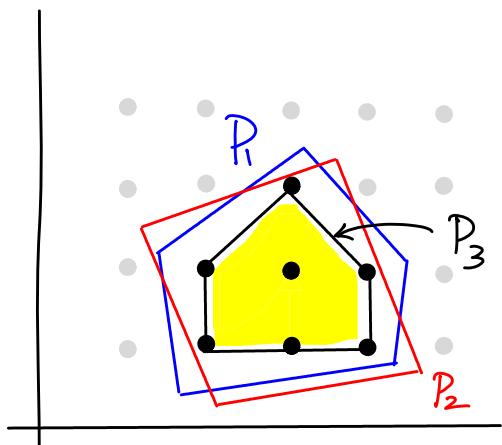


What if $f_1 < 0$ here? Then $\text{hypo}(f)$ will be b-MIP-r and $\text{epi}(f)$ will not be b-MIP-r (the roles are reversed).

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 $\exists \bar{x}: A\bar{x} \leq \bar{b}$ then

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

$$\exists \bar{u} \geq 0 \text{ such that } \bar{u}^T A = \bar{a}^T, \bar{u}^T \bar{b} \leq \beta$$

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

② $\exists \bar{x}: A\bar{x} \leq \bar{b} \iff \nexists \bar{u} \geq 0, \bar{u}^T A = \bar{0}^T, \bar{u}^T \bar{b} < 0.$
 (cannot derive $\bar{0}^T \bar{x} \leq -1$ from $A\bar{x} \leq \bar{b}$)

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

Today: * comparing formulations
* sharp/ideal formulation

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

$$\textcircled{3} \quad \exists \bar{x}: A\bar{x} = \bar{b} \iff \nexists \bar{u} \neq 0: \bar{u}^T A = \bar{b}^T, \quad \bar{u}^T \bar{b} = -1 \quad \begin{matrix} \text{can be any} \\ \text{nonzero } \# \end{matrix}$$

$$A\bar{x} = \bar{b} : [A|\bar{b}] \xrightarrow{\text{EROs}} \left[\begin{array}{c|c} \text{echelon form} \end{array} \right]$$

If the echelon form has as row of the form $[0 \ 0 \ \dots \ 0 | \ \blacksquare] \neq 0$,
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).

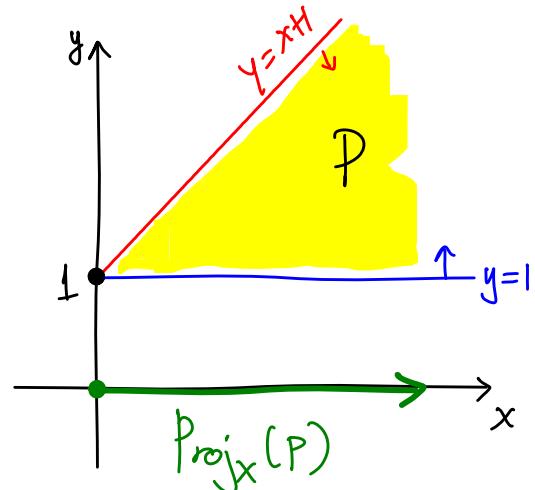
Def If $P = \{(x, y) \mid A\bar{x} + B\bar{y} \leq \bar{b}\}$, then the **projection** of P on to the space of \bar{x} variables is

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

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

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

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



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

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 ' : $\bar{x} \in \text{Proj}_{\bar{x}}(P) \Rightarrow \exists \bar{y} | A\bar{x} + B\bar{y} \leq \bar{b}$
 $\Rightarrow \bar{v}^T A \bar{x} \leq \bar{v}^T \bar{b}$ holds and $\bar{v} \geq 0, \bar{v}^T B = \bar{0}^T$.

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

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}).

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

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

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

Back to 2D example:

$$\begin{aligned} y \geq 1 \\ y \leq x+1 \end{aligned} \Rightarrow \begin{cases} -y \leq -1 \\ y \leq x+1 \end{cases} \xrightarrow{\text{ADD}} x \geq 0, \text{ which is } \text{Proj}_x(P).$$

$$\text{Equivalently, } \left\{ \begin{array}{l} -y \leq -1 \\ -x+y \leq 1 \end{array} \right\} = \underbrace{\begin{bmatrix} 0 \\ -1 \end{bmatrix}}_A x + \underbrace{\begin{bmatrix} -1 \\ 1 \end{bmatrix}}_B y \leq \underbrace{\begin{bmatrix} -1 \\ 1 \end{bmatrix}}_b.$$

What $\bar{v} \geq \bar{0}$ with $\bar{v}^T B = \bar{0}$ 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 $\{ \bar{v} \geq \bar{0}, \bar{v}^T B = \bar{0} \} = \underbrace{\text{cone}\{\bar{v}^1, \dots, \bar{v}^k\}}$

def $\equiv \left\{ \sum_{i=1}^k \lambda_i \bar{v}^i \mid \lambda_i \geq 0 \right\}$, then the projection cone is finitely generated

$$\text{Proj}_{\bar{x}}(P) = \{ \bar{x} \mid (\bar{v}^i)^T A \bar{x} \leq (\bar{v}^i)^T \bar{b}, i=1, \dots, k \}.$$

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

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

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

Definition of Comparison

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

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

and

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

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 $\text{Proj}_{(\bar{x}, \bar{y})}(P_1) \subset \text{Proj}_{(\bar{x}, \bar{y})}(P_2)$.

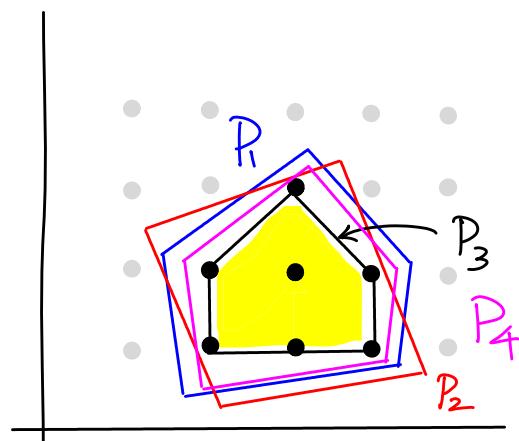
P_j , $j=1, 2, 3, 4$ are formulations of S .

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

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

$$P_1 = \{ \bar{x} \mid x_1 \leq x_2, \dots, x_1 \leq x_n, 0 \leq x_i \leq 1, i=1, \dots, n \} \text{ and}$$

$$P_2 = \{ \bar{x} \mid (n-1)x_1 \leq x_2 + \dots + x_n, 0 \leq x_i \leq 1, i=1, \dots, n \}$$

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 $x_i \leq x_{i+1}, i=2, \dots, n$, to get $(n-1)x_1 \leq x_2 + \dots + x_n$.

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

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

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

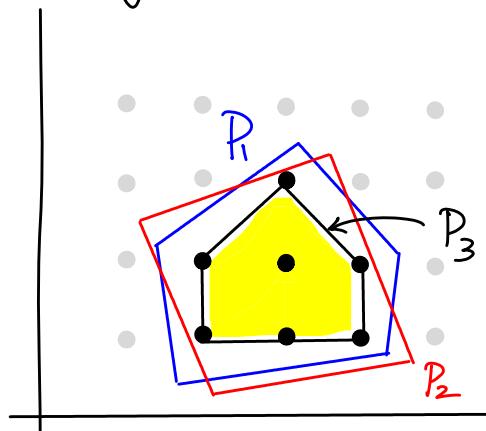
Def Given $S \subseteq \mathbb{Z}^n \times \mathbb{R}^m$, $P \subseteq \mathbb{R}^n \times \mathbb{R}^m$ is a sharp or ideal formulation for S if

- (1) If $\begin{bmatrix} \bar{c} \\ \bar{d} \end{bmatrix} \in \mathbb{R}^{n+m}$ such that $\max \left\{ [\bar{c}^\top \bar{d}^\top] \begin{bmatrix} \bar{x} \\ \bar{y} \end{bmatrix} \mid \begin{bmatrix} \bar{x} \\ \bar{y} \end{bmatrix} \in P \right\}$ 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

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

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

→ more on this and other details in the next lecture...

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

Today: \star sharp formulations
 \star TSP Formulations

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

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

$$(n-1)x_1 \leq x_2 + \dots + x_n \quad (1)$$

$$x_2 \leq 1 \quad (2)$$

$$x_j \geq 0, j=3, \dots, n \quad (n-2)$$

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:

$$x_i \geq x_1, i=2, \dots, n \quad (1)$$

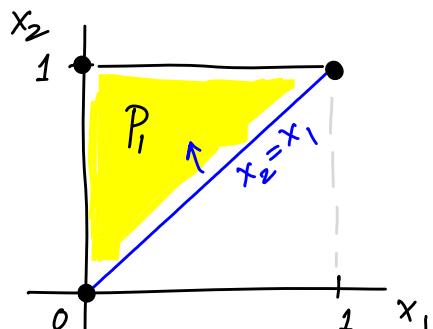
$$x_i \geq 0, i=1, \dots, n \quad (2)$$

$$x_i \leq 1, i=1, \dots, n \quad (3)$$

First, check intuition in 2D:

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

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):

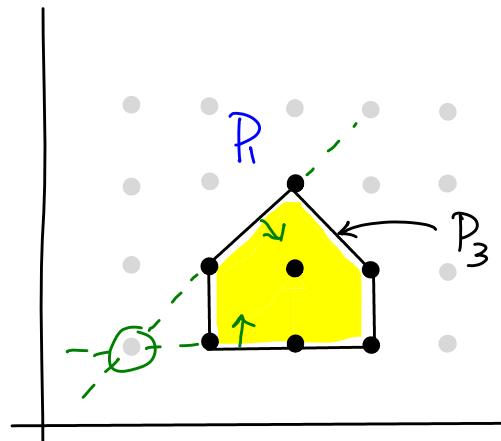
$$\Rightarrow x_i = 0 \forall i \text{ or } x_i = 1 \forall i.$$

(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.

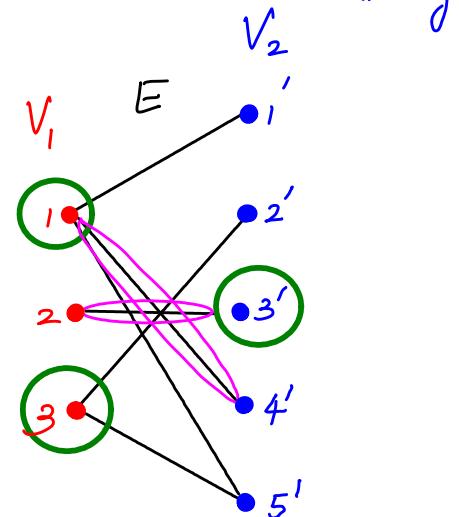
We now consider several examples of sharp formulation.

More Examples of Sharp Formulations

1. Given a bipartite graph $G_1 = (V, UV_2, E)$, let $S_m \subseteq \mathbb{Z}^{|E|}$ be the collection of incidence vectors of all matchings.

$$\text{Then } P_m = \left\{ \bar{x} \in \mathbb{R}^{|E|} \mid \begin{array}{l} \sum_{e \ni i} x_e \leq 1 \quad \forall i \in V_1, \\ \sum_{e \ni j} x_e \leq 1 \quad \forall j \in V_2 \end{array} \right\}$$

is a sharp formulation for S_m .



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

2. Given $G_1 = (V, UV_2, E)$ 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

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

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

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 $x_1, x_2, x_3 \in \{0, 1\}$.

$$S_{ij} = \left\{ \bar{x} \mid \bar{x} \in \mathbb{R}^3, (x_i=0) \vee (x_j=0) \right\} \text{ and}$$

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

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

For instance,

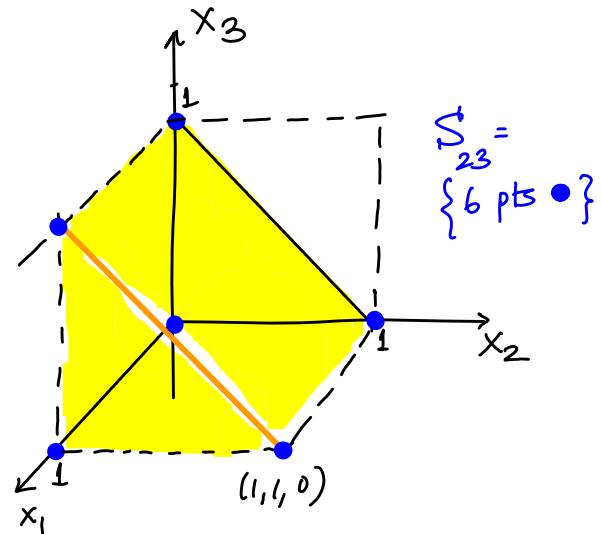
$$S_{23} = \{(0, 0, 0), (1, 0, 0), (0, 1, 0), (1, 1, 0), (0, 0, 1), (1, 0, 1)\} \text{ and}$$

$$P_{23} = \left\{ \bar{x} \in \mathbb{R}^3 \mid \begin{array}{l} x_1 \geq 0, x_2 \geq 0, x_3 \geq 0 \\ x_1 \leq 1, x_2 \leq 1, x_3 \leq 1 \end{array} \right\}.$$

could remove!

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

We could also just plot P_{23} !



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

Now, let

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

and

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

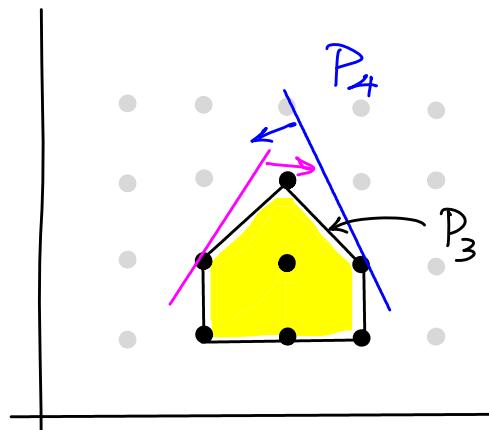
Is P a sharp formulation for S ? No!

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

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 $(\frac{1}{2}, \frac{1}{2}, \frac{1}{2}) \in P$, and indeed gives a higher value for $x_1 + x_2 + x_3$.

Also, $(\frac{1}{2}, \frac{1}{2}, \frac{1}{2})$ 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 $\text{conv}(S)$ 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

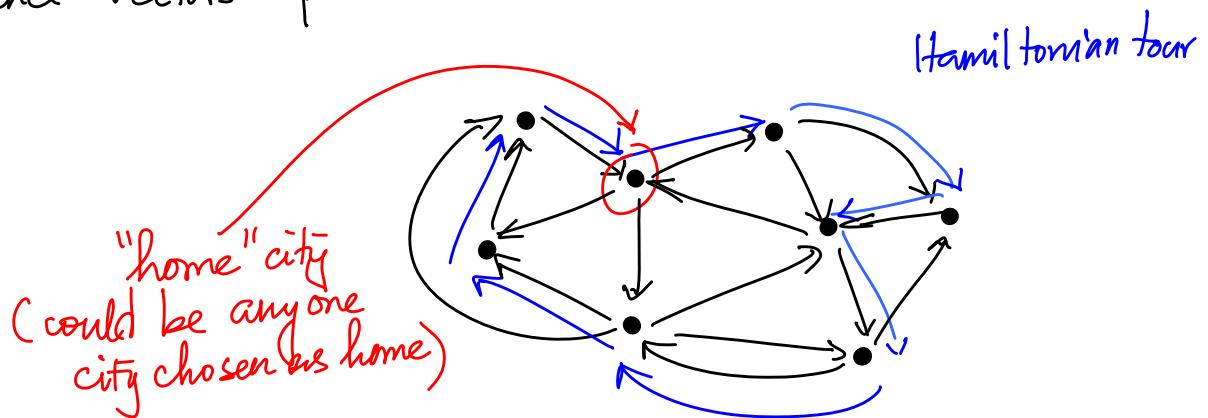
* c_{ij} : cost (or distance) from City i to City j is defined on a directed graph $G = (V, E)$.
↳ directed

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.

→ smallest total costs
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



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

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

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

$$\left. \begin{array}{l} \sum_{j:(i,j) \in E} x_{ij} = 1 \quad \forall i \\ \sum_{j:(i,j) \in E} x_{ji} = 1 \quad \forall i \\ 0 \leq x_{ij} \leq 1 \end{array} \right\} \quad (1)$$

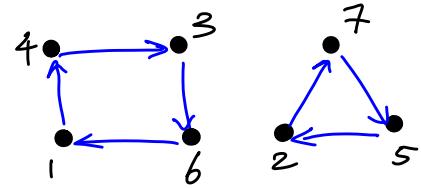
$\bar{x} \in \mathbb{Z}^{|E|}$

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

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

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!

First approach 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 5th node in the tour, starting from node 1.

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

Today: TSP formulations and comparisons

Recall u_i = position of node i in tour.

We want to impose

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

We write

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

Let's check:

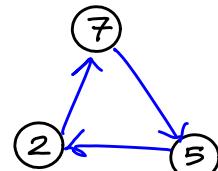
$$\text{if } x_{ij}=1 \quad (2) \Rightarrow u_i - u_j + 1 \leq 0 \Rightarrow u_j \geq u_i + 1. \quad \checkmark$$

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

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.

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

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 $S = \{ \bar{x} \in \mathbb{Z}^{|E|} \mid \exists \bar{u} : (\bar{x}, \bar{u}) \text{ satisfies (1) and (2)} \}$. (82)

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

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

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

' \supseteq ': $\bar{x} \notin S \Rightarrow \bar{x} \text{ violates (1) or}$
 $\bar{x} \text{ satisfies (1), but there is no } \bar{u}$
 to satisfy (2).

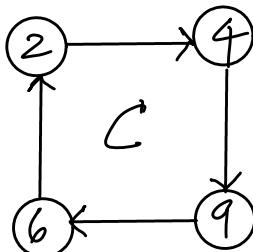
Case 1: \bar{x} violates (1): trivial.

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

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

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

e.g.,



Consider

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

for each $i, j \in C$.

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

$$X(C) = \sum_{(i,j) \in C} x_{ij}. \quad \text{Hence } X(C) \leq \left(1 - \frac{1}{n}\right) |C|. \quad \text{there will be exactly } |C| x_{ij}'s \text{ set to 1!}$$

But x_{ij} 's violate this inequality!

□

Remark

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

$$\begin{aligned} 1 \leq u_i \leq n & \quad (a) \\ u_i - u_j + 1 \leq n(1 - x_{ij}), \quad \forall i, \forall j \neq 1 & \quad (b) \\ n - u_i \leq (n-1)(1 - x_{ii}), \quad \forall i \neq 1 & \quad (c) \end{aligned}$$

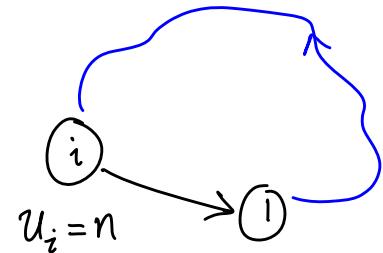
then (1) & (3) together give a valid formulation for S .

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

3(c) forces $x_{ii}=1 \Rightarrow u_i \geq n \quad \forall i \neq 1$.

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

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



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

(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

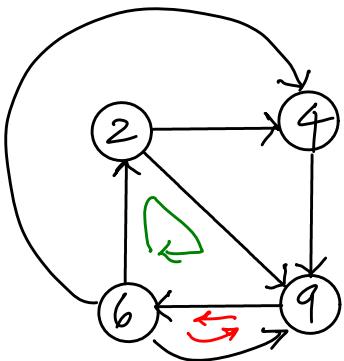
$$\forall W \subset V, |W| > 1, \sum_{\substack{i,j \in W \\ (i,j) \in E}} x_{ij} \leq |W| - 1 \quad \text{--- (4)}$$

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.,

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



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

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

$\Rightarrow x_{ij}$ 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 $W \subseteq V$ 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 best 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

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

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

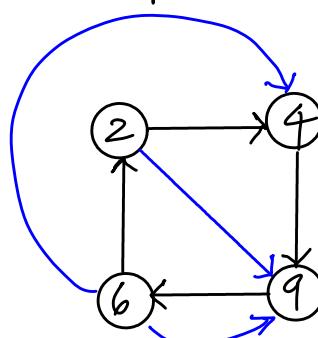
$$\sum_{\substack{i,j \in W \\ (i,j) \in E}} x_{ij} \leq |C| - 1 \quad (\times)$$

almost "1 better than (Δ) ".

more x_{ij} terms than included in $X(C)$.

Thus (\times) 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

$$\mathcal{P}_{MTZ} = \left\{ (\bar{x}, \bar{u}) \in \mathbb{R}^{|E|} \times \mathbb{R}^{|N|} \mid (\bar{x}, \bar{u}) \text{ satisfy (1) and (2)} \right\}, \text{ and}$$

$$\mathcal{P}_{\text{Subtour}} = \left\{ \bar{x} \in \mathbb{R}^{|E|} \mid \bar{x} \text{ satisfies (1) and (4)} \right\}.$$

To compare, we compute $\text{Proj}_{\bar{x}}(\mathcal{P}_{MTZ})$.

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

$$= \left\{ \bar{x} \mid \bar{x} \text{ satisfies (2) for all cycles } C, i \notin C \right\}.$$

There could be exponentially many such cycles.

Indeed, \mathcal{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 $\text{Proj}_{\bar{x}}(\mathcal{P}_{MTZ})$.

Proof

\mathcal{P}_{MTZ} is given by (1) and

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

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

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

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

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

Can be written in matrix form as

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

\bar{I} is the identity matrix, \bar{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{I} is the vector of ones.

$$\begin{array}{c}
 \text{arcs} \\
 \left\{ \begin{array}{|c|c|} \hline
 n\bar{I}_m & \bar{B} \\
 \hline
 \end{array} \right. \begin{array}{c} \text{nodes, except 1} \\ \hline
 \begin{matrix} +1 & -1 \\ \vdots & \vdots \\ i & j \end{matrix} \\
 \hline
 \end{array} \begin{array}{c} \bar{x} \\ \hline
 \bar{u} \end{array} \end{array} \leq \begin{bmatrix} n-1 \\ n-1 \\ \vdots \\ n-1 \end{bmatrix}$$

u_2, \dots, u_n

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

Today:

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

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

$$u_i - u_j + n x_{ij} \leq n-1 \quad \forall i \neq 1, \forall j \neq 1; \rightarrow \text{matrix form is}$$

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

\bar{I} is the identity matrix, B is the arc-node incidence matrix of G_1 , with column for node 1 removed, and any non-zero entry corresponding to arcs incident to node 1 zeroed out, and \bar{I} is the vector of ones.

$$\begin{array}{c} \text{arcs} \\ \left\{ \begin{array}{|c|c|} \hline n \bar{I}_m & B \\ \hline \end{array} \right. \end{array} \xrightarrow{\text{nodes, except 1}} \begin{array}{c} \bar{x} \\ \vdots \\ \bar{u} \end{array} \leq \begin{array}{c} n-1 \\ n-1 \\ \vdots \\ n-1 \end{array}$$

nodes, except 1

u_2, \dots, u_n

The **node-arc incidence matrix** of a directed graph $G_1 = (V_1, E)$ 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 $A \bar{x} + B \bar{y} \leq b$ to the space of \bar{x} variables by eliminating the "unwanted" \bar{y} variables.

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

\bar{v} ?

$$C = \left\{ \bar{v} \geq 0 \mid \forall i \neq 1, \sum_j v_{ij} = \sum_j v_{ji} \right\}$$

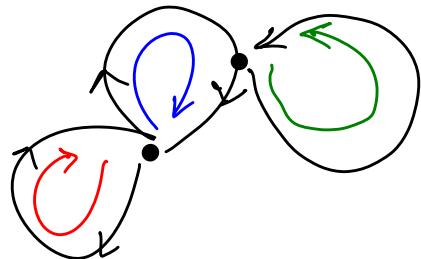
come in and go out at i
 equal # times

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

or circuit, generalization of a cycle

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

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



If 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.

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

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

$$\Rightarrow \text{Proj}_{\bar{x}}(P_{MTZ}) = \left\{ \bar{x} \mid (\bar{v}^i)^T (nI) \bar{x} \leq (\bar{v}^i)^T (n-1) I, i=1, \dots, k \right\}.$$

and system (1)

We do not get any inequalities stronger than \triangleleft here.

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

\rightarrow is for $(i, j) \in G$; assumed to be set all together here WLOG.

then

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

$$n X(G) \leq (n-1) |G|$$

$$\Rightarrow X(G) \leq (1 - \frac{1}{n}) |G|, \text{ which is } \triangleleft.$$

\Rightarrow The subtour formulation is stronger!

Sharp Formulation of a Disjunction

Let $S = Q_1 \cup \dots \cup Q_k$ where $Q_i = \{\bar{x} \mid A_i \bar{x} \leq \bar{b}^i\}$, $i=1, \dots, k$.

$\bar{x} \in \mathbb{R}^n$, are non-empty polyhedra with the same recession cone. Then $P \subseteq \underbrace{\mathbb{R}^n}_{\bar{x}} \times \underbrace{\mathbb{R}^k}_{\bar{y}} \times (\underbrace{\mathbb{R}^n \times \dots \times \mathbb{R}^n}_{k \text{ copies, for } \bar{x}^1, \dots, \bar{x}^k})$

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

$$P = \left\{ \begin{array}{l} A_1 \bar{x}^1 \leq \bar{b}^1 y_1 \\ \vdots \\ A_k \bar{x}^k \leq \bar{b}^k y_k \\ \bar{x}^1 + \dots + \bar{x}^k = \bar{x} \\ y_1 + \dots + y_k = 1 \\ 0 \leq y_i \leq 1 \end{array} \right\}$$

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

is a sharp formulation for S .

S is the same (\star) set for which we wrote (\star -big-M) and (\star -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 $\text{Proj}_{\bar{x}}(P) = \text{conv}(S)$.

We need $\text{conv}\left(\bigcup_{i=1}^k Q_i\right)$ 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 $\bar{a}^\top \bar{x} \leq \beta$ is a **valid inequality** for $X \subseteq \mathbb{R}^n$ if $\bar{a}^\top \bar{x} \leq \beta \quad \forall \bar{x} \in X$.

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

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

$\iff \bar{a}^\top \bar{x} \leq \beta$ is valid for each of Q_1, \dots, Q_k .

$\iff \exists \bar{u}^i \geq 0, \quad \bar{a}^\top = (\bar{u}^i)^\top A_i, \quad (\bar{u}^i)^\top \bar{b}^i \leq \beta, \quad \text{i.e.,}$

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

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

$$\begin{array}{l}
 \bar{a}^T \bar{x} = \bar{0} \\
 \bar{v}^{1T} A_1 \bar{x} - \bar{b}^1 y_1 = \bar{0} \\
 \bar{v}^{2T} A_2 \bar{x} - \bar{b}^2 y_2 = \bar{0} \\
 \vdots \\
 \bar{v}^{kT} A_k \bar{x} - \bar{b}^k y_k = \bar{0} \\
 \beta' \xrightarrow{\quad} y_1 + y_2 + \dots + y_k = 1 \\
 \beta'_1 - y_1 \leq 0 \\
 \beta'_2 - y_2 \leq 0 \\
 \vdots \\
 \beta'_k - y_k \leq 0
 \end{array}$$

We need

$$\begin{aligned}
 \bar{a}^T &= (\bar{v}^1)^T A_1 \rightarrow \text{eliminates } \bar{x}^1 \\
 &\vdots \\
 \bar{a}^T &= (\bar{v}^k)^T A_k \rightarrow \text{eliminates } \bar{x}^k
 \end{aligned}$$

$$\begin{aligned}
 \bar{a} &\geq \bar{0}, \bar{v}^i \geq \bar{0}, \\
 \beta' &\geq 0, \beta'_i \geq 0 \\
 \text{and } \beta' &\leq \beta
 \end{aligned}$$

and

$$\begin{aligned}
 (\bar{v}^1)^T \bar{b}^1 + \beta' - \beta'_1 &= 0 \rightarrow \text{eliminate } y_1 \\
 &\vdots \\
 (\bar{v}^k)^T \bar{b}^k + \beta' - \beta'_k &= 0 \rightarrow \text{eliminate } y_k
 \end{aligned}
 \quad \left. \begin{array}{l} (-\bar{v}^1)^T \bar{b}^1 + \beta'_1 \geq 0 \\ \vdots \\ (-\bar{v}^k)^T \bar{b}^k + \beta'_k \geq 0 \end{array} \right\}$$

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.

$$\left\{ \begin{array}{l} \bar{\alpha}^T = (\bar{x}^i)^T A_i, \quad i=1, \dots, k \\ \beta' \geq (\bar{x}^i)^T \bar{b}^i, \quad i=1, \dots, k \\ \beta' \leq \beta \end{array} \right\}$$

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

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 results in further elucidating properties and strengths of formulations, as well as comparing them.

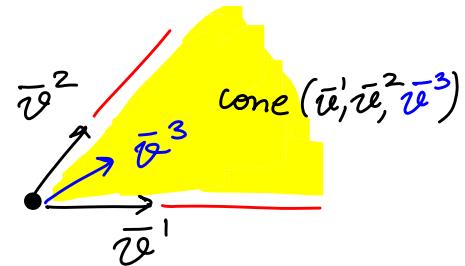
* $C \subseteq \mathbb{R}^n$ is convex if $\lambda \bar{x} + (1-\lambda) \bar{y} \in C \quad \forall \bar{x}, \bar{y} \in C, \lambda \in [0, 1]$.

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

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

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

k is finite $\Rightarrow C$ 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)

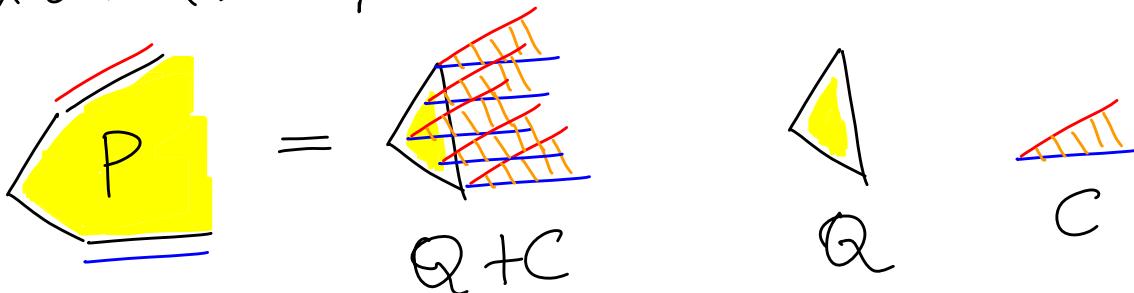
Today: * Definitions on polyhedra
* Integral polyhedra

- * $P \subseteq \mathbb{R}^n$ is a (convex) polyhedron if $P = \{\bar{x} \mid A\bar{x} \leq \bar{b}\}$.
 P is the intersection of finitely many affine half-spaces
 $\{\bar{x} \mid \bar{a}^\top \bar{x} \leq \beta\}, \bar{a} \neq 0, \beta \neq 0.$ 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.
 $P = \text{conv}(\bar{v}^1, \dots, \bar{v}^k) = \left\{ \bar{x} \mid \bar{x} = \sum_{i=1}^k \lambda_i \bar{v}^i, 0 \leq \lambda_i \leq 1, \sum_{i=1}^k \lambda_i = 1 \right\}.$

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 .
 $\hookrightarrow \bar{x} \in P \iff \exists \bar{y} \in Q, \bar{z} \in C, \text{ s.t. } \bar{x} = \bar{y} + \bar{z}.$



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.

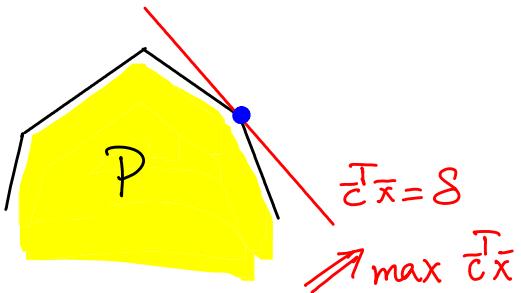
* Farkas' lemma:

$$\exists \bar{x} \mid A\bar{x} \leq \bar{b} \iff$$

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

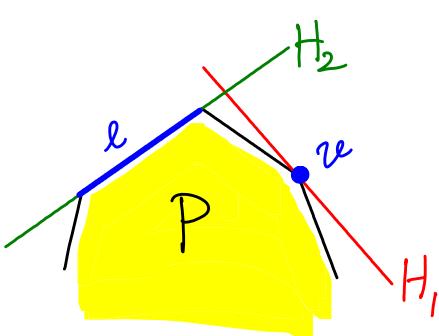
* ① let $P = \{\bar{x} \mid A\bar{x} \leq \bar{b}\}$, $S = \max \{\bar{c}^T \bar{x} \mid \bar{x} \in P\}$, $\bar{c} \neq 0$.

Then the affine hyperplane $\{\bar{x} \mid \bar{c}^T \bar{x} = S\}$ is a supporting hyperplane of P .



The line $\bar{c}^T \bar{x} = S$ "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_e 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 $F \neq \emptyset$, $F \neq P$, and F is a face of P .

$\bar{a}^T \bar{x} \leq \beta$: $\underline{[\bar{a}, \beta]}$ represents the face defined by $\bar{a}^T \bar{x} = \beta$.
 valid inequality $\xrightarrow{\text{Also}} [\bar{a}, \beta]$ supports P .
 compact notation

* Alternatively, F is a face of $P \Leftrightarrow F = \{\bar{x} \mid \bar{x} \in P, A'\bar{x} = \bar{b}'\}$ where $A'\bar{x} \leq \bar{b}'$ 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 $P \Leftrightarrow F'$ 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
 $\bar{a}^T \bar{x} = \beta \quad \forall \bar{x} \in F$. \Rightarrow also, binding

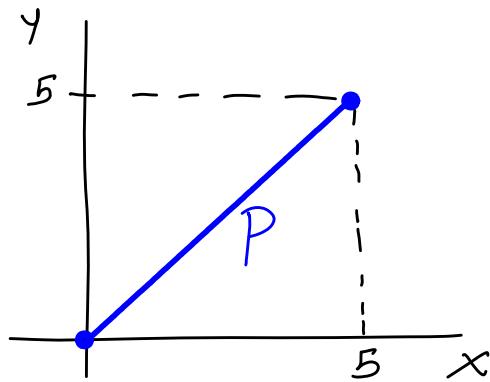
* An inequality $\bar{a}^T \bar{x} \leq \beta$ from $A\bar{x} \leq \bar{b}$ is an **implicit equality** if $A\bar{x} \leq \bar{b} \Rightarrow \bar{a}^T \bar{x} = \beta$.

* 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

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

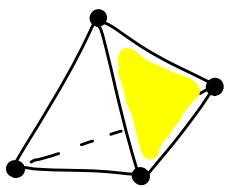
Example

$$\begin{aligned}y &\geq x \\y &\leq x \\x &\leq 5 \\x &\geq 0\end{aligned}$$



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 $\text{rank}(A') = 1$. 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.
- * $\dim\{\bar{x}\} = 0$. (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.

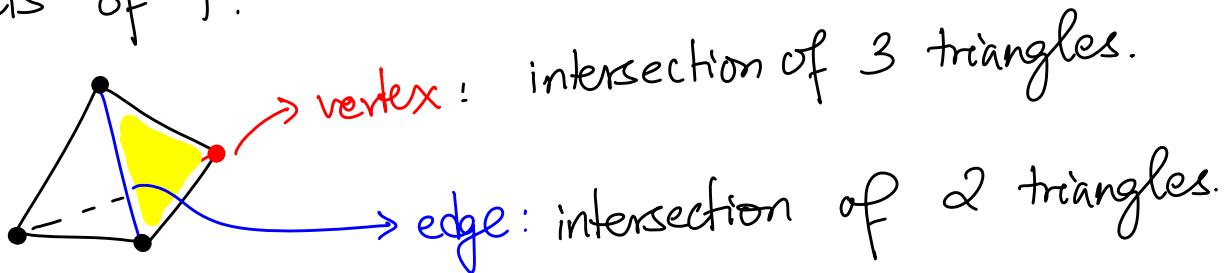
Let $A'\bar{x} \leq \bar{b}'$ be the subsystem of implicit equalities in $A\bar{x} \leq \bar{b}$, and $A^+\bar{x} \leq \bar{b}^+$ be the remaining inequalities.

If no inequality in $A^+\bar{x} \leq \bar{b}^+$ is redundant in $A\bar{x} \leq \bar{b}$, then for any facet F of P ,

$F = \{\bar{x} \in P \mid \bar{a}^{+T}\bar{x} = \beta^+\}$ for an inequality $\bar{a}^{+T}\bar{x} \leq \beta^+$ from $A^+\bar{x} \leq \bar{b}^+$.

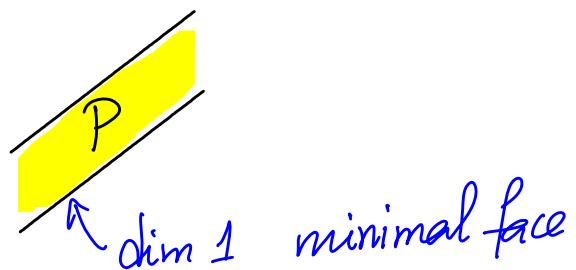
In this case, $\bar{a}^{+T}\bar{x} = \beta^+$ determines the facet F .

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

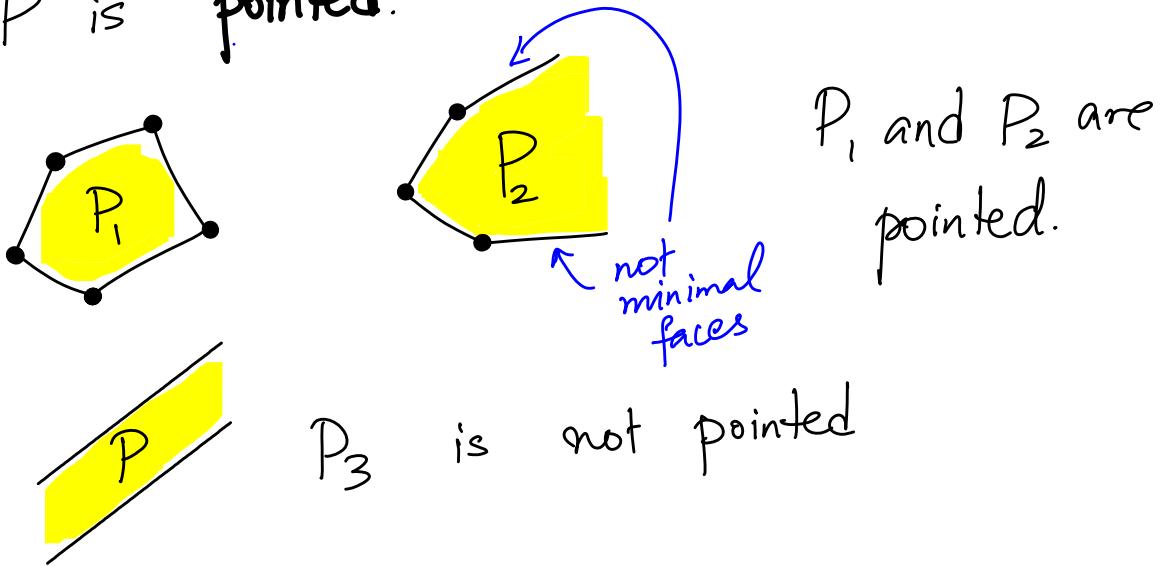


- * A **minimal face** of P is a face of P not containing any other face of P .

For the tetrahedron, vertices are minimal faces.

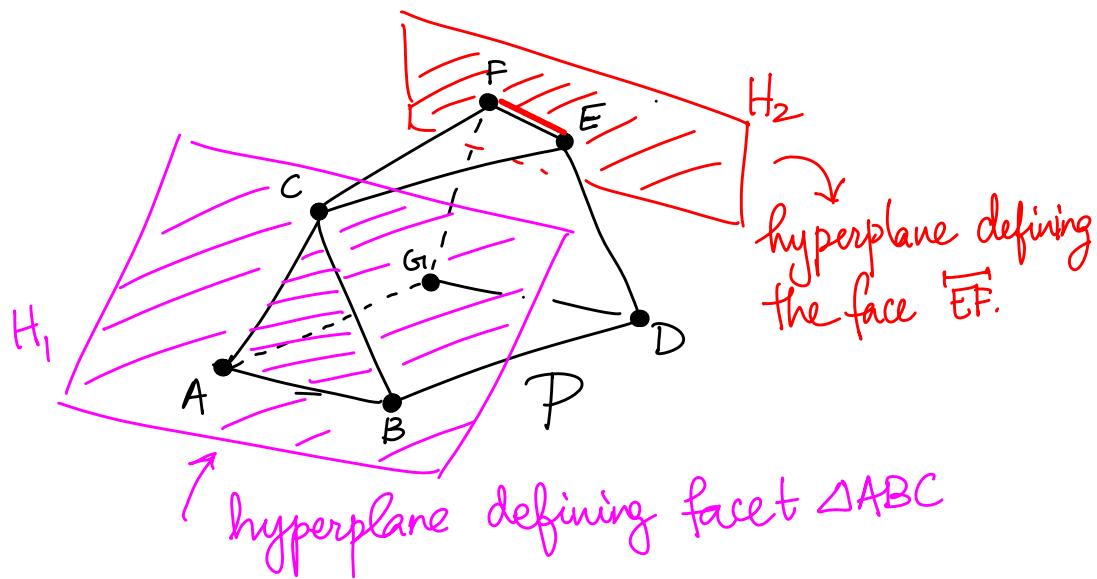


- * A vertex of P is $\bar{z} \in P$ such that $\{\bar{z}\}$ is a minimal face of dimension zero.
- * If each minimal face of P has dimension zero, then P is **pointed**.



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 quadrilaterals are all faces of P .

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

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

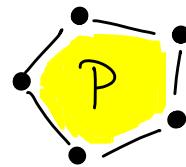
H_1 is the supporting hyperplane defining face $\triangle ABC$, and H_2 defines the face which is edge \overline{EF} .

Special Cases: Well-Solved IPs

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

We study problems of the form

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



where $\text{conv}(X)$ 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., $P = \{ \bar{x} \mid A\bar{x} \leq \bar{b} \}$ 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.

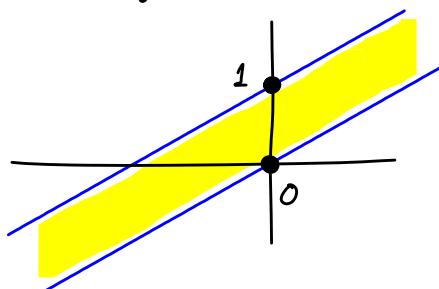
Integral Polyhedra

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 $\bar{w}' = [w_1+1, w_2, \dots, w_n]^T = \bar{w} + \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$, 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 $\bar{w}'^T \bar{u}$ are integral.

Also, $\bar{w}, \bar{w}' \in \mathbb{Z}^n \Rightarrow v_i \in \mathbb{Z}$.

We repeat the argument for v_2, v_3, \dots, v_n . □

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 $A\bar{x} \leq \bar{b}$).

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

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

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

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

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

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

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

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

If a basic solution \bar{x} satisfies $\bar{x} \geq \bar{0}$, 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 $A \in \mathbb{Z}^{m \times n}$, $\text{rank}(A) = m$. Then $P = \{\bar{x} \mid A\bar{x} = \bar{b}, \bar{x} \geq 0\}$

is integral for all $\bar{b} \in \mathbb{Z}^m$ iff A is unimodular. ensures
 P is pointed

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

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 $\bar{B}' \bar{b}$ 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 $\text{rank}(A) = m$ (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).

$A = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 1 \end{bmatrix}$ 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 $P = \{ \bar{x} \mid A\bar{x} \leq \bar{b}, \bar{x} \geq \bar{0} \}$ is integral $\Leftrightarrow \bar{b} \in \mathbb{Z}^m$ for which $P \neq \emptyset$ 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. \rightarrow determinant is preserved under transposes
- (iii) $[A \ I_m]$ is unimodular \rightarrow full row rank now!
- (iv) $\begin{bmatrix} A \\ -A \\ I_n \\ -I_n \end{bmatrix}$ is TU.

Back to proof of Theorem 9.

$P = \{ \bar{x} \mid A\bar{x} \leq \bar{b}, \bar{x} \geq \bar{0} \}$ is integral \Leftrightarrow
 $\text{Proj}_{\bar{x}}(P^z)$ is integral, where $P_z = \{ \bar{z} \mid [A \ I]\bar{z} = \bar{b}, \bar{z} \geq \bar{0} \}$
 is integral, where $\bar{z} = \begin{bmatrix} \bar{x} \\ \bar{s} \end{bmatrix}$. \rightarrow 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 $\nexists \bar{b} \in \mathbb{Z}^m$ for which $P \neq \emptyset$.

\bar{x} is uvs (unrestricted in sign) here. We can replace \bar{x} by $\bar{x}^+ - \bar{x}^-$, where $\bar{x}^+, \bar{x}^- \geq 0$, 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 ERDs 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)

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

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

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 TL

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 TL.

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

$$k=1. \quad A_{ij} \in \{-1, 0, 1\}. \quad \checkmark$$

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

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

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

$$\det(B) = 0.$$

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

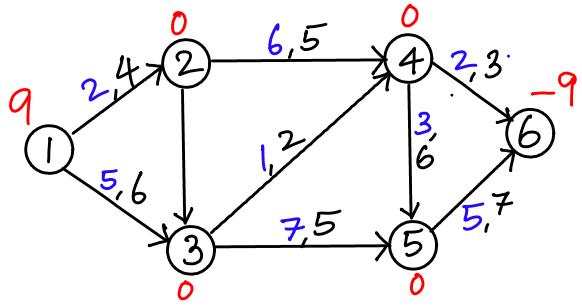
As every column has one +1 and -1.

□

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.

$$G = (V, E)$$



$$b(i) \xrightarrow{i} c_{ij}, u_{ij} \xrightarrow{j} b(j)$$

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) .

$$\begin{aligned} \min \quad & \sum_{(i,j) \in A} c_{ij} x_{ij} \\ \text{s.t.} \quad & \sum_{j: (i,j) \in A} x_{ij} - \sum_{j: (j,i) \in A} x_{ji} = b(i) \quad \forall i \in V \end{aligned}$$

outflow - inflow

supply/demand

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

we assume lower
bounds are all zero

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

$$\begin{array}{ll} \min & \bar{c}^T \bar{x} \\ \text{s.t.} & \begin{array}{l} \bar{A} \bar{x} = \bar{b} \\ \bar{I} \bar{x} \leq \bar{u} \\ \bar{x} \geq \bar{0} \end{array} \end{array}$$

$\rightarrow \begin{bmatrix} \bar{A} \\ \bar{I} \end{bmatrix} \bar{x} \left(\begin{array}{l} = \\ \leq \end{array} \right) \begin{bmatrix} \bar{b} \\ \bar{u} \end{bmatrix}$

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.

$$A = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \\ 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 & 1 \\ -1 & 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \\ 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 & 1 \\ -1 & 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \\ 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 & 1 \\ -1 & 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \\ 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 & 1 \\ -1 & 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \end{bmatrix}$$

$$\begin{bmatrix} (i,j) \\ i \\ j \end{bmatrix}$$

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 Th.

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:

$$\begin{aligned}
 \text{(P)} \quad \text{primal LP} \\
 \max \quad Z &= 2x_1 + 3x_2 \\
 \text{s.t.} \quad & x_1 + 4x_2 \leq 5 \quad y_1 \geq 0 \\
 & -2x_1 + 3x_2 = 4 \quad y_2 \text{ urs} \\
 & 5x_2 \geq 7 \quad y_3 \leq 0 \\
 & x_1 \leq 0, \quad x_2 \geq 0 \\
 & \leq \quad \geq
 \end{aligned}$$

$$\begin{aligned}
 \min w &= 5y_1 + 4y_2 + 7y_3 \\
 \text{s.t.} \quad & y_1 - 2y_2 \leq 2 \\
 & 4y_1 + 3y_2 + 5y_3 \geq 3 \\
 & y_1 \geq 0, \quad y_2 \text{ urs}, \quad y_3 \leq 0
 \end{aligned}
 \quad \begin{array}{l} \text{(D)} \\ \text{dual LP} \end{array}$$

Normal vars and normal constraints

max-LP: \leq is normal

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

min-LP: \geq 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
variables	\min		\max
	≥ 0		$\leq \rightarrow$ normal
	≤ 0		$\geq \rightarrow$ opposite to normal
constraints	\geq		≥ 0
	\leq		≤ 0
	$=$		URS

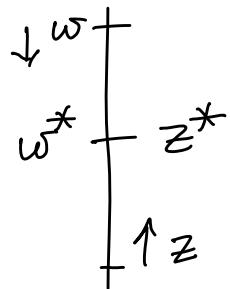
LP duality in matrix form:

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

$$\begin{aligned} \min w &= \bar{b}^T \bar{y} \\ \text{s.t.} \quad \bar{A}^T \bar{y} &= \bar{c} \quad (D) \\ \bar{y} &\geq \bar{0} \end{aligned}$$

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 LFs.



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)

$$\text{LP duality: } \max \{ \bar{c}^T \bar{x} \mid A\bar{x} \leq \bar{b} \} = \min \{ \bar{b}^T \bar{y} \mid A^T \bar{y} = \bar{c}, \bar{y} \geq 0 \} \quad \textcircled{*}$$

Def A system $A\bar{x} \leq \bar{b}$ is **totally dual integral (TDI)** if the minimum in $\textcircled{*}$ 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 ...)

$$\text{LP duality: } \max \{ \bar{c}^T \bar{x} \mid A\bar{x} \leq \bar{b} \} = \min \{ \bar{b}^T \bar{y} \mid A^T \bar{y} = \bar{c}, \bar{y} \geq 0 \} \quad \textcircled{*}$$

Def A system $A\bar{x} \leq \bar{b}$ is **totally dual integral (TDI)** if the minimum in $\textcircled{*}$ 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 — its implication goes only one way, i.e., it is not an "if-and-only-if" result.

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

Proof As \bar{b} is integral, and $A\bar{x} \leq \bar{b}$ is TDI, $\max \{ \bar{c}^T \bar{x} \mid A\bar{x} \leq \bar{b} \}$ 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

$$\begin{array}{ll} \max & c_1x_1 + c_2x_2 \\ \text{s.t.} & x_1 + x_2 = b_1 \quad y_1 \geq 0 \\ & x_2 \leq b_2 \quad y_2 \geq 0 \\ & = = \end{array}$$

$$\begin{array}{ll} \min & b_1y_1 + b_2y_2 \\ \text{s.t.} & y_1 = c_1 \\ & y_1 + y_2 = c_2 \\ & y_1, y_2 \geq 0 \end{array}$$

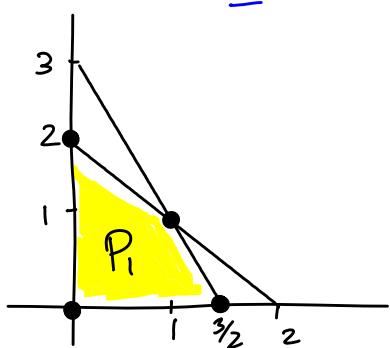
let $b_1, b_2 \in \mathbb{Z}_{\geq 0}$. For $c_1, c_2 \in \mathbb{Z}$, we solve system in (D) to get

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

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

Example 2

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



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.

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

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

$$\xrightarrow{\text{then } -R_2} \left[\begin{array}{ccc|c} 1 & 0 & 1 & -2 \\ 0 & 1 & 1 & -1 \end{array} \right] \text{ gives}$$

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

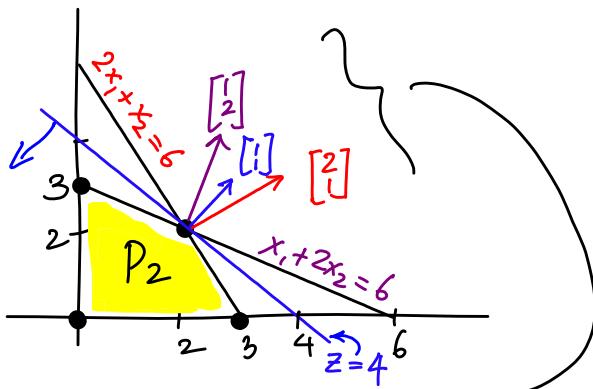
But, for $c_1=1, c_2=0$, (D) has a unique optimal solution @ $y_2 = y_4 = \frac{1}{2}, w^* = \frac{3}{2}$.

Note that $\max\{x_1 | \bar{x} \in P_1\} = \frac{3}{2}$

If 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!

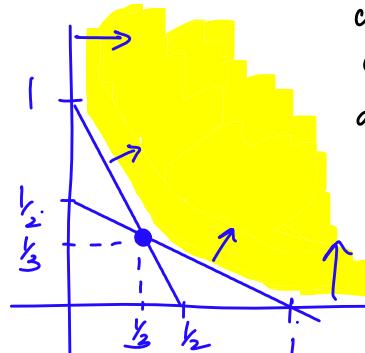
Example 3

$$\begin{aligned} \max \quad & z = x_1 + x_2 \\ \text{s.t.} \quad & \left\{ \begin{array}{l} x_1 + 2x_2 \leq 6 \\ 2x_1 + x_2 \leq 6 \\ x_1, x_2 \geq 0 \end{array} \right\} \quad \left\{ \begin{array}{l} y_1 \geq 0 \\ y_2 \geq 0 \end{array} \right. \\ (P_2) \quad & \geq \quad \geq \\ & z^* = 4 \text{ at } \begin{bmatrix} 2 \\ 2 \end{bmatrix} \end{aligned}$$



$$\begin{aligned} \min \quad & w = b_1 y_1 + b_2 y_2 \\ \text{s.t.} \quad & y_1 + 2y_2 \geq 1 \\ & 2y_1 + y_2 \geq 1 \\ & y_1, y_2 \geq 0 \\ & w^* = 4 \text{ at } \begin{bmatrix} 1/3 \\ 1/3 \end{bmatrix} \end{aligned} \quad (D)$$

We could treat $x_i \geq 0$ 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!



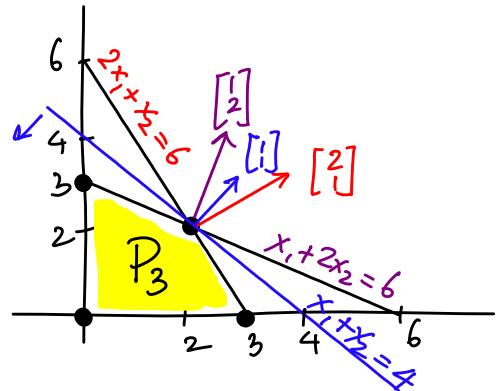
Normal vectors of the constraints and $z = x_1 + x_2$. We should be able to express $[1, 2]$ as an integer linear combination of $\begin{bmatrix} 1 \\ 2 \end{bmatrix}$ and $\begin{bmatrix} 2 \\ 1 \end{bmatrix}$, for an integer (optimal) solution to exist. Hence (P_2) is not TDI.

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.

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

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



Now, $[1]$ can indeed be expressed as an integer linear combination of $[2]$, $[1]$, and $[1]$.

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.

Theorem 8.13 (Bertsimas-Weismantel)

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

Corollary 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

(13-5)

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: $\beta' \leq \bar{a}^T \bar{x} \leq \beta$
 $\bar{x} \in \{0,1\}^n$

$a_1x_1 + \dots + a_nx_n$ ←

goal is to check feasibility: $\exists \bar{x} \in \{0,1\}^n$ 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

$$z_l(T) \leq z(T) \leq z_u(T)$$

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 $z_l(S), z_u(S)$.

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 $z_l(T_i), z_u(T_i), i=1, \dots, k$.

Set $\mathcal{L} = \mathcal{L} \cup \{T_1, \dots, T_k\}$.

(iii) Let $z_l(S) = \max \{ z_l(S), \max \{ z_l(T) \mid T \in \mathcal{L} \} \}$
 ↳ save the solution \bar{x} here
 (iv) Prune all $T \in \mathcal{L}$ with $z_u(T) \leq z_l(S)$ integer feasible

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

(v) If $\mathcal{L} = \emptyset$ 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

$$\{ \bar{x} \in S^* \mid \bar{c}^T \bar{x} > z_l(S) \} \subseteq \mathcal{L}.$$

- * 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: $z(S) > z_l(S)$

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: $z(S) = z_l(S)$.

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

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

Let's compare the updates of z_l, z_u :

consider
current best value, and
those from all children

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

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

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

1. Partition S : let $x_i \in \mathbb{Z}$ in S , but $x_i = k + s$ in the LP solution for S , where $k \in \mathbb{Z}$, $0 < s < 1$. 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_{ej} , $j=1,2$. 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 $z_{ej} = -\infty$.

We will have

$$\max_j \{z_j\} = z \quad \text{--- (1)}$$

$$\max_j \{z_{ej}\} \leq z \leq \max_j \{z_{uj}\} \quad \text{--- (2)}$$

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

In general, z_{ej} 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.

Another example of a relaxation:

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

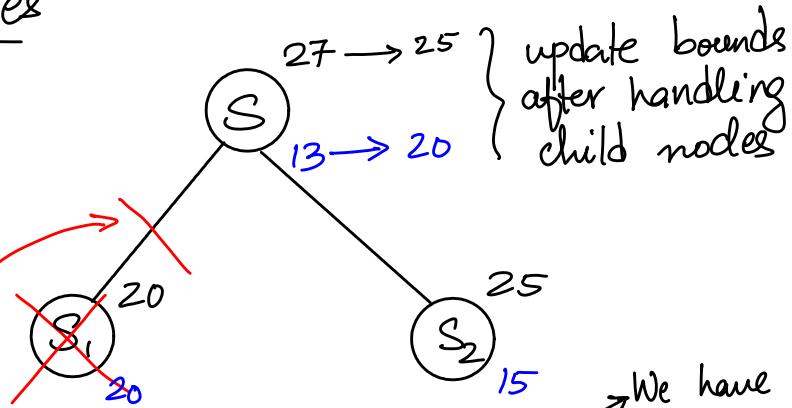
To get a relaxation of S , throw away the subtour constraints.

How do we use (2) : update of bounds

Three examples

1.

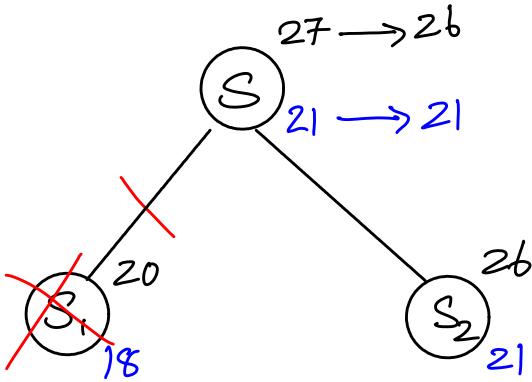
Notation for pruning: \times or



prune S_1 by optimality.

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

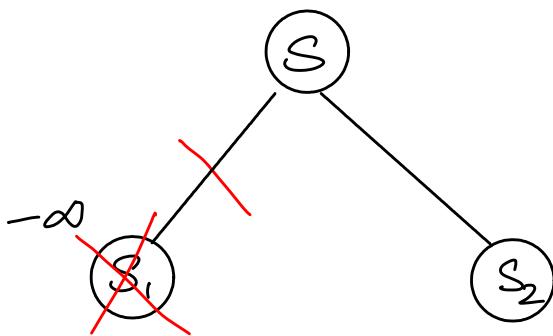
2.



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.

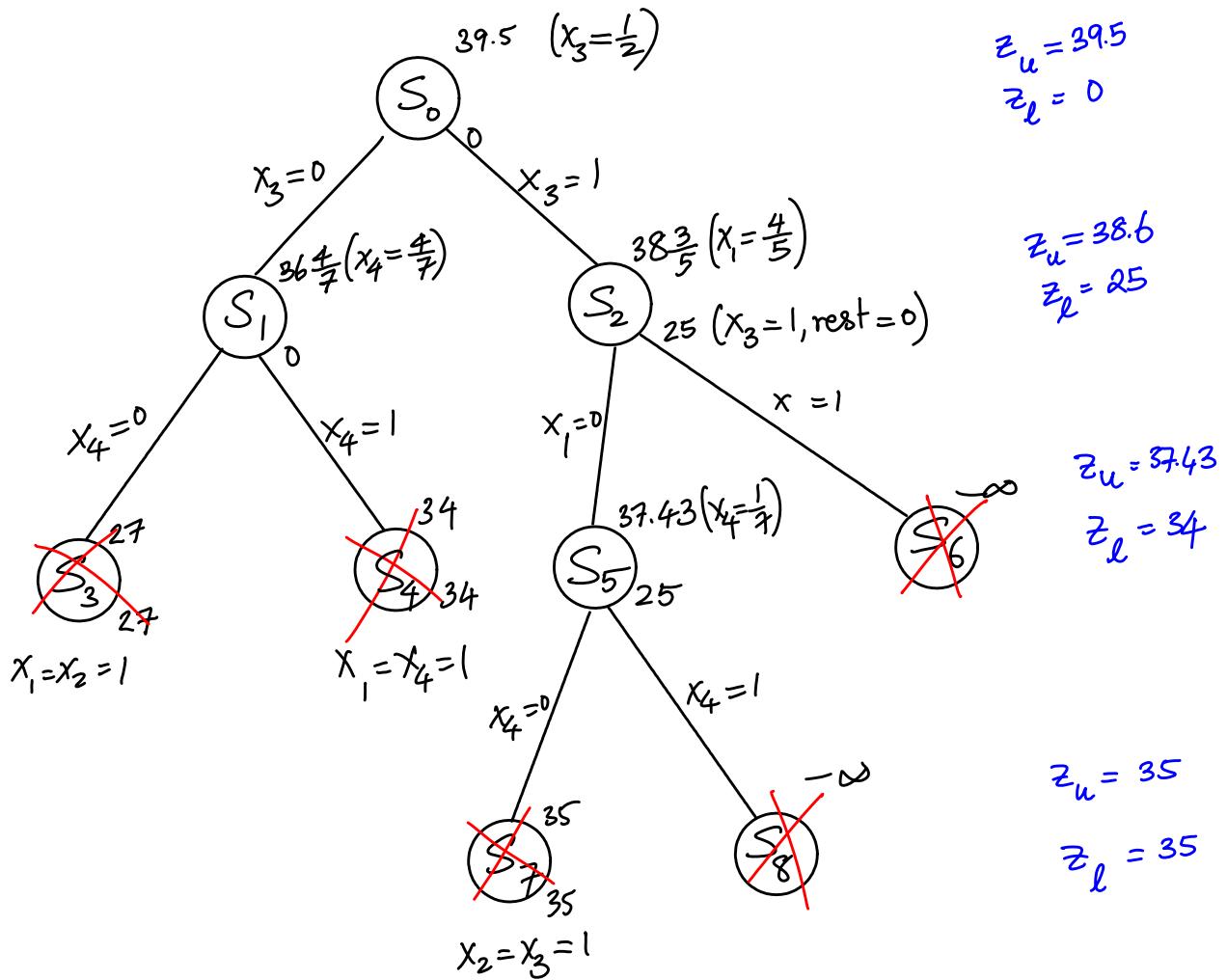
S_1 is not feasible even as an LP - no point considering it any further.

$$\begin{array}{l} S_i \\ z_{u_i} \\ z_{l_i} \end{array}$$

Illustration of B&B on n=4 knapsack problem

Prob 3, Chap 7 of Wolsey, Integer programming

$$\begin{aligned} \text{max } Z &= 17x_1 + 10x_2 + 25x_3 + 17x_4 \\ \text{s.t. } &5x_1 + 3x_2 + 8x_3 + 7x_4 \leq 12 \\ &\bar{x} \in \{0,1\}^4 \end{aligned}$$



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)

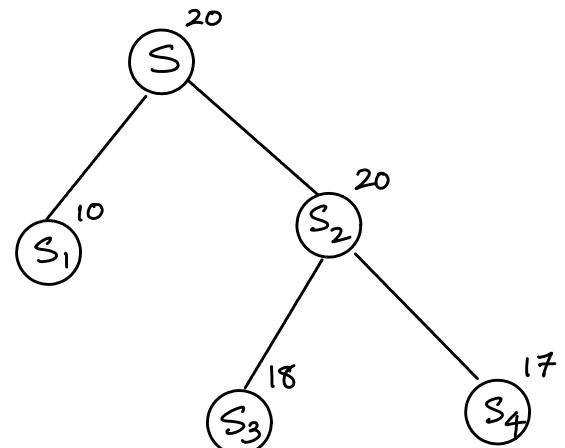
- Today:
- * B&B strategies
 - * reduced cost fixing in B&B
 - * types of branching

Node Selection Strategies

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

Consider this example:

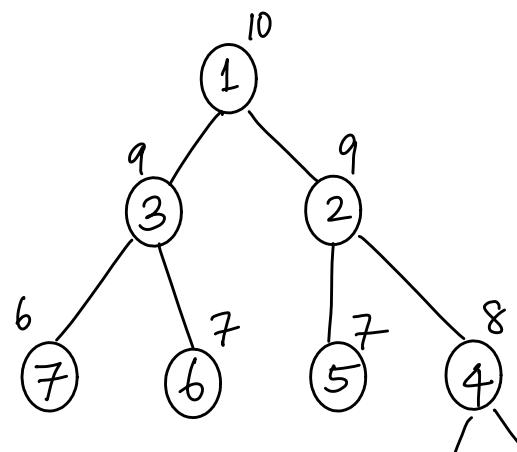
If we subdivide S_1 , z_u will remain at 20. If $z^* = 15$ (optimal objective function value) and we knew it, we would not subdivide S_1 . On the other hand, subdividing S_2 decreases z_u to 18.



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

→ global upper bound

- * Rapidly decreases Z_u .
- * Never subdivides a node T_k with $Z_u(T_k) < z^*$,
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.)

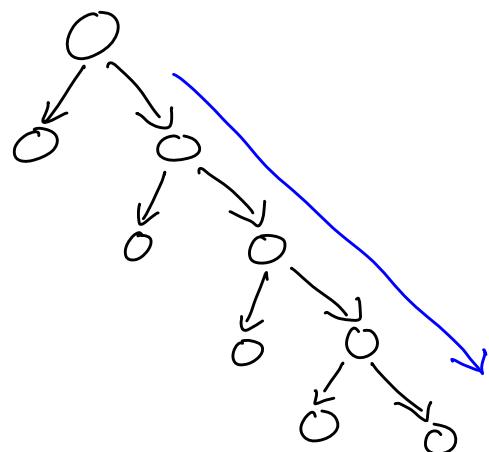
Disadvantages of BNF strategy

- * The B&B tree is widespread, and memory needed to store the list of subproblems L may be huge.
- * May take a long time to find an integer feasible solution (i.e., a node T_k with $Z_u(T_k) = Z_l(T_k)$).

Depth-First Search (DFS) B&B Strategy

Exact opposite to BNF → always select the problem that was added to L the last (LIFO order).

A typical DFS B&B tree:



Advantages of DFS B&B Strategy

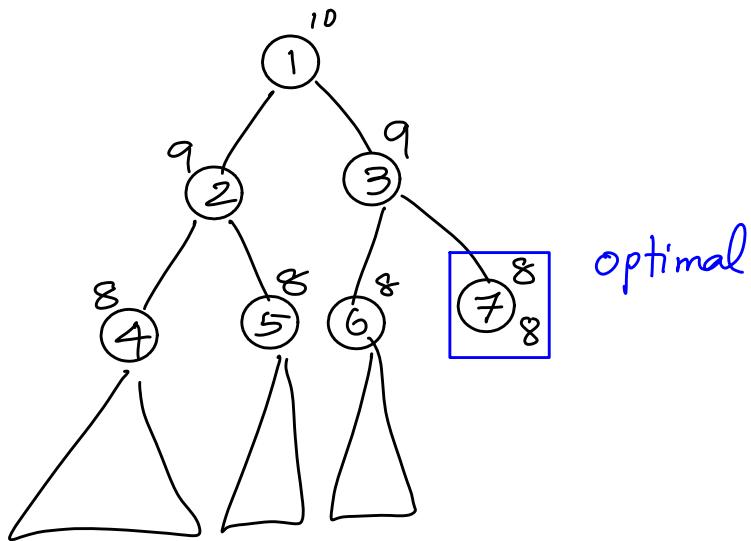
- * Maximum depth of B&B tree is n ; at any point, DFS stores at most $2n$ subproblems in L .
- * Since it gets down deep quickly in the B&B tree, DFS finds integer feasible solutions relatively quickly.

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.

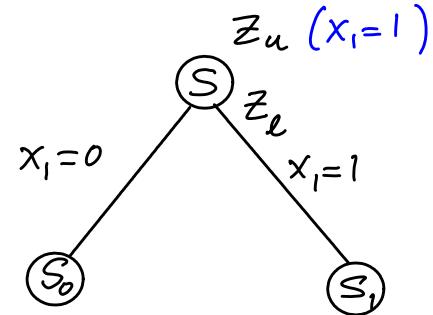
Reduced Cost fixing in B&B

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

$$Z_u(S_0) = \text{LP optimum at } S_0 \leq Z_d?$$

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



LP relaxation at S

$$Z_u(S) = \begin{cases} \max \bar{c}^T \bar{x} \\ \text{s.t. } A\bar{x} \leq \bar{b} \rightarrow \bar{y} \geq \bar{0} \quad (\text{P}) \\ \bar{x} \leq \bar{1} \rightarrow \bar{u} \geq \bar{0} \\ -\bar{x} \leq \bar{0} \rightarrow \bar{v} \geq \bar{0} \end{cases} \quad \begin{matrix} \text{Primal} \\ \text{LP} \end{matrix}$$

Dual

$$\begin{cases} \min \bar{b}^T \bar{y} + \bar{i}^T \bar{u} \\ \text{s.t. } A^T \bar{y} + \bar{u} - \bar{v} = \bar{c} \\ \bar{y}, \bar{u}, \bar{v} \geq \bar{0} \end{cases} \quad \begin{matrix} (\text{D}) \\ \text{dual} \\ \text{LP} \end{matrix}$$

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 also = opt(D), the optimal obj. fn of dual (D)
2. $u_i \geq Z_u(S) - Z_d$

Then $Z_u(S_0) \leq Z_d$. 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, $v_j=0$ here (as $-x_1 \leq 0$ is not binding).

Proof

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

$$\bar{y}' = \bar{y}, \quad \bar{u}' = \bar{u}, \quad \bar{v}' = \bar{v} \text{ except for } u'_1 = 0, v'_1 = -u_1.$$

$$\Rightarrow \text{The optimal obj. fn. value at } (D) \wedge (x_i=0) \leq Z_u(S) - u_1 \\ \leq Z_l \text{ by (2).}$$

Hence we can prune S_0 , i.e., fix $x_1=1$.

□

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 ($\leq 100!$).

Example

$$(P) \left\{ \begin{array}{ll} \max & 2x_1 + x_2 \\ \text{s.t.} & x_1 + 2x_2 \leq 2 \quad y \\ & x_1 \leq 1 \quad u_1 \\ & x_2 \leq 1 \quad u_2 \\ & -x_1 \leq 0 \quad v_1^e \\ & -x_2 \leq 0 \quad v_2^e \end{array} \right.$$

$$\begin{aligned} & \min 2y + u_1 + u_2 \\ & \text{s.t. } y + u_1 - v_1^e = 2 \quad (D) \\ & \quad 2y + u_2 - v_2^e = 1 \\ & \quad y, u_1, u_2, v_1^e, v_2^e \geq 0 \end{aligned}$$

$$Z_l = Z^* = 2 \text{ with } \bar{x}^* = \begin{bmatrix} 1 \\ 0 \end{bmatrix}.$$

$$Z_u = 5/2 \text{ with } \bar{x} = \begin{bmatrix} 1 \\ 1/2 \end{bmatrix}.$$

For (D) , opt. solution is
 $y = \frac{1}{2}, u_1 = \frac{3}{2}, u_2 = 0$.
 $u_1 \geq Z_u - Z_l = \frac{5}{2} - 2 = \frac{1}{2}$.
So, fix $x_1=1$ by Theorem 13.

Types of Branching

① Binary branching

Solve LP relaxation at S_i .

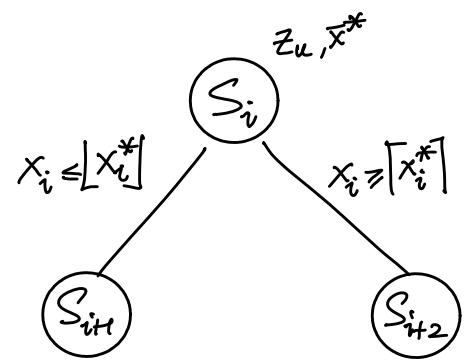
Let the optimal solution to this

LP relaxation be \bar{x}^* with x_i^* non-integral, where $x_i \in \mathbb{Z}$ is required. Create two branches

by adding $x_i \leq \lfloor x_i^* \rfloor$ and $x_i \geq \lceil x_i^* \rceil$.

Example: $x_5 = 13.6$ (in \bar{x}^*). Create the branches $x_5 \leq 13$ and $x_5 \geq 14$.

Binary variables are indeed covered in this case.



② Integer Branching

Choose a variable x_j that needs to be integral, find

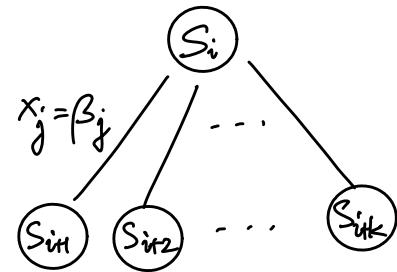
$$S_{ij} = \min \{x_j \mid \bar{x} \in \text{LP relaxation at } S_i\},$$

$$\Gamma_{ij} = \max \{x_j \mid \bar{x} \in \text{LP relaxation at } S_i\}.$$

Create branches by adding constraints

$$x_j = \beta_j \text{ where } \beta_j \in \{\lceil S_{ij} \rceil, \lceil S_{ij} \rceil + 1, \dots, \lceil \Gamma_{ij} \rceil\}.$$

So, create $\lceil \Gamma_{ij} \rceil - \lceil S_{ij} \rceil + 1$ nodes.



$$k = \lceil \Gamma_{ij} \rceil - \lceil S_{ij} \rceil + 1$$

e.g., $S_{ij} = 13.64$, $\Gamma_{ij} = 16.39$
for $S_{ij} \leq x_j \leq \Gamma_{ij}$, we create 3 branches with $x_j = 14, 15, 16$.

MATH 567 : Lecture 16 (03/04/2025)

Today:

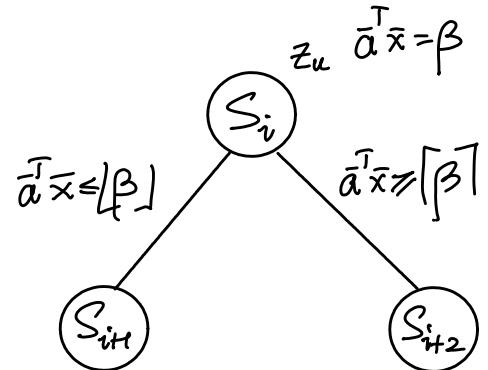
- * branching on constraint
- * Jeroslav's IP
- * cutting planes

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 $\bar{a}^T \bar{x} \geq \lceil \beta \rceil$.



Example 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 ③, but for a constraint $\bar{a}^T \bar{x}$, $\bar{a} \in \mathbb{Z}^n$.

Example 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 $\beta = 7, 8, 9, 10, 11$ ($7 = \lceil 6.71 \rceil$, $11 = \lfloor 11.99 \rfloor$).

Jeroslow's IP (1974)

$$\begin{aligned} \min \quad & x_{n+1} \\ \text{s.t.} \quad & 2x_1 + 2x_2 + \dots + 2x_n + x_{n+1} = n \text{ for odd } n \\ & x_j \in \{0, 1\}, j=1, 2, \dots, n+1. \end{aligned}$$

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:

$$\begin{aligned} 2x_1 + 2x_2 + \dots + 2x_n &= 2k+1 \\ x_j &\in \{0, 1\}, j=1, 2, \dots, n. \end{aligned}$$

The goal here is to prove that the above IP is integer infeasible using B&B.

Say, x_1, \dots, x_j for $j \leq k$ are fixed already (wlog). Also, assume $x_r = 1$ for $r=1, \dots, i$ for $i < j$, and $x_r = 0$ for $r=i+1, \dots, j$.

The LP feasibility problem at the current node is

$$\begin{aligned} 2x_{j+1} + \dots + 2x_{2k+1} &= 2k+1 - 2i. \\ 0 \leq x_r \leq 1, r &= j+1, \dots, 2k+1. \end{aligned}$$

$$\Rightarrow \underbrace{x_{j+1} + \dots + x_{2k+1}}_{2k+1-j} = \frac{2k+1-2i}{2} = k-i+\frac{1}{2}$$

$0 \leq x_r \leq 1, r=j+1, \dots, 2k+1.$

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 $2^k = 2^{\lfloor \frac{n}{2} \rfloor}$ nodes.

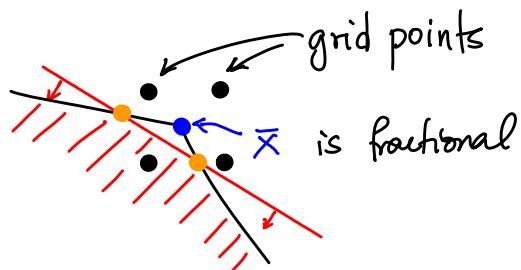
But we could prove integer infeasibility at the root node itself by branching on the constraint $x_1 + x_2 + \dots + x_n$!

$$\begin{aligned} \max / \min \quad & \sum_{j=1}^n x_j \\ \text{s.t.} \quad & 2 \sum_{j=1}^n x_j = 2k+1 \\ & 0 \leq x_j \leq 1, j=1, 2, \dots, 2k+1. \end{aligned}$$

$S(\min) = \gamma(\max) = k + \frac{1}{2}$, and hence $[S] > \lfloor \gamma \rfloor$.

So we create zero nodes!

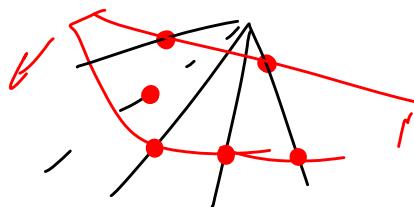
Cutting Planes



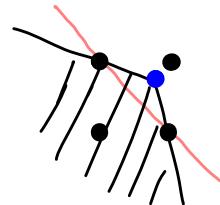
A cutting plane cuts off a non-integral corner point (in the feasible region of the LP relaxation).

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-integral 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: $\bar{a}^\top \bar{x} \leq \beta$ is valid for $P \subseteq \mathbb{R}^n$ if $\bar{a}^\top \bar{x} \leq \beta \wedge \bar{x} \in P$.

Chvátal-Gomory (CG) Cuts

Vášek Chvátal ("Vášek HoTal").

Most other classes of cuts could be derived by applying the CG cut procedure repeatedly.

Pure integer case

$$(1) \quad Y = \{ \bar{x} \in \mathbb{Z}^n \mid A\bar{x} \leq \bar{b} \}.$$

$\bar{x} \geq \bar{0} \Rightarrow (\bar{u}^T A)\bar{x} \leq \bar{u}^T \bar{b}$ is valid for Y .

If $\bar{u}^T A$ is integral, then

$$(\bar{u}^T A)\bar{x} \leq \lfloor \bar{u}^T \bar{b} \rfloor \text{ is valid for } Y.$$

$$(2) \quad P = \{ \bar{x} \in \mathbb{R}^n \mid A\bar{x} \leq \bar{b}, \bar{x} \geq \bar{0} \}.$$

$\bar{x} \geq \bar{0} \Rightarrow (\bar{u}^T A)\bar{x} \leq \bar{u}^T \bar{b}$, is valid for P . (1)

$\Rightarrow \lfloor (\bar{u}^T A) \rfloor \bar{x} \leq \bar{u}^T \bar{b}$, is valid for P (2)

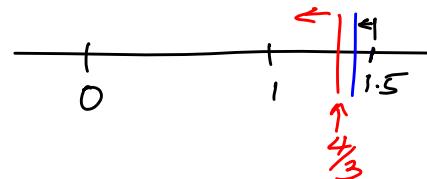
Since $\bar{x} \geq \bar{0}$, (2) weakens (1).

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

$\Rightarrow 3x \leq \lfloor 4.5 \rfloor$ is valid for P

$3x \leq 4$ is valid for $P \cap \mathbb{Z}$.



Mixed Integer Case (of the GJ cut)

Mixed integer rounding (MIR)

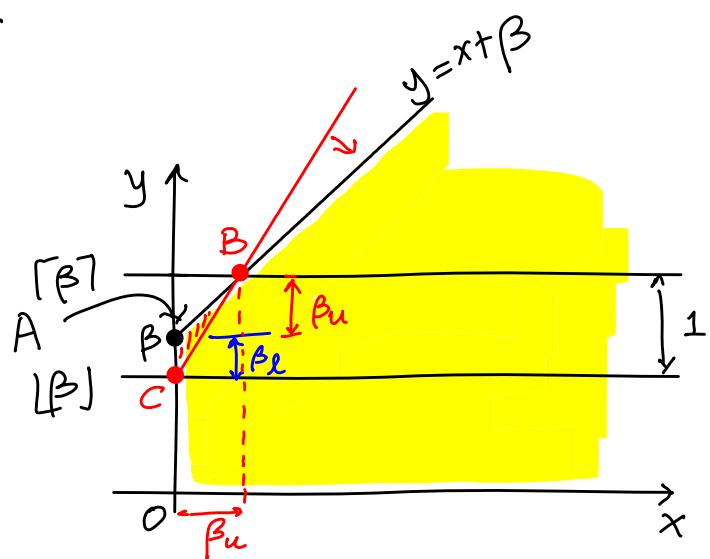
$$X = \{(x, y) \in \mathbb{R}_{\geq 0} \times \mathbb{Z} \mid y \leq x + \beta\}.$$

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

$$\begin{aligned}\beta_l &= \beta - \lfloor \beta \rfloor && \left. \begin{array}{l} \text{lower and} \\ \text{upper} \\ \text{fractional} \\ \text{parts.} \end{array} \right\} \\ \beta_u &= \lceil \beta \rceil - \beta\end{aligned}$$

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 .

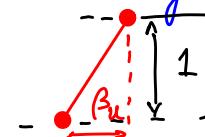
$x \geq 0$ is needed to get the fractional corner point $A(0, \beta)$ in the first place.

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

$$\begin{aligned}\lceil \beta \rceil &= \lfloor \beta \rfloor + 1 = m \beta_u + \lfloor \beta \rfloor \\ \Rightarrow m &= \frac{1}{\beta_u}.\end{aligned}$$

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

$$X = \left\{ (\bar{x}, \bar{y}) \in \mathbb{R}_{\geq 0}^m \times \mathbb{Z}_{\geq 0}^n \mid \sum_{j \in N} a_j y_j + \sum_{j \in M} a_j x_j = \beta \right\}$$

where $N = \{1, 2, \dots, n\}$ and $M = \{1, 2, \dots, m\} \setminus N$.
 $\Rightarrow N, M$ 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 $a_j > 0$ ($x_j \geq 0 \wedge j \in M$)

$$\Rightarrow \underbrace{\sum_{j: a_j \leq \beta} a_j y_j}_{\gamma_j} + \underbrace{\sum_{j: a_j > \beta} a_j y_j}_{\gamma_j - a_j u} + \sum_{a_j < 0} a_j x_j \leq \beta$$

$$\Rightarrow \left(\underbrace{\sum_{j: a_j \leq \beta} a_j y_j}_{y} + \underbrace{\sum_{j: a_j > \beta} a_j y_j}_{\gamma_j - a_j u} \right) \leq \beta + \left(\underbrace{\sum_{j: a_j > \beta} a_j y_j}_{x} - \sum_{a_j < 0} a_j x_j \right)$$

We now apply MIR to get $y \leq \frac{1}{\beta_u} x + \lfloor \beta \rfloor$.

$$\Rightarrow \left(\sum_{\substack{a_j \leq \beta_e \\ a_j > \beta_e}} [a_j] y_j + \sum_{a_j > \beta_e} \underbrace{[a_j] y_j}_{\downarrow} \right) = \lfloor \beta \rfloor + \left(\sum_{\substack{a_j \leq \beta_e \\ a_j > \beta_e}} \frac{a_j}{\beta_u} y_j - \sum_{a_j < 0} \frac{a_j}{\beta_u} x_j \right)$$

$[a_j] + 1$

$$\Rightarrow \sum_{\substack{a_j \leq \beta_e}} [a_j] y_j + \sum_{a_j > \beta_e} \left([a_j] + \left(\frac{\beta_u - a_j}{\beta_u} \right) \right) y_j + \frac{1}{\beta_u} \sum_{a_j < 0} a_j x_j \leq \lfloor \beta \rfloor$$

is the MIR cut.

Note: If $|M|=0$, i.e., there are no x_j 's, the usual CG cut

$$\sum_{j \in N} [a_j] y_j \leq \lfloor \beta \rfloor.$$

But the MIR cut gives

$$\sum_{\substack{a_j \leq \beta_e}} [a_j] y_j + \sum_{a_j > \beta_e} \left([a_j] + \left(\frac{\beta_u - a_j}{\beta_u} \right) \right) y_j \leq \lfloor \beta \rfloor,$$

$\underbrace{\geq 0}$

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 MIR cut with $|M|=1$, $|N|=2$ as the "MIR inequality".

Example

$$X = \{(\bar{x}, \bar{y}) \in \mathbb{R}_{\geq 0}^2 \times \mathbb{Z}_{\geq 0}^3 \mid \frac{2x_1 - x_2 + \frac{10}{3}y_1 + y_2 + \frac{11}{4}y_3}{a_4 a_5 a_1 a_2 a_3} = \frac{21}{2} \}$$

$$a_{1L} = \frac{1}{3}, a_{1U} = \frac{2}{3}, a_{3L} = \frac{3}{4}, a_{3U} = \frac{1}{4}, \beta_L = \beta_U = \frac{1}{2}.$$

$$\Rightarrow \frac{10}{3}y_1 + y_2 + \frac{11}{4}y_3 - x_2 \leq \frac{21}{2} \text{ is valid for } X.$$

Note that we have removed the $2x_1$ term from lhs.

$$\Rightarrow \left[\frac{10}{3} \right] y_1 + y_2 + \left(\left[\frac{11}{4} \right] + \frac{\left(\frac{1}{2} - \frac{1}{4} \right)}{\frac{1}{2}} \right) y_3 - \frac{1}{2} x_2 \leq \left[\frac{21}{2} \right]$$

is valid for X .

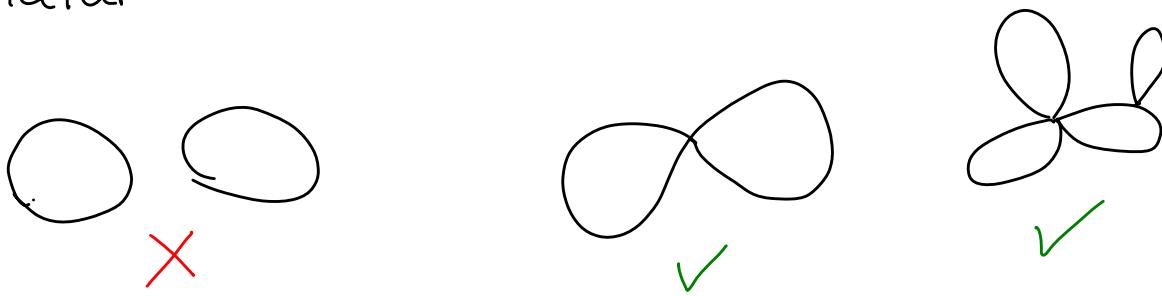
$$\Rightarrow 3y_1 + y_2 + \frac{5}{2}y_3 - 2x_2 \leq 10 \text{ is valid for } X.$$

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.



* $\sum_{(i,j) \in W} c_{ij} \geq L \leftarrow \text{data}$

Come up with formulations similar to the MTZ and subtour formulations for TSP.

Knapsack Cuts for pure 0-1 programs

IDEA:

Given $\left\{ \begin{array}{l} \max \bar{c}^T \bar{x} \\ \text{s.t. } A\bar{x} \leq \bar{b} \\ \bar{x} \in \{0,1\}^n \end{array} \right\}$, pick $\bar{a}^T \bar{x} \leq \beta$ from $A\bar{x} \leq \bar{b}$,

generate cuts for $Y = \{ \bar{x} \in \{0,1\}^n \mid \bar{a}^T \bar{x} \leq \beta \}$, and
add these cuts to the original IP.

Assume $a_i, \beta \in \mathbb{Z}$. WLOG, assume $a_i \geq 0 \forall i$ (in \bar{a}).
If $a_i < 0$, we could replace x_i with $(1-x_i)$ and a_i
with $-a_i$ 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

$$\text{let } Y = \left\{ \bar{x} \in \{0,1\}^7 \mid \underline{11x_1 + 6x_2 + 6x_3 + 5x_4 + 5x_5 + 4x_6 + x_7 \leq 19} \right\}$$

$C_1 = \{1, 4, 5\}$ 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 \bar{x}_0 is $a_3 + a_4 + a_5 + a_6 (= 20)$.

Claim C is a cover $\Rightarrow \bar{x}(C) \leq |C|-1$ is valid for Y .

$$\text{Here, } \bar{x}(C) = \sum_{j \in C} x_j.$$

$$C_1: x_1 + x_4 + x_5 \leq 2 \quad \underbrace{\text{is valid for } Y}_{(1)}$$

$$C_2: x_3 + x_4 + x_5 + x_6 \leq 3 \quad \underbrace{\text{is valid for } Y}_{(2)}$$

$$C_3: x_3 + x_4 + x_5 + x_6 + x_7 \leq 4 \quad \underbrace{\text{is valid for } Y}_{(3)}.$$

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 \leq inequality with $x_7 \geq 0$, 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, $x_3 + x_4 + x_5 + x_6 \leq 3$ can be strengthened
(2)

to $x_1 + x_2 + x_3 + x_4 + x_5 + x_6 \leq 3$ ————— (F).

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 $\bar{a}(C) \geq \beta$, 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 $\forall i \in C$.

$$\text{let } Y = \left\{ \bar{x} \in \{0, 1\}^7 \mid \underbrace{1x_1 + 6x_2 + 6x_3 + 5x_4 + 5x_5 + 4x_6 + x_7 \leq 19} \right\} \quad (*)$$

$C_1 = \{1, 4, 5\}$ 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 .

$$\text{Here, } \bar{x}(C) = \sum_{j \in C} x_j.$$

$$C_1: \underbrace{x_1 + x_4 + x_5 \leq 2}_{\text{is valid for } Y} \quad (1)$$

$$C_2: \underbrace{x_3 + x_4 + x_5 + x_6 \leq 3}_{\text{is valid for } Y} \quad (2)$$

$$C_3: \underbrace{x_3 + x_4 + x_5 + x_6 + x_7 \leq 4}_{\text{is valid for } Y} \quad (3)$$

Def The **extension** of a cover C is

$$E(C) = \left\{ j \notin C, j \in N \mid a_j \geq \max_{i \in C} \{a_i\} \right\} \cup C.$$

$$\text{e.g., } E(\{3, 4, 5, 6\}) = \{1, 2, 3, 4, 5, 6\}.$$

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

$$x_1 + x_2 + x_3 + x_4 + x_5 + x_6 \leq 3 \quad (4).$$

This is an extended cover cut/inequality.

But, $2x_1 + x_2 + x_3 + x_4 + x_5 + x_6 \leq 3$, is also valid for Y. (5)

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 $x_1 = 1 \Rightarrow (x_2 + \dots + x_6) \leq 1 \quad (19 - 11 = 8)$.

Note that (5) is stronger than (4).

How did we get (5)? By **lifting** coefficient (\leq)!

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 with $1 \notin C$, we know $\bar{x}(C) \leq |C| - 1$ is a valid inequality for $(\bar{a}^T \bar{x})(C) \leq \beta$, where $(\bar{a}^T \bar{x})(C) = \sum_{j \in C} a_j x_j$. We want a_i such that $a_i x_i + \bar{x}(C) \leq |C| - 1$ is valid for $a_i x_i + (\bar{a}^T \bar{x})(C) \leq \beta$.

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 $\alpha_1 + (\bar{a}^\top \bar{x})(G) \leq \beta$.

$$\text{let } z = \left\{ \begin{array}{l} \max \bar{x}(C) \\ \text{s.t. } (\bar{a}^\top \bar{x})(G) \leq \beta - \alpha_1 \\ \bar{x} \in \{0,1\}^n \end{array} \right\} \quad (\text{KP})$$

Then we have $z \leq |C|-1 - \alpha_1 \Rightarrow \alpha_1 \leq |C|-1 - z$,
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 .

So, we set $\alpha_1 = |C|-1 - z_u$.

In general, we do not want
to solve a subproblem as
an IP — always solve only
LPs as subproblems.

Example

$$Y = \left\{ \bar{x} \in \{0,1\}^7 \mid 1x_1 + 6x_2 + 6x_3 + 5x_4 + 5x_5 + 4x_6 + x_7 \leq 19 \right\} \quad (*)$$

Consider $C_2 = \{3, 4, 5, 6\} \neq 1$.

$$(\text{KP}) \text{ here is } z = \left\{ \begin{array}{l} \max x_3 + x_4 + x_5 + x_6 \\ \text{s.t. } 6x_3 + 5x_4 + 5x_5 + 4x_6 \leq 19 - 11 = 8 \\ x_3, x_4, x_5, x_6 \in \{0,1\} \end{array} \right\}.$$

$$z=1 \text{ here } (x_j=1 \text{ for any one } j \in C_2). \Rightarrow \alpha_1 = |C_2|-1-z = 4-1-1=2.$$

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
 knapsack 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.

$$\begin{aligned} \max \quad & c_1 x_1 + \dots + c_n x_n \\ \text{s.t.} \quad & a_1 x_1 + \dots + a_n x_n \leq \beta \\ & 0 \leq x_j \leq u_j \end{aligned} \quad g_j, a_j \geq 0$$

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.,
 $\beta \leftarrow \beta - a_i x_i$ after setting x_i in the previous step.

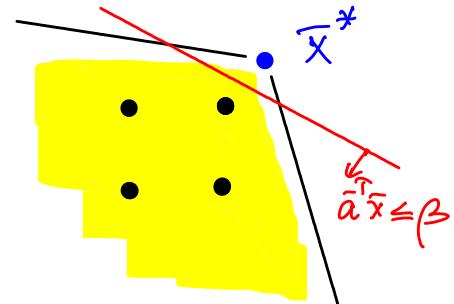
Separation Problem

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 $Y = \{ \bar{x} \in \{0,1\}^n \mid \bar{a}^\top \bar{x} \leq \beta \}$, $a_i, \beta \in \mathbb{Z}_{\geq 0}$, 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 $(\bar{a}^\top \bar{x}^*)(C) > \beta$ and $\bar{x}^*(C) \geq |C| - 1$.

Define $\bar{y} \in \{0,1\}^n$ as the incidence vector of C . We need

$$\left\{ \begin{array}{l} \sum_{j=1}^n x_j^* y_j > \sum_{j=1}^n y_j - 1 \\ \sum_{j=1}^n a_j y_j > \beta \\ y_j \in \{0,1\} \forall j \end{array} \right\}$$

$$\iff \left\{ \begin{array}{l} 1 > \sum_{j=1}^n (1-x_j^*) y_j \\ \sum_{j=1}^n a_j y_j \geq \beta + 1 \\ y_j \in \{0,1\} \forall j \end{array} \right\} \xrightarrow{\text{as } a_j, \beta \in \mathbb{Z}_{\geq 0}}$$

So, we can find

$$z = \left\{ \begin{array}{l} \min \sum_{j=1}^n (1-x_j^*) y_j \\ \text{s.t. } \sum_{j=1}^n a_j y_j \geq \beta + 1 \\ y_j \in \{0,1\} \forall j \end{array} \right\}.$$

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

$$Y = \left\{ \bar{x} \in \{0,1\}^7 \mid 1x_1 + 6x_2 + 6x_3 + 5x_4 + 5x_5 + 4x_6 + x_7 \leq 19 \right\} \quad \textcircled{X}$$

let $\bar{x}^* = [0, 0, 1, 1, 1, \frac{3}{4}, 0]^T$. Find a separating cover for \bar{x}^* .

We solve

$$\min z = y_1 + y_2 + \frac{1}{4}y_6 + y_7$$

$$\text{s.t. } 1y_1 + 6y_2 + 6y_3 + 5y_4 + 5y_5 + 4y_6 + y_7 \geq 20$$

$$y_j \in \{0, 1\}, j=1, \dots, 7.$$

Optimal solution: $\bar{y} = [0, 0, 1, 1, 1, 1, 0]^T$, $z^* = \frac{1}{4}$.

Hence \bar{x}^* violates $x_3 + x_4 + x_5 + x_6 \leq 3$.

$$\text{Indeed, } \bar{x}^*(C) = 3 \frac{3}{4} \neq 3.$$

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.

$$\text{if } x_j \in \{0, 1\} \text{ for } j, \quad x_j^2 \leftarrow x_j, \quad x_i x_j \leftarrow y_{ij} \in \{0, 1\}.$$

$$\text{let } P_i = \left\{ \bar{x} \mid A_i \bar{x} \leq \bar{b}^i \right\}, \quad i=1,2, \quad P_i \neq \emptyset.$$

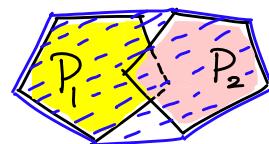
Assume $\text{rec}(P_1) = \text{rec}(P_2)$. Thus the sharp representation for $P_1 \cup P_2$ is

$$\left. \begin{array}{l} A_1 \bar{x}^1 \leq \bar{b}^1 y_1 \\ A_2 \bar{x}^2 \leq \bar{b}^2 y_2 \\ \bar{x} = \bar{x}^1 + \bar{x}^2 \\ y_1 + y_2 = 1 \\ y_1, y_2 \in \{0, 1\} \end{array} \right\} \xrightarrow{*-\text{sharp}}$$

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 $*\text{-sharp}$.

② $\text{Proj}_{\bar{x}} (\text{LP-relaxation of } *\text{-sharp}) = \text{conv}(P_1 \cup P_2).$

if you project out $\bar{x}^1, \bar{x}^2, y_1, y_2$



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)

$$X = \{ \bar{x} \in \mathbb{Z}^n \mid A\bar{x} \leq \bar{b} \} \xrightarrow{\text{includes}} 0 \leq x_j \leq 1$$

$$K = \{ \bar{x} \in \mathbb{R}^n \mid A\bar{x} \leq \bar{b} \}$$

1. Select $j \in \{1, 2, \dots, n\}$.

2. Create the non-linear system

$$\left. \begin{array}{l} (A\bar{x} - \bar{b})x_j \leq 0 \\ (A\bar{x} - \bar{b})(1-x_j) \leq 0 \\ x_j(1-x_j) = 0 \end{array} \right\} M_j^{NL}(K)$$

non linear, as there are quadratic terms $x_i x_j$

holds, as $x_j \in \{0, 1\}$

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).

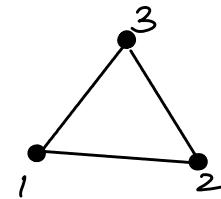
The polyhedron thus obtained is $M_j(K)$.

4. Let $P_j(K) = \text{Proj}_{\bar{x}}(M_j(K))$. $\xrightarrow{\text{has the cut(s) we seek}}$

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.

Example 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., $\begin{cases} x_1 + x_2 \leq 1 \\ x_2 + x_3 \leq 1 \\ x_1 + x_3 \leq 1 \\ 0 \leq x_i \leq 1, i=1,2,3 \\ x_i \in \mathbb{Z} \end{cases} \quad K$



Want to derive
 $x_1 + x_2 + x_3 \leq 1$

Apply LS procedure with $j=1$:

$$x_1^2 + x_1 x_2 \leq x_1, \text{ replace } x_1^2 \text{ by } x_1$$

$$\Rightarrow x_1 x_2 \leq 0$$

But from $-x_2 \leq 0$, we get $-x_1 x_2 \leq 0 \Rightarrow x_1 x_2 \geq 0$.

$$\Rightarrow x_1 x_2 = 0.$$

Similarly, $x_1 x_3 = 0$.

Consider $(x_2 + x_3 \leq 1)(1 - x_1)$:

$$x_2 + x_3 - x_1 \cancel{x_2} - x_1 \cancel{x_3} \leq 1 - x_1$$

$$= 0 \quad = 0$$

$$\Rightarrow \boxed{x_1 + x_2 + x_3 \leq 1}$$

This is an instance of "odd-hole" inequality.

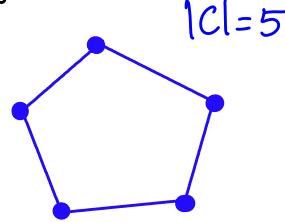
Def An **odd hole** is $C \subseteq V$ with $|C|$ odd, with edges connecting the vertices making a simple cycle, i.e., a "hole".

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 $j \in C$.

$$\sum_{(i,j) \in C} x_{ij} \leq 2 \text{ here.}$$



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 divide by 2, and round down (CG procedure) to

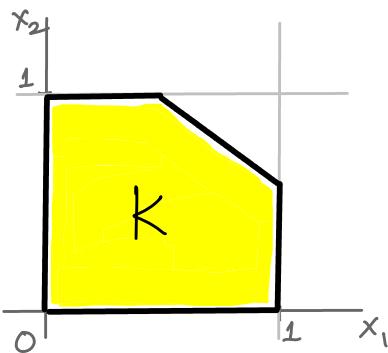
get

$$\bar{x}(C) \leq \left\lfloor \frac{|C|}{2} \right\rfloor = \frac{|C|-1}{2}.$$

But there are other problem instances where the LS procedure gives inequalities which cannot be derived by other procedures.

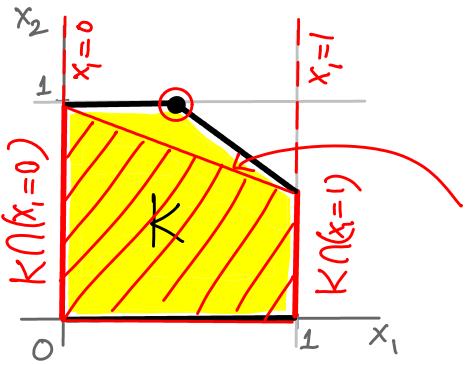
Theorem 14 If $Q_j(K) = \text{conv}([K \cap (x_j=0)] \cup [K \cap (x_j=1)])$
 then $P_j(K) = Q_j(K)$. Theorem 13 was on reduced cost fixing in lecture 15!

Before presenting the proof, we illustrate the concept in 2D. Consider a nontrivial polytope in the unit square.



Consider $Q_1(K) = \text{conv}([K \cap (x_1=0)] \cup [K \cap (x_1=1)])$.

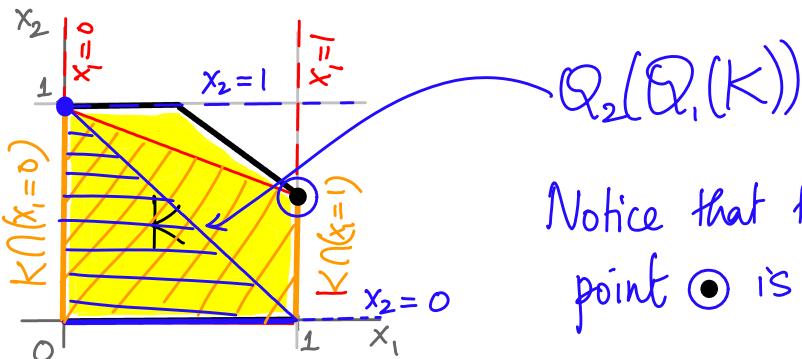
Note: the polytope need not be "symmetric"
 - or show the same behavior



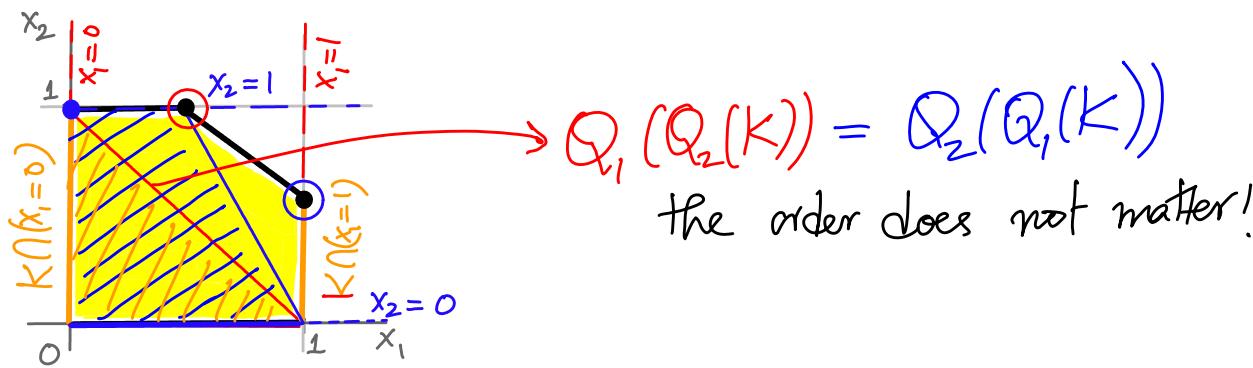
$$Q_1(K) = \text{conv}([K \cap (x_1=0)] \cup [K \cap (x_1=1)])$$

Notice how the fractional point \bullet 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 \bullet is also cutoff now.



Recall Theorem 14: $P_j(K) = Q(K) := \text{conv}([K \cap (x_j=0)] \cup [K \cap (x_j=1)])$.

Proof (\Leftarrow) $P_j(K) \supseteq Q_j(K)$

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 $M_j^{NL}(K)$

$$\left. \begin{array}{l} (A\bar{x}-\bar{b})x_j' \leq 0 \\ (A\bar{x}-\bar{b})(1-x_j') \leq 0 \\ x_j'(1-x_j') = 0 \end{array} \right\}, \text{ eliminate nonlinear terms, linearize, and project to get } P_j(K).$$

$$\Rightarrow Q_j(K) \subseteq P_j(K).$$

$$(\Rightarrow) P_j(K) \subseteq Q_j(K).$$

We show that $P_j(K)$ contains the sharp formulation of union of polyhedra, whose convex hull is $Q_j(K)$.

$$M_j(K) \text{ has } \left\{ \begin{array}{l} (A\bar{x} - \bar{b})_{j \cdot} \leq \bar{0} \\ (A\bar{x} - \bar{b})(1-x_j) \leq \bar{0} \\ x_j(1-x_j) = 0 \end{array} \right\}$$

$$\begin{aligned} A\bar{x}_{j \cdot} - \bar{b}_{j \cdot} &\leq \bar{0} \\ A\bar{x}_{j \cdot} - b_{j \cdot} &\leq \bar{0} \\ [\bar{x}_{j \cdot}]_j &= 0 \end{aligned}$$

Write $\bar{x}_{j \cdot}$ as \bar{x}^1 , $\bar{x}_{j \cdot}(1-x_j)$ as \bar{x}^2 , $x_j \leftarrow y_1$, $(1-x_j) \leftarrow y_2$

$$\Rightarrow A\bar{x}^1 \leq \bar{b}y_1$$

$$A\bar{x}^2 \leq \bar{b}y_2$$

$$\bar{x} - \bar{x}_{j \cdot} - \bar{x}_{j \cdot}(1-x_j) = \bar{0} \Rightarrow \bar{x} = \bar{x}^1 + \bar{x}^2$$

$$x_j + (1-x_j) = 1 \Rightarrow y_1 + y_2 = 1$$

$$x_j^2 - x_j = 0 \Rightarrow (\bar{x}^1)_j = y_1 \equiv \bar{e}_j^T \bar{x}^1 = y_1$$

$$[\bar{x}_{j \cdot}(1-x_j)]_j = 0 \Rightarrow \bar{x}_j^2 = 0 \equiv \bar{e}_j^T \bar{x}^2 = 0 = 0 \cdot y_2$$

$$\begin{aligned} A\bar{x}^1 &\leq \bar{b}y_1 \\ \bar{e}_j^T \bar{x}^1 &= y_1 \\ A\bar{x}^2 &\leq \bar{b}y_2 \\ \bar{e}_j^T \bar{x}^2 &= 0 \cdot y_2 \\ \bar{x} &= \bar{x}^1 + \bar{x}^2 \\ y_1 + y_2 &= 1 \end{aligned}$$

$\overbrace{\text{polyhedron of the sharp formulation of } P_1 \cup P_2}$

where $P_1 = \left\{ \bar{x} \mid A\bar{x} \leq \bar{b}, \underbrace{\bar{e}_j^T \bar{x}}_{x_j=1} = 1 \right\}$ and $P_2 = \left\{ \bar{x} \mid A\bar{x} \leq \bar{b}, \underbrace{\bar{e}_j^T \bar{x}}_{x_j=0} = 0 \right\}$.

$$\Rightarrow P_j(K) \subseteq Q_j(K).$$

□

MATH 567 : Lecture 20 (03/25/2025)

Today: * A different proof for $P_j(K) \subseteq Q_j(K)$
 * Disjunctive programming

Recall $Q_j(K) = \text{conv}([K \cap (x_j=0)] \cup [K \cap (x_j=1)])$; Theorem 14 $P_j(K) = Q_j(K)$.

A different proof We first state and prove a lemma.

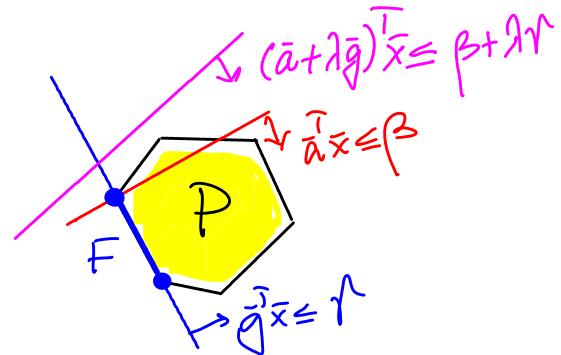
Lemma 15 Let $P = \{\bar{x} \in \mathbb{R}^n \mid A\bar{x} \leq \bar{b}, \bar{g}^T \bar{x} \leq \gamma\}$ and

$$F = P \cap \{\bar{x} \in \mathbb{R}^n \mid \bar{g}^T \bar{x} = \gamma\}, \text{ i.e.,}$$

F is a face of P . Suppose $\bar{a}^T \bar{x} \leq \beta$ is valid for F but not valid for P . Then there exists $\lambda \geq 0$ such that $(\bar{a} + \lambda \bar{g})^T \bar{x} \leq \beta + \lambda \gamma$ is valid for P .

Proof (Farkas' lemma)

$$F \left\{ \begin{array}{l} A\bar{x} \leq \bar{b} \\ \bar{g}^T \bar{x} \leq \gamma \\ -\bar{g}^T \bar{x} \leq -\gamma \end{array} \right. \begin{array}{l} \bar{u} \geq 0 \\ v_1 \geq 0 \\ v_2 \geq 0 \end{array} \quad \begin{array}{l} P \\ \bar{a}^T \bar{x} \leq \beta \\ \bar{g}^T \bar{x} = \gamma \end{array}$$



Can derive $\bar{a}^T \bar{x} \leq \beta$ from F :

$$\Rightarrow \bar{u}^T A + v_1 \bar{g}^T - v_2 \bar{g}^T = \bar{a}^T \quad \left. \begin{array}{l} \bar{u}^T \bar{b} + v_1 \gamma - v_2 \gamma \leq \beta \end{array} \right\}$$

$$\bar{u}^T \bar{a} + v_1 \bar{g}^T = \bar{a}^T + v_2 \bar{g}^T$$

$$\bar{u}^T \bar{b} + v_1 \gamma = \beta + v_2 \gamma$$

Another inequality can be derived using multipliers (\bar{u}, v_i) from P :

$$\Rightarrow (\bar{a} + v_2 \bar{g})^T \bar{x} \leq \beta + v_2 \gamma \text{ is valid for } P.$$

$v_2 = 0$ works for the lemma. □

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 .
 $x_j \leq 0$ or
 $x_j \leq 1$ 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

$$\bar{a}^T \bar{x} - \lambda x_j \leq \beta \text{ is valid for } K, \quad (1)$$

$$\text{and } \bar{a}^T \bar{x} - \mu(1-x_j) \leq \beta \text{ is valid for } K. \quad (2)$$

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 $M_j^{NL}(K)$

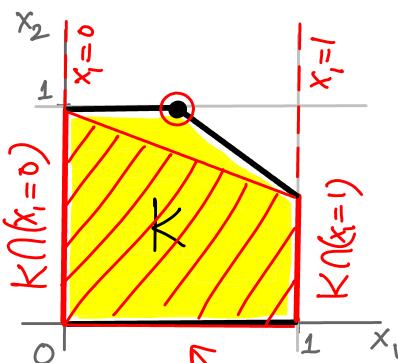
$$\left\{ \begin{array}{l} (1-x_j)(\bar{a}^T \bar{x} - \lambda x_j) \leq (1-x_j)\beta \\ x_j(\bar{a}^T \bar{x} - \mu(1-x_j)) \leq x_j\beta \\ x_j(1-x_j)=0 \end{array} \right\} \text{ parts of } M_j^{NL}(K).$$

Adding them gives $\bar{a}^T \bar{x} - (\lambda + \mu)(x_j(1-x_j)) = \beta$.

$\Rightarrow \bar{a}^T \bar{x} \leq \beta$ is valid for $M_j^{NL}(K)$, and hence for $P_j(K)$.

□

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.

$(x_1=0) \vee (x_1=1)$ disjunction

A **disjunctive program** (DP) is an optimization problem of the following form:

$$\left\{ \begin{array}{ll} \max & \bar{c}^T \bar{x} \\ \text{s.t.} & \bar{x} \in K \\ & \bar{x} \in D_1 \cap D_2 \dots \cap D_p \end{array} \right\} \quad (\text{DP})$$

where $K = \{\bar{x} \in \mathbb{R}^n \mid A\bar{x} \leq \bar{b}\}$ and

$D_i = D_{i1} \cup D_{i2} \dots \cup D_{ik_i}$, $i=1, \dots, p$, i.e., the i^{th} disjunction has k_i alternatives.

The set K is the LP-relaxation of (DP).

D_{il} are polyhedra ($l=1, \dots, k_i$), 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 $D_{i_2} = \{ \bar{x} \in \mathbb{R}^n \mid x_i = 1 \}$.
 $K = \{ \bar{x} \in \mathbb{R}^n \mid A\bar{x} \leq \bar{b} \}$ includes the bounds $0 \leq x_i \leq 1$ for $i = 1, \dots, p$, $p \leq n$.
 Then (DP) is the usual 0-1 (M)IP. if $p < n$, we get MIP.

2. $k_i = 2 \forall i$, $D_{i_1} = \{ \bar{x} \in \mathbb{R}^n \mid x_{l_1} = 0 \}$ and $D_{i_2} = \{ \bar{x} \in \mathbb{R}^n \mid x_{l_2} = 0 \}$,
 while K contains bounds $x_{l_1} \geq 0 \vee l_2$. Here (DP) is a linear program
 with complementarity constraints of the form $x_{l_1} x_{l_2} = 0$.

We can solve DP "easily" if we have all inequalities for
 $\text{conv}[K \cap (D_1 \cap \dots \cap D_p)]$. But when do we get efficient representations?

Notation $A \cap_c B = \text{conv}(A \cap B)$.

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 $K_0 = K = \{ \bar{x} \mid A\bar{x} \leq \bar{b} \}$

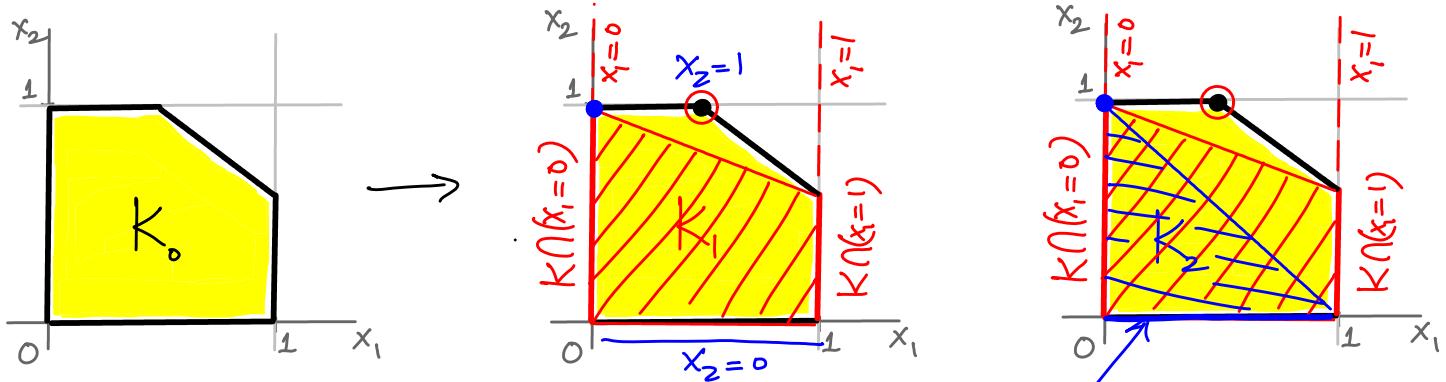
Step i ($1 \leq i \leq p$)

if $K_{i-1} = \{ \bar{x} \mid A_{i-1}\bar{x} \leq \bar{b}^{i-1} \}$ generate all
 inequalities for $K_{i-1} \cap_c D_i$

Set $K_i = K_{i-1} \cap_c D_i = \text{conv}[K_{i-1} \cap D_i]$;

$i \leftarrow i+1$;

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.

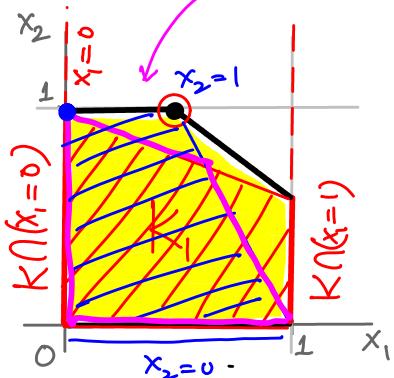
Here, $K_2 = \text{conv}[K \cap D_1 \cap D_2] = K \cap_c (D_1 \cap D_2)$.

Hence, this is a "good instance".

Remark

$\text{conv}[K \cap D_1] \cap \text{conv}[K \cap D_2] \neq \text{conv}[K \cap (D_1 \cap D_2)]$!

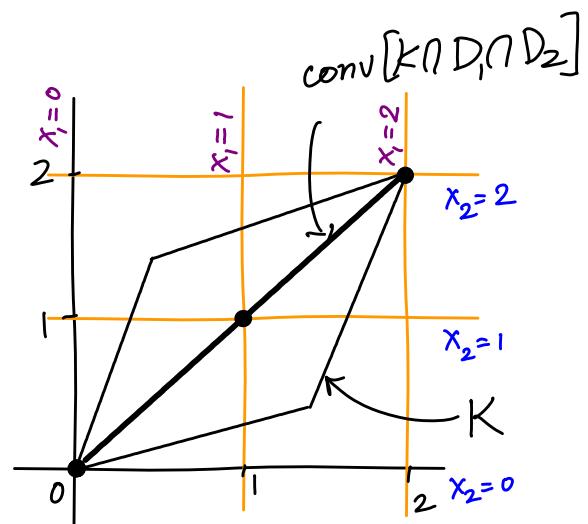
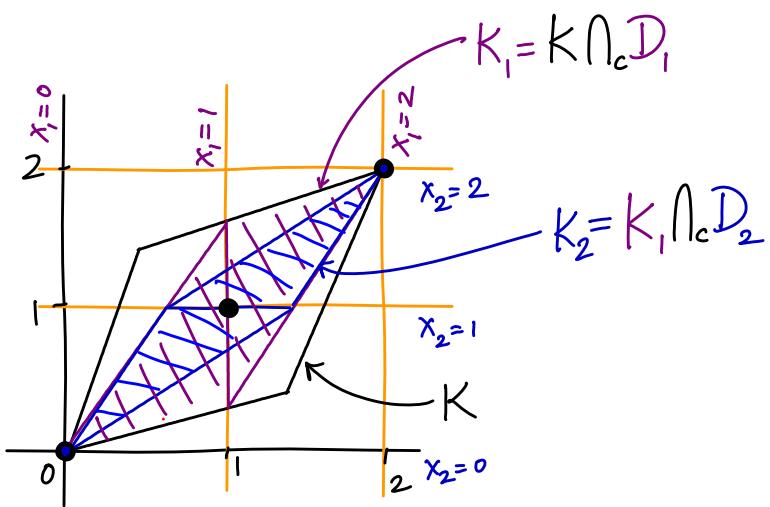
(typically)



A "bad" instance

$$p=2, k_i=3, i=1,2$$

$$D_i = (x_i=0) \vee (x_i=1) \vee (x_i=2), \quad i=1,2.$$



Here, $K_2 \neq \text{conv}[K \cap D_1 \cap D_2]$.

Q. When is $K_p = K \cap_c (D_1 \cap \dots \cap D_p)$, where

$$K_p = ((K \cap_c D_1) \cap_c D_2) \dots \cap_c D_p ?$$

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., $D_{ij} = \{\bar{x} | (\bar{a}^{ij})^T \bar{x} = b_{ij}\}$ where $(\bar{a}^{ij})^T \bar{x} \leq \beta$ 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 $H = \{\bar{x} | \bar{a}^T \bar{x} = \beta\}$ is a hyperplane such that $\bar{a}^T \bar{x} \leq \beta \nforall \bar{x} \in S$. Then $H \cap \text{conv}(S) = \text{conv}(H \cap S)$.

Proof (Theorem 16)

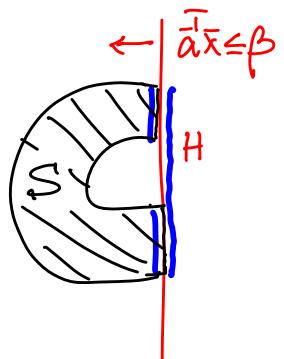
We show the result for $p=2, k_i=2, i=1, 2$.

We need to show

$$(K \cap_c D_i) \cap_c D_j = K \cap_c (D_i \cap D_j)$$

$$\begin{aligned} (K \cap_c D_i) \cap_c D_j &= \text{conv} [\text{conv}(K \cap D_i) \cap D_j] \xrightarrow{D_i \cup D_j} \\ &= \text{conv} [(\text{conv}(K \cap D_i) \cap D_{j_1}) \cup (\text{conv}(K \cap D_i) \cap D_{j_2})] \\ &= \text{conv} [\text{conv}(K \cap D_i \cap D_{j_1}) \cup \text{conv}(K \cap D_i \cap D_{j_2})] \end{aligned}$$

by Proposition 17.



$$\begin{aligned}
 &= \text{conv} [(K \cap D_i \cap D_{j_1}) \cup (K \cap D_i \cap D_{j_2})] \\
 &= \text{conv} [K \cap D_i \cap D_j] = K \cap_c (D_i \cap D_j).
 \end{aligned}$$

The theoretical algorithm might not work well in practice. Getting efficient descriptions of the convex hulls in each step might be difficult. \square

A practical Algorithm

Step 0: $K_0 = K = \{ \bar{x} \mid A\bar{x} \leq \bar{b} \}$

Step i : K_i : current relaxation, and
 $(i \geq 1)$ \bar{x}^i : optimal solution over K_i

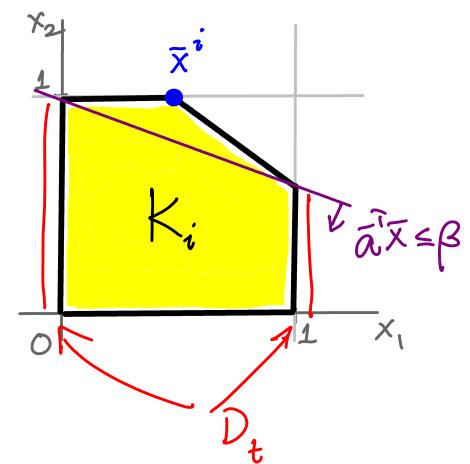
Find $\bar{a}^\top \bar{x} \leq \beta$ such that

- ① $\bar{a}^\top \bar{x} \leq \beta$ is valid for $K_i \cap D_t$ for some $t > i$.
- ② $\bar{a}^\top \bar{x} \leq \beta$ is violated by \bar{x}^i (i.e., $\bar{a}^\top \bar{x}^i > \beta$).

Set $K_{i+1} \leftarrow$ LP relaxation of $K_i \cap D_t \cap \{ \bar{x} \mid \bar{a}^\top \bar{x} \leq \beta \}$.

How do we find (\bar{a}, β) ?

Solve an LP with \bar{a}, β as variables.



$$\max \quad \beta - \bar{a}^T \bar{x}^i \quad \text{is given}$$

s.t. $\left(\begin{array}{l} \bar{a}^T \bar{x} \leq \beta \text{ is derivable from } K_i \cap D_t \\ \text{by Farkas' lemma} \end{array} \right) \quad (1)$

normalization constraint : e.g.,

$$\sum_{i=1}^n |a_{il}| + |\beta| \leq 1. \quad \text{we can linearize this constraint}$$

Without the normalization, the LP could be unbounded. If (β, \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 $[\bar{a}^T] \bar{x} \leq [\beta]$ 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.

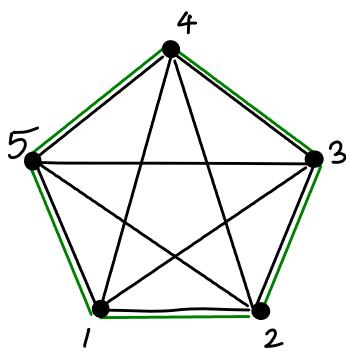
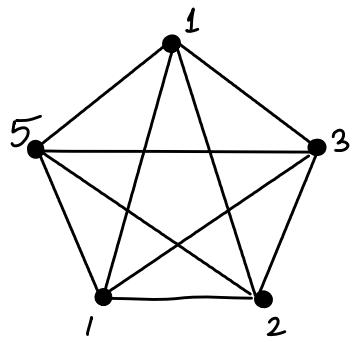
Ideally, we want to derive inequalities with small rank, so that we do not have to apply the cut-procedure too many times.

Back to LS Procedure

Q: How many steps to generate a good inequality?

Example: node packing on complete graph with 5 nodes.

$$K = \left\{ \begin{array}{l} x_i + x_j \leq 1 \forall (i, j) \\ 0 \leq x_i \leq 1 \forall i \end{array} \right\}$$



complete graph

Node packing problem:

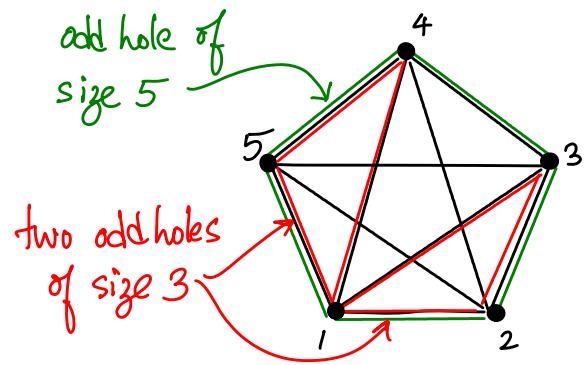
A good inequality is $x_1 + x_2 + x_3 + x_4 + x_5 \leq 1$ ————— \otimes

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

$$\left\{ \begin{array}{l} (A\bar{x} - \bar{b})x_1 \leq 0 \\ (A\bar{x} - \bar{b})(1-x_1) \leq 0 \\ x_1(1-x_1) = 0 \end{array} \right\}.$$



We get odd hole inequalities of size 3:

$$x_1 + x_2 + x_3 \leq 1$$

$$x_1 + x_2 + x_4 \leq 1$$

:

and $x_1 + x_2 + x_3 + x_4 + x_5 \leq 2$, odd-hole inequality of size 5.

We do not get \otimes .

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 \otimes in $P_2(P_1(K))$.

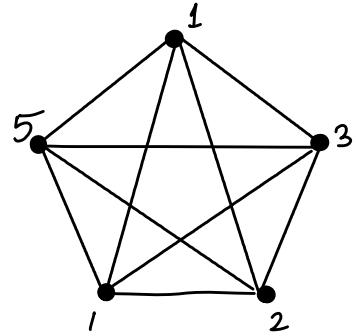
$P_3(P_2(P_1(K)))$ gives $x_1 + \dots + x_5 \leq 1$ —— \otimes !

\Rightarrow LS-rank of \otimes is 3.

In general, LS rank of $x_1 + \dots + x_k \leq 1$ is $\leq k-2$,
and is often $= k-2$.

Q. Could we derive $x_1 + x_2 + x_3 + x_4 + x_5 \leq 1$ — \star
in one step? As a rank-1 cut.

YES!



Semidefinite Relaxation

Recall:

$$M_j^{NL}(K) = \left\{ \begin{array}{l} (A\bar{x} - \bar{b})x_j \leq 0 \\ (A\bar{x} - \bar{b})(1-x_j) \leq 0 \\ x_j(1-x_j) = 0 \end{array} \right\}, \quad j=1, \dots, n.$$

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 $M_+(K) \equiv M(K) \cap \left\{ \bar{x} \mid \underbrace{(a_0 + \bar{a}^\top \bar{x})^2 \geq 0}_{\text{is positive semidefinite}} + \begin{bmatrix} a_0 \\ \bar{a} \end{bmatrix} \in \mathbb{R}^{n+1} \right\}$.

→ $\begin{bmatrix} I & \bar{x}^\top \\ \bar{x} & \bar{x}\bar{x}^\top \end{bmatrix}$ is positive semidefinite

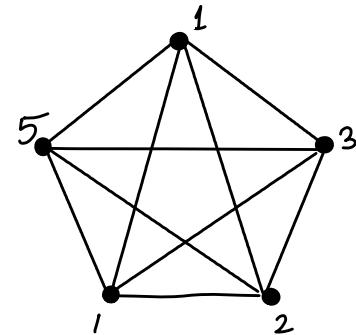
You would think this restriction is always satisfied! But imposing it explicitly makes the difference —
see Notes to follow...

$M_+(K)$ 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



$M_+(K)$ has $(1 - x_1 - x_2 - \dots - x_5)^2 \geq 0$

$$\Rightarrow 1 - 2 \sum_{i=1}^5 x_i + \sum_{i=1}^5 x_i^2 + 2 \sum_{i \neq j} x_i x_j \geq 0$$

\downarrow
 x_i

$$\Rightarrow 1 - \sum_{i=1}^5 x_i \geq 0, \text{ which is } \times!$$

$M(K)$ has $(x_i + x_j \leq 1)x_i \Rightarrow x_i x_j \leq 0$ as $x_i^2 \leq x_i$

$$\begin{aligned} M(K) \text{ also has } (-x_j \leq 0)x_i &\Rightarrow x_i x_j \geq 0 \\ &\Rightarrow x_i x_j = 0. \end{aligned}$$

Hence the semidefinite relaxation rank of \times is 1!

Notes

① $M^{NL}(K)$ contains inequalities for

$$X = \begin{pmatrix} 1 & \bar{x}^T \\ \bar{x} & \bar{x}\bar{x}^T \end{pmatrix} = \left[\begin{array}{c|cccc} 1 & x_1 & x_2 & \dots & x_n \\ \hline \bar{x}_1 & x_1^2 & & & \\ \bar{x}_2 & & x_2^2 & & x_i x_j \\ \vdots & & & \ddots & \\ \bar{x}_n & & x_j x_i & \ddots & x_n^2 \end{array} \right].$$

Inequalities for X can be written as

$$B \bullet X \geq 0, \text{ where } A \bullet B = \text{trace}(A^T B)$$

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

$$C \bullet \begin{pmatrix} 1 & \bar{x}^T \\ \bar{x} & Y \end{pmatrix} \geq 0, \text{ where } \text{diag}(Y) = \bar{x}.$$

③ $(a_0 + \bar{a}^T \bar{x})^2 \geq 0$ can be written equivalently as

$$\begin{bmatrix} a_0 & \bar{a}^T \end{bmatrix} \begin{bmatrix} 1 & \bar{x}^T \\ \bar{x} & \bar{x}\bar{x}^T \end{bmatrix} \begin{bmatrix} a_0 \\ \bar{a} \end{bmatrix} \geq 0 \Rightarrow \begin{bmatrix} a_0 & \bar{a}^T \end{bmatrix} \begin{bmatrix} a_0 + \bar{a}^T \bar{x} \\ a_0 \bar{x} + (\bar{x}\bar{x}^T)\bar{a} \end{bmatrix} = \begin{bmatrix} a_0 & \bar{a}^T \end{bmatrix} \begin{bmatrix} (a_0 + \bar{a}^T \bar{x}) \\ (a_0 + \bar{a}^T \bar{x})\bar{x} \end{bmatrix} \\ = (a_0 + \bar{a}^T \bar{x})(a_0 + \bar{a}^T \bar{x}) \geq 0.$$

In other words, $M_+(K)$ has $\begin{bmatrix} 1 & \bar{x}^T \\ \bar{x} & Y \end{bmatrix} \geq 0$ as added constraints.