

Week 3

Note Title

4/10/2021

Standard form LP

$$\begin{aligned} \min_{x \in \mathbb{R}^n} \quad & z = p^T x \\ \text{s.t.} \quad & Ax \geq b \\ & x \geq 0 \end{aligned}$$

canonical form LP

$$\begin{aligned} \min_{\substack{x_N \in \mathbb{R}^n \\ x_B \in \mathbb{R}^m}} \quad & z = p^T x_N + 0^T x_B \\ \text{s.t.} \quad & x_B = Ax_N - b, \quad x_B, x_N \geq 0 \end{aligned}$$

$$\begin{aligned} N &= \{1, \dots, n\} \\ B &= \{n+1, \dots, n+m\} \end{aligned}$$

tableau representation :

original variables

$$\begin{array}{lcl} \text{slack variables} \left\{ \begin{array}{l} x_{n+1} \\ \vdots \\ x_{n+m} \\ z \end{array} \right. & = & \begin{array}{c|ccc} & x_1 & \dots & x_n & 1 \\ \hline & A_{11} & \dots & A_{1n} & -b_1 \\ & \vdots & \ddots & \vdots & \vdots \\ & A_{m1} & \dots & A_{mn} & -b_m \\ \hline & p_1 & \dots & p_n & 0 \end{array} \end{array}$$

or

$$\begin{array}{c} x_N \quad 1 \\ x_B = \begin{bmatrix} A & -b \end{bmatrix} \\ z = \begin{bmatrix} p^T & 0 \end{bmatrix} \end{array}$$

An easy, but important, observation:

(1) The $n+m$ linear inequality constraints are

$$x_1 \geq 0$$

$$x_2 \geq 0$$

$$\vdots$$

$$x_n \geq 0$$

$$x_{n+1} \geq 0$$

$$\vdots$$

$$x_{n+m} \geq 0$$

(written in this way, we almost do not distinguish the origin variables with the slack variables)

If $x_1 = x_2 = \dots = x_n = 0$, then (i) the first n constraints are obviously satisfied, (ii) $z = 0$, and (iii)

$$x_{n+1} = -b_1$$

$$x_{n+2} = -b_2$$

$$\vdots$$

$$x_{n+m} = -b_m.$$

$$x_{n+k} \geq 0 \text{ is satisfied} \Leftrightarrow -b_k \geq 0 \Leftrightarrow b_k \leq 0$$

In fact, in this case $x_1 = \dots = x_n = 0$ is a vertex of the feasible region.

To conclude :

$$b \leq 0 \text{ (ie. all entries of } b \text{ are non-positive)} \iff$$

the origin $\begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$ satisfies all $m+n$ constraints (and is a vertex of the feasible region)

E.g. $n=2$, $m=1$

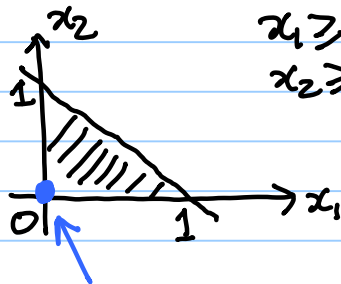
$$A = [-1 \ -1]$$

$$b = [-1] \leq 0$$

$$-x_1 - x_2 \geq -1 \iff x_1 + x_2 \leq 1$$

$$x_1 \geq 0$$

$$x_2 \geq 0$$



belongs to
the feasible region

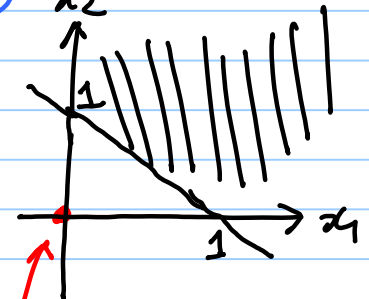
$$A = [1, 1]$$

$$b = [1] \not\leq 0$$

$$x_1 + x_2 \geq 1$$

$$x_1 \geq 0$$

$$x_2 \geq 0$$



does not belong to
the feasible region

Now, imagine that we perform a series of Jordan exchanges :

$$\begin{array}{c}
 \begin{array}{cc} x_N & 1 \\ \hline x_B = & A & -b \\ z = & p^T & 0 \end{array}
 \end{array}
 \rightarrow \dots \rightarrow
 \begin{array}{c}
 \begin{array}{cc} x_{N'} & 1 \\ \hline x_{B'} = & H & h \\ z = & c^T & \alpha \end{array}
 \end{array}$$

$$\begin{aligned}
 N &= \{1, \dots, n\} \\
 B &= \{n+1, \dots, n+m\}
 \end{aligned}$$

$$\begin{aligned}
 N' &\subset \{1, \dots, m+n\}, |N'| = n \\
 B' &= \{1, \dots, m+n\} \setminus N', \text{ so } |B'| = m.
 \end{aligned}$$

This means : • we now express $x_{B'}$ as a $Hx_{N'} + h$

- z , originally defined as $p_1x_1 + \dots + p_nx_n$, is now ^{re-}expressed as

$$z = \sum_{i \in N'} c_i x_i + \alpha$$

Recall from
Week 2 what
a vertex is.

→ • If $h \geq 0$, then $x_{N'} = 0$, which implies $x_B = h$, corresponds to a vertex of the feasible region.

- When $x_{N'} = 0$, $z = \alpha$.

Terminologies

- If $h \geq 0$, we call the tableau

	$x_{N'}$	1
$x_{B'}$	H	h
z	c^T	α

feasible.

Note: Even if some entries of h are negative,

$x_{B'} = Hx_{N'} + h$ still correctly represents the linear relationships between $x_{B'}$ and $x_{N'}$. It is just that

$x_{N'} = 0$ does not correspond to a vertex.

(see example in class.)

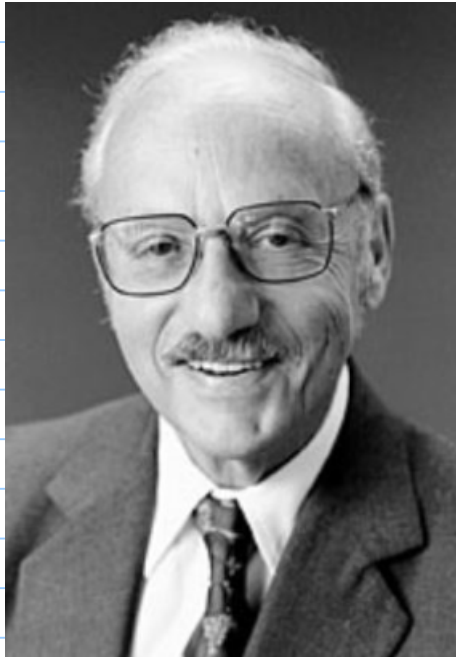
- The variables on top are referred to as "non-basic" (hence the 'N') those on the left are referred to as "basic" (hence the 'B').

Basic idea of the simplex method for solving LP :

At each iteration of the simplex method, we exchange one element between B and N, performing the corresponding Jordan exchange on the tableau representation, much as we did in Chapter 2 in solving systems of linear equations. We ensure that the tableau remains feasible at every iteration, and we try to choose the exchanged elements so that the objective function z decreases at every iteration. We continue in this fashion until either

1. a solution is found, or
2. we discover that the objective function is unbounded below on the feasible region, or
3. we determine that the feasible region is empty.

Geometrically, a cleverly chosen Jordan exchange corresponds to moving from one vertex to a neighboring vertex with a smaller objective value z .



Geroge B. Dantzig (1914-2005)

A simple example

Example 3-1-1.

$$\begin{array}{ll} \min_{x_1, x_2} & 3x_1 - 6x_2 \\ \text{subject to} & \begin{array}{rclcl} x_1 & + & 2x_2 & \geq & -1, \\ 2x_1 & + & x_2 & \geq & 0, \\ x_1 & - & x_2 & \geq & -1, \\ x_1 & - & 4x_2 & \geq & -13, \\ -4x_1 & + & x_2 & \geq & -23, \\ & & x_1, x_2 & \geq & 0. \end{array} \end{array} \quad \left. \vphantom{\begin{array}{rclcl} x_1 & + & 2x_2 & \geq & -1, \\ 2x_1 & + & x_2 & \geq & 0, \\ x_1 & - & x_2 & \geq & -1, \\ x_1 & - & 4x_2 & \geq & -13, \\ -4x_1 & + & x_2 & \geq & -23, \\ & & x_1, x_2 & \geq & 0. \end{array}} \right\} \begin{array}{l} \text{all } b_i \leq 0, \text{ so } \begin{bmatrix} 0 \\ 0 \end{bmatrix} \text{ is a} \\ \text{vertex} \end{array}$$

The slack variables are defined as:

$$\begin{array}{rclcl} x_3 & = & x_1 & + & 2x_2 & + & 1, \\ x_4 & = & 2x_1 & + & x_2, & & \\ x_5 & = & x_1 & - & x_2 & + & 1, \\ x_6 & = & x_1 & - & 4x_2 & + & 13, \\ x_7 & = & -4x_1 & + & x_2 & + & 23. \end{array}$$

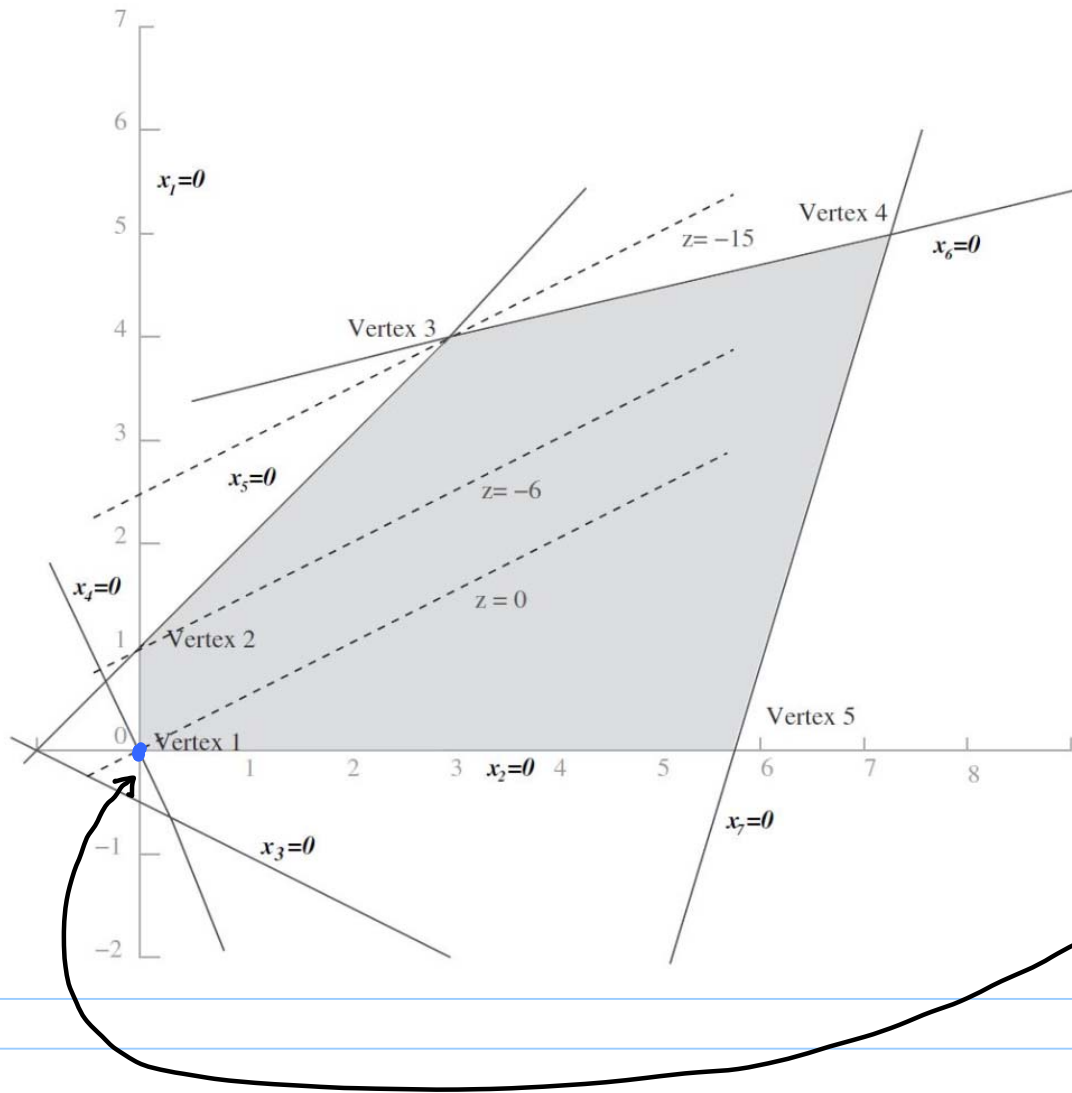


Tableau representation:

	x_1	x_2	1
$x_3 =$	1	2	1
$x_4 =$	2	1	0
$x_5 =$	1	-1	1
$x_6 =$	1	-4	13
$x_7 =$	-4	1	23
$z =$	3	-6	0

And it is a feasible tableau.

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow \begin{bmatrix} x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 13 \\ 23 \end{bmatrix} \geq 0$$

and $z = 0$

We now seek a clever pivot — a Jordan exchange of a basic variable with a non-basic one — that

- ① yields a decrease in the objective z , and
- ② keeps the tableau feasible.

① is quite easy: choose any non-basic variable in a column with a **negative** value in the last row.

$$z = 3x_1 - 6x_2$$

↑
if it becomes basic, x_1 increases from 0 to some positive value, this would **increase** z



←
if it becomes basic, x_2 increases from 0 to some positive value, this would **decrease** z



② is slightly trickier, but we just need to ask the following question:

Since we want to minimize z , we would like to increase x_2 (the "entering variable") as much as possible.

Q: How much can we increase x_2 without violating the constraints?

A: If x_2 increases from 0 to $\lambda > 0$ (and x_1 stays zero) then

$$\begin{aligned}x_3 &= 2\lambda + 1 \\x_4 &= \lambda \\x_5 &= -\lambda + 1 \\x_6 &= -4\lambda + 13 \\x_7 &= \lambda + 23.\end{aligned}$$

And

$$\begin{aligned}x_3 &= 2\lambda + 1 \geq 0 \Rightarrow \lambda \geq -1/2 \\x_4 &= \lambda \geq 0 \Rightarrow \lambda \geq 0 \\x_5 &= -\lambda + 1 \geq 0 \Rightarrow \lambda \leq 1 \\x_6 &= -4\lambda + 13 \geq 0 \Rightarrow \lambda \leq 13/4 \\x_7 &= \lambda + 23 \geq 0 \Rightarrow \lambda \geq -23\end{aligned}$$

i.e. The largest value we can increase x_2 to is $\lambda = 1$.

And this corresponds to $x_5 = 0$

↑
the "blocking variable"

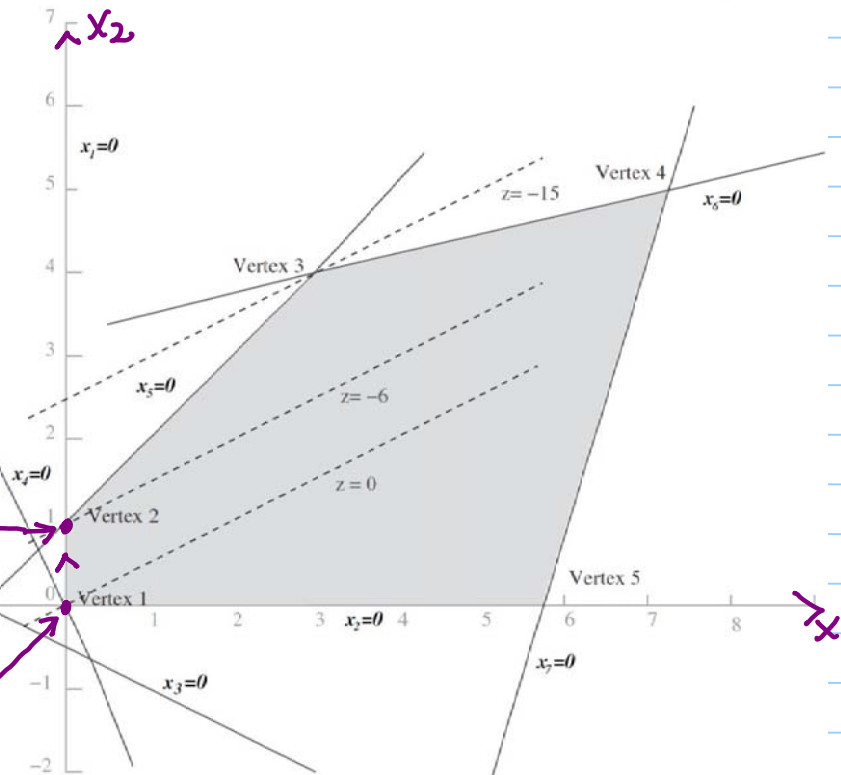
	x_1	x_2	1	
x_3	=	1	2	1
x_4	=	2	1	0
x_5	=	1	-1	1
x_6	=	1	-4	13
x_7	=	-4	1	23
z	=	3	-6	0

» $T = \text{ljx}(T, 3, 2);$

	x_1	x_5	1
$x_3 =$	3	-2	3
$x_4 =$	3	-1	1
$x_2 =$	1	-1	1
$x_6 =$	-3	4	9
$x_7 =$	-3	-1	24
$z =$	-3	6	-6

$x_1=0$
 $x_2=1$
 \uparrow
 $x_1=0$
 $x_5=0$

$x_1=0$
 $x_2=0$



This is the
 first step of the
 simplex method.
 By moving from
 $\begin{bmatrix} 0 \\ 0 \end{bmatrix}$ to $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$,
 z decreases from
 0 to -6.

Given a feasible tableau

$$\begin{array}{c} x_N \quad 1 \\ x_B = \begin{array}{|c|c|} \hline H & h \\ \hline c^T & d \\ \hline \end{array} \end{array},$$

a step of the simplex method is a Jordan exchange between a basic and non-basic variable according to the following pivot selection rules :

1. *Pricing* (selection of pivot column s): The pivot column is a column s with a negative element in the bottom row. These elements are called *reduced costs*.
2. *Ratio Test* (selection of pivot row r): The pivot row is a row r such that

$$-h_r/H_{rs} = \min_i \{-h_i/H_{is} \mid H_{is} < 0\}.$$

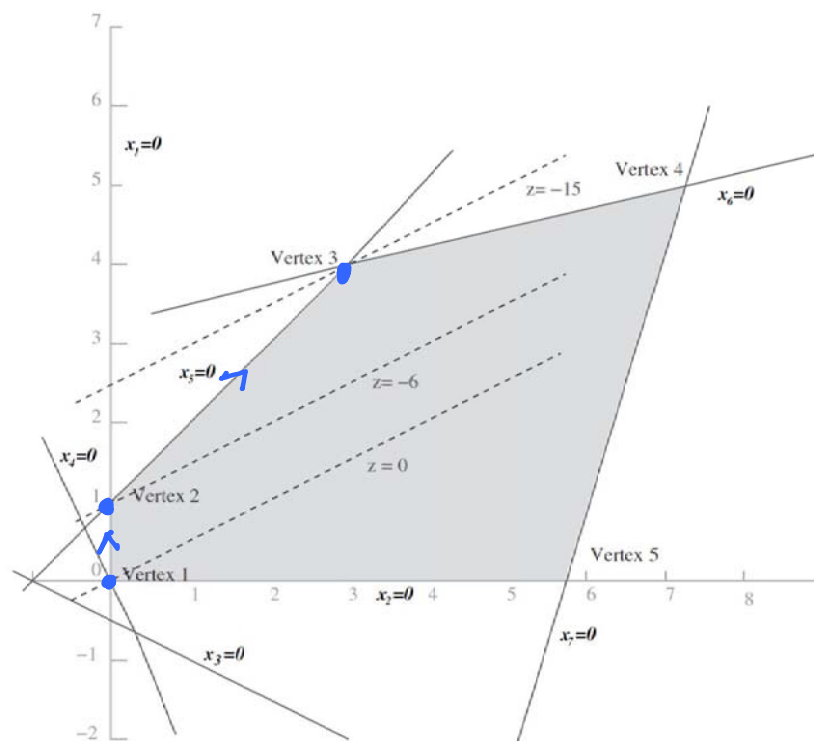
Back to the example, here is the next step:

	x_1	x_5	1
$x_3 =$	3	-2	3
$x_4 =$	3	-1	1
$x_2 =$	1	-1	1
$x_6 =$	-3	4	9
$x_7 =$	-3	-1	24
$z =$	-3	6	-6

$\gg T = \text{ljx}(T, 4, 1);$

$\frac{9}{3} \leftarrow$
 $\frac{24}{3}$

	x_6	x_5	1
$x_3 =$	-1	2	12
$x_4 =$	-1	3	10
$x_2 =$	-0.33	0.33	4
$x_1 =$	-0.33	1.33	3
$x_7 =$	1	-5	15
$z =$	1	2	-15



By moving from $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$ to $\begin{bmatrix} 3 \\ 4 \end{bmatrix}$, z decreases from -6 to -15.

Note that there are no more negative entries in the last row.

$$Z = x_6 + 2x_5 - 15.$$

Since every point in the feasible region satisfies

$$x_5 \geq 0, x_6 \geq 0$$

The min value of is -15 , and is attained when

$$x_5 = x_6 = 0 \quad (\Leftrightarrow x_1 = 3, x_2 = 4).$$

We say that the last tableau

	x_6	x_5	1
x_3 =	-1	2	12
x_4 =	-1	3	10
x_2 =	-0.33	0.33	4
x_1 =	-0.33	1.33	3
x_7 =	1	-5	15
z =	1	2	-15

is optimal.

The simplex method solves the LP after 2 simplex steps.

Algorithm 3.1 (Simplex Method).

1. Construct an initial tableau. If the problem is in standard form (3.1), this process amounts to simply adding slack variables.
2. If the tableau is not feasible, apply a Phase I procedure to generate a feasible tableau, if one exists (see Section 3.4). For now we shall assume the origin $x_N = 0$ is feasible.
3. Use the pricing rule to determine the pivot column s . If none exists, **stop**; (a): tableau is optimal. $\Leftrightarrow b \leq 0$
4. Use the ratio test to determine the pivot row r . If none exists, **stop**; (b): tableau is unbounded.
5. Exchange $x_{B(r)}$ and $x_{N(s)}$ using a Jordan exchange on H_{rs} .
6. Go to Step 3.

Interestingly, and perhaps confusing for you, the inner workings of Phase I depend on the Phase II procedure!

Stop (a) indicates optimality, as

$$z = c^T x_N + \alpha$$

α
0

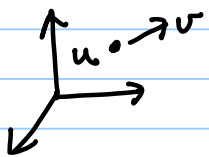
Any point in the feasible region must satisfy $x_N \geq 0$

so $z \geq \alpha$, and $\min z = \alpha$, with $x_N = 0$ as a minimizer.

↑
the corresponding values of x_1, \dots, x_n (original variables) can be easily read off from the tableau.

Stop (b) means $\min z = -\infty$, and we can read off from the tableau a "ray"

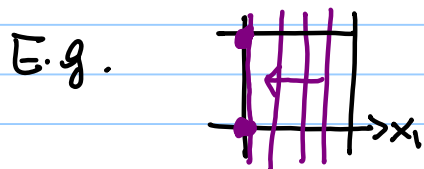
$x(\lambda)$ so that $\lim_{\lambda \rightarrow +\infty} z(x(\lambda)) = -\infty$.
" $u + \lambda v$



See Example 3-3-1.

Non-uniqueness of minimizer

Linear programs may have more than one solution.



$$\min x_1 \text{ s.t. } 0 \leq x_1 \leq 1, \quad 0 \leq x_2 \leq 1$$

$$\min p^T x \text{ s.t. } Ax \geq b, x \geq 0$$

Proposition: If $x^1, \dots, x^K \in \mathbb{R}^n$ are solutions of a LP, any other point in the convex hull of these solutions, defined by

$$\left\{ x \in \mathbb{R}^n \mid x = \sum_{i=1}^K \alpha_i x^i, \quad \sum_{i=1}^K \alpha_i = 1, \quad \alpha_i \geq 0, \quad i=1, \dots, K \right\},$$

is also a solution.

Proof: ① check that every point in the convex hull is feasible.

By assumption, x^1, \dots, x^K are feasible, i.e. $x^1, \dots, x^K \geq 0$
 $Ax^1, \dots, Ax^K \geq b$

so $\sum_{i=1}^K \alpha_i x^i \geq 0$, and $A\left(\sum_{i=1}^K \alpha_i x^i\right) = \sum_{i=1}^K \alpha_i Ax^i \geq \sum_{i=1}^K \alpha_i b = \left(\sum_{i=1}^K \alpha_i\right)b = 1 \cdot b = b.$

- ② check that every point in the convex hull attains the same optimal objective value.

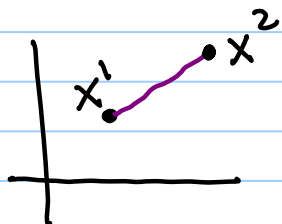
By assumption, $p^T x^i = z_{\text{opt}} = \text{min value of the LP.}$

$$\text{Then, } p^T \left(\sum_{i=1}^K \alpha_i x^i \right) = \sum_{i=1}^K \alpha_i p^T x^i = \sum_{i=1}^K \alpha_i z_{\text{opt}} = \left(\sum_{i=1}^K \alpha_i \right) z_{\text{opt}} = z_{\text{opt}}. \quad \text{Q.E.D.}$$

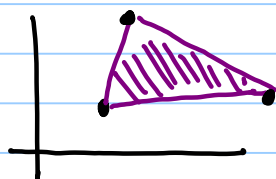
Convex hull of $x^1, \dots, x^K =$ the smallest convex set containing x^1, \dots, x^K

Detailed explanation omitted (with regret). Here are some examples:

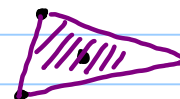
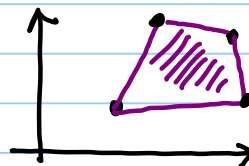
$K=2, n=2$



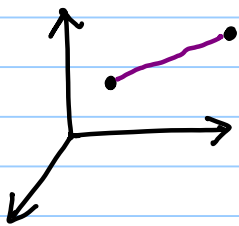
$K=3, n=2$



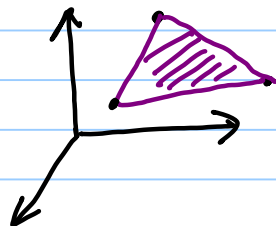
$K=4, n=2$



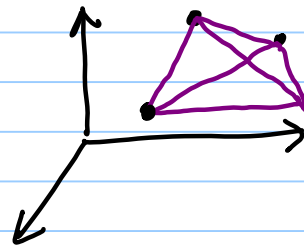
$K=2, n=3$



$K=3, n=2$

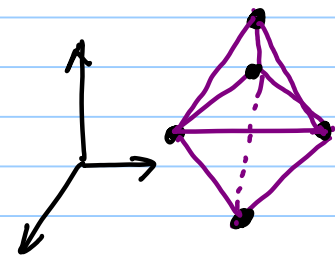


$K=4, n=3$



tetrahedron

$K=5, n=3$



Example 3-3-3.

min
 x_1, x_2, x_3

s.t.

$z =$

$$-x_1 - x_2 - x_3$$

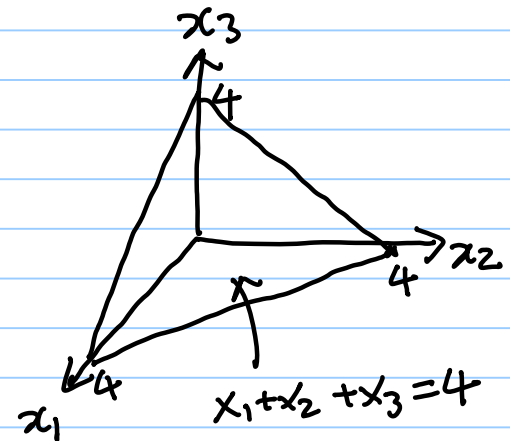
$$x_1 - x_2 + x_3 \geq -2$$

$$-x_1 + x_2 + x_3 \geq -3$$

$$x_1 + x_2 - x_3 \geq -1$$

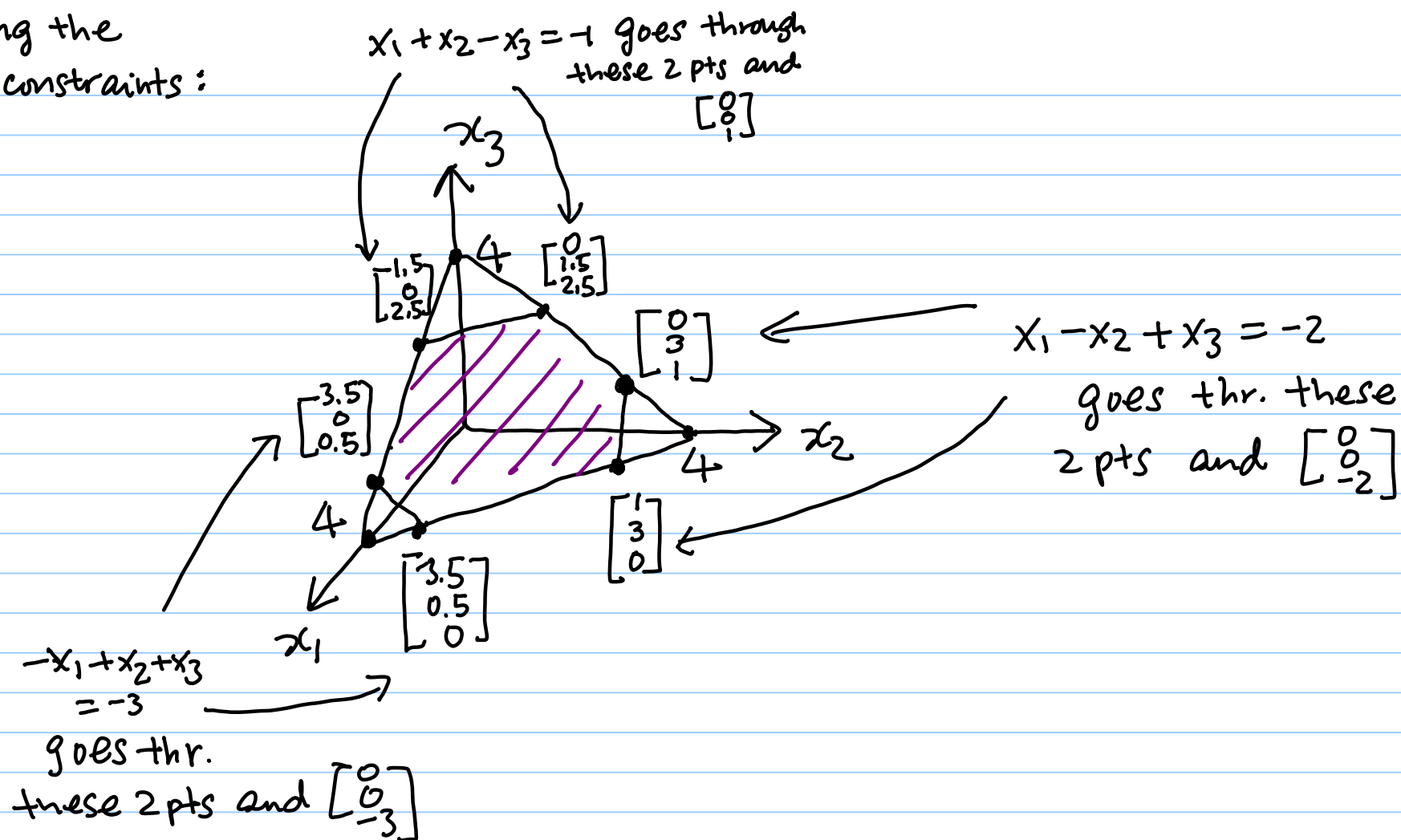
$$-x_1 - x_2 - x_3 \geq -4$$

$$x_1, x_2, x_3 \geq 0$$



It's clear that
 $z \geq -4$

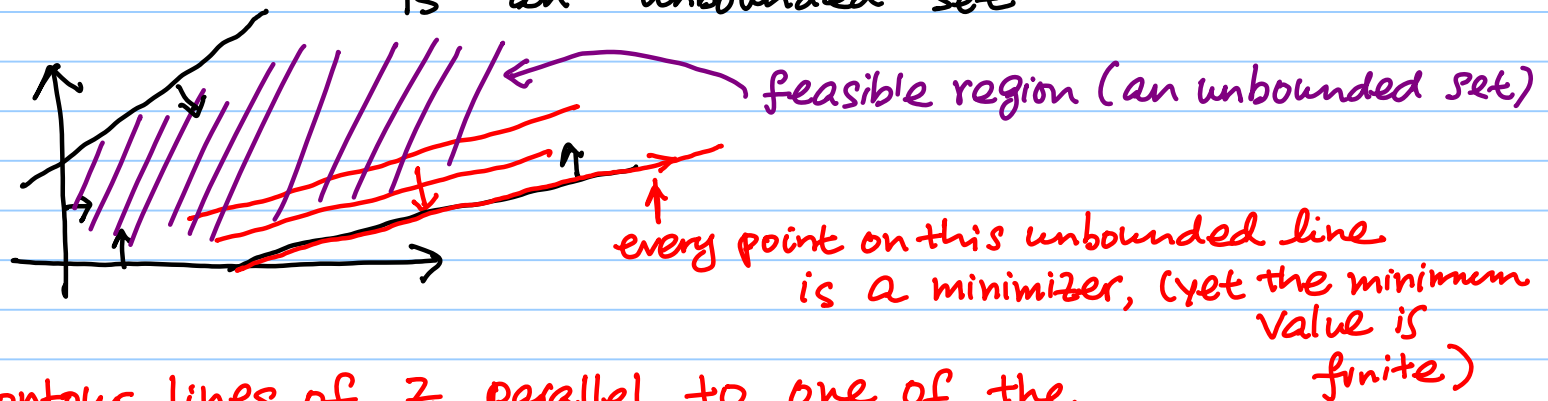
visualizing the
other 3 constraints:



Note that it is also possible to have a LP s.t.

- the feasible region is unbounded
- the min value is bounded
- but the solution set (i.e. the set of minimizers) is an unbounded set

E.g.



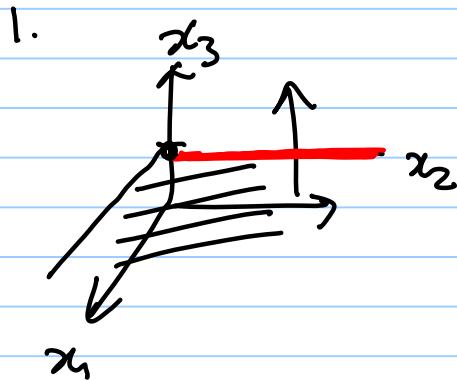
Contour lines of Z parallel to one of the boundary edges of the feasible region.

Exercise 3-3-7

$$-x_3 \geq -1$$

$$x_4 := -x_3 + 1$$

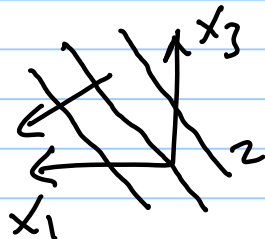
$$x_1 \geq 0, x_2 \geq 0, x_3 \geq 1$$



2. $x_1 + x_2 + x_3$ $\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$ $\min = 1$

3. $x_1 + x_3$ $\begin{bmatrix} 0 \\ \lambda \geq 0 \\ 1 \end{bmatrix}$

4. $-x_1 + x_3$ $\min = -\infty$



In class : simplex method in action

Note that the origin is not part of the feasible region.

(But clearly $x_1=0, x_2=0, x_4=0$ is feasible.)

The Phase I Procedure (Sec 3.4)

$$\begin{array}{l} \text{Origin LP} \\ \min p^T x \\ \text{s.t. } Ax \geq b \\ x \geq 0 \end{array} \Leftrightarrow \begin{array}{l} x_{n+i} := A_i \cdot x - b_i \geq 0 \\ i=1, \dots, m \end{array}$$

$$S = \{x \in \mathbb{R}^n : Ax \geq b, x \geq 0\}$$

when $b \not\leq 0$, how do we identify a vertex, or determine that S is empty?

$$\begin{array}{l} \text{Phase I LP} \\ \min z_0 = x_0 \\ x_0, x \\ \text{s.t. } x_{n+i} := \begin{cases} A_i \cdot x - b_i & \text{if } b_i \leq 0 \\ A_i \cdot x - b_i + x_0 & \text{if } b_i > 0 \end{cases} \\ x_0 \geq 0 \\ x_1 \geq 0 \\ \vdots \\ x_n \geq 0 \\ \vdots \\ x_{m+n} \geq 0 \end{array}$$

Note: the phase I LP concerns only the feasible region, it has nothing to do with the vector p .

(I) while the original LP may or may not be feasible, the Phase I LP is always feasible:

$$\text{set } x_0 = \max \left(\max_{1 \leq i \leq m} b_i, 0 \right) \quad (> 0 \text{ when you need Phase I })$$

$$\text{and } x_1 = \dots = x_n = 0$$

then the remaining constraints ($x_{n+i} \geq 0, i=1, \dots, m$) are obviously satisfied.

(II) \bar{x} is feasible for the original LP



$(0, \bar{x})$ is feasible for the Phase I LP



$$0 \leq A_i \cdot \bar{x} - b_i \quad \forall i$$



(because $z_0 \geq 0$)

$(0, \bar{x})$ is a solution for the Phase I LP

(Note: There are as many vertices for the original LP as there are solutions for the Phase I LP. So, the solution of the Phase I LP is typically far from unique.)

(III) (contrapositive of (I))

If (x_0^*, x^*) is a solution of the Phase I LP, but

$$x_0^* > 0,$$

then the original LP must be infeasible (i.e. $S = \emptyset$.)

Example 3-4-1.