

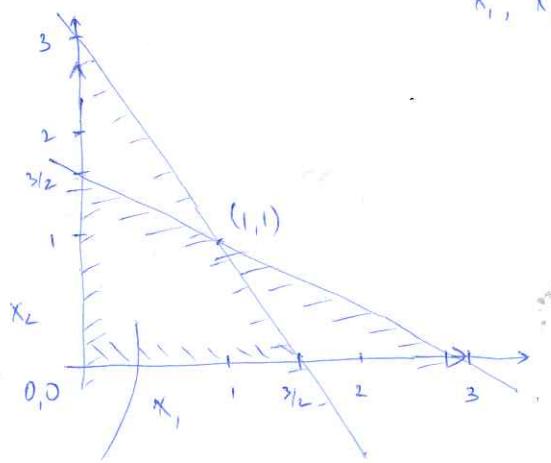
## Linear Programming: lecture 20.

Problem of minimizing a linear, multivariable objective, subject to linear constraints

Eg.: LP1: maximize  $x_1 + x_2$  ] objective.

subject to:  $x_1 + 2x_2 \leq 3$   
 $2x_1 + x_2 \leq 3$   
 $x_1, x_2 \geq 0$

} constraints



feasible region.

fix  $c$ , consider line  $x_1 + x_2 = c$ . (slope  $-1$ ,  $x_2$ -intercept at  $c$ )

if there exists feasible point on this line, then  $\exists$  feasible soln w/ objective value  $c$ .

Hence, our goal is to max.  $c$  s.t.  $\exists$  feasible  $x_1, x_2$  on the line  $x_1 + x_2 = c$

this happens at the "corner"  $(1,1)$

"corners" are v.v.v. imp. in linear programming; this is where all the action happens!

(2)

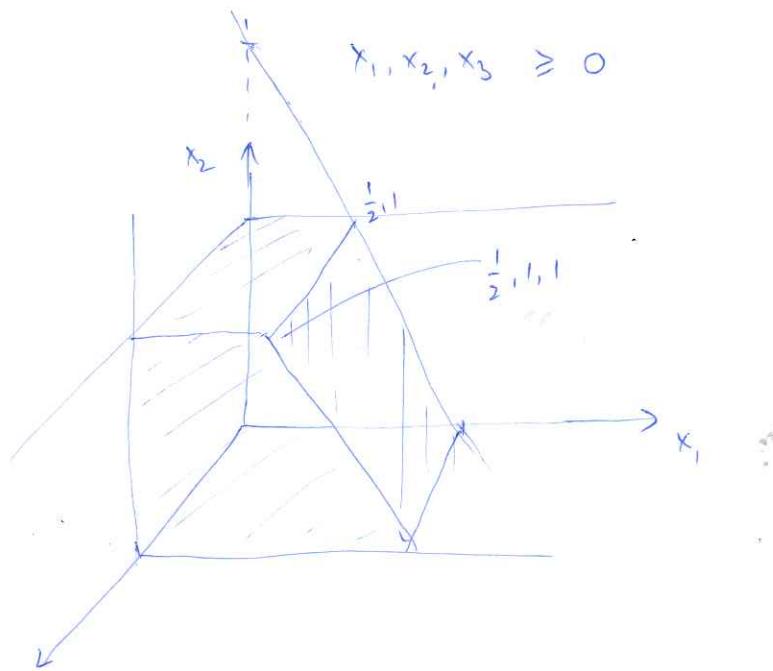
- dimension of an LP is (generally) the # of variables.

$$LP2: \max x_1 + x_2 + x_3$$

$$\text{s.t. } 2x_1 + x_2 \leq 2$$

$$x_2 \leq 1$$

$$x_3 \leq 1$$



again, maximizing at the "corner"  $(\frac{1}{2}, 1, 1)$

more generally: an LP is of the form:

$$\min c^T x \quad x = (x_1, \dots, x_n)$$

$$\text{s.t. } a_i^T x \geq b_i \quad i \in M_1$$

$$a_i^T x \leq b_i \quad i \in M_2$$

$$a_i^T x = b_i \quad i \in M_3$$

$$x_j \geq 0 \quad j \in N_1$$

$$x_j \leq 0 \quad j \in N_2$$

$M_1, M_2, M_3, N_1, N_2$  are index sets.

we will stick to LPs of the form

$$\min c^T x$$

$$\text{s.t. } a_i^T x \geq b_i \quad i \in [m]$$

$$x \geq 0$$

this is w/o loss of generality, since:

- $a_i^T x \leq b_i \Leftrightarrow -a_i^T x \geq -b_i$
- $a_i^T x = b_i \Leftrightarrow a_i^T x \geq b_i, a_i^T x \leq b_i$
- if  $x_j \leq 0$ , replace  $x_j$  by  $-x_j$ ,  $x_j \geq 0$
- if  $x_j$  is "free", i.e., neither  $x_j \geq 0$  nor  $x_j \leq 0$ ,  
replace  $x_j$  by  $x_j^+ - x_j^-$ , and  $x_j^+, x_j^- \geq 0$

or, equivalently:

$$\min c^T x$$

$$\begin{aligned} \text{s.t. } Ax &\geq b && - m \text{ constraints,} \\ &&& n \text{ variables, } A \in \mathbb{R}^{m \times n}. \\ &x \geq 0 && \end{aligned}$$

"Solving" a linear program: Some geometry.

Given  $a \in \mathbb{R}^n$ ,  $b \in \mathbb{R}$ ,

the set  $\{x \in \mathbb{R}^n : a^T x = b\}$  is a hyperplane

the set  $\{x \in \mathbb{R}^n : a^T x \leq b\}$  is a half-space.

a polyhedron is the intersection of a finite set of halfspaces:

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

- a bounded polyhedron is called a polytope.

(thus, the feasible region of any LP is a polyhedron).

now let's try & understand "corners". Let  $P = \{x : Ax \leq b\}$  be a polyhedron.

[a corner]

- A constraint  $a_i^T x \leq b_i$  is tight/active/binding at  $x^* \in P$  if  $a_i^T x^* = b_i$ .
- constraints  $a_i^T x \leq b_i, a_j^T x \leq b_j$  are linearly independent if vectors  $a_i, a_j$  are linearly independent. (can extend to more than 2 constraints in the usual way)

Defn:  $x^* \in P$  is a basic solution if  $n$  l.i. constraints are tight at  $x^*$ .

(note:  $x^*$  is the unique pt. in  $\mathbb{R}^n$  where these  $n$  constraints are tight).

$x^* \in P$  is a basic feasible solution if  $x^*$  is basic, and  $Ax^* \leq b$ , i.e.,  $x^*$  is feasible.

(note: # of basic solutions  $\leq \binom{m}{n}$ )

→ Now here is why corners/bfs's are important.

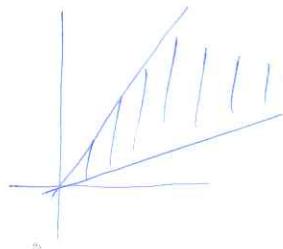
Theorem: Suppose polyhedron  $P$  is nonempty, and has at least one bfs. Consider the objective of minimizing  $c^T x$ . Then either optimal value is  $-\infty$ , or there is an optimal bfs.

Theorem: If polyhedron  $P$  does not contain a line, is bounded, it contains at least one bfs.

(hence if  $P$  is bounded, it contains at least one bfs)

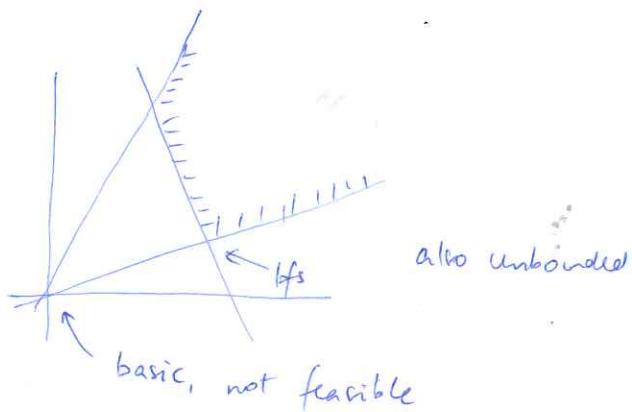
Some examples:

- unbounded polyhedron:



Note that a polyhedron of the form  $P = \{x : Ax \geq b, x \geq 0\}$  does not contain a line, and hence contains at least one bfs.

- basic solution that is not feasible:



[Now here is why bfs's / corners are important]

For polytopes, we then have a simple algorithm for finding the optimal solution (i.e., solving an LP):

- ① enumerate all basic solutions ( $\binom{m}{n}$  possible solutions)
- ② check if each is feasible
- ③ choose bfs that minimizes  $c^T x$ .

Let's consider some of the problems we've seen, and try & write them as LPs.

- ① maximum matchings (given undirected graph  $G = (V, E)$ )

Say variable  $x_e$  for each  $e \in E$ ,  $x_e = 1 \Rightarrow e$  in matching  
 $= 0$  o.w.

$$\max \sum_{e \in E} x_e$$

$$\forall v, \sum_{e \text{ incident to } v} x_e \leq 1$$

$$x_e \geq 0$$

$x_e \in \{0, 1\}$  ← integer constraints, give an integer linear program (ILP)

convince yourself that:

- ①  $M$  is a matching iff  $\{x : x_e=1 \text{ if } e \in M, =0 \text{ o.w.}\}$  is a feasible solution.
- ② optimal solution corresponds to maximum matching.

- ② maximum  $f$ -s-t flow, capacity (given directed graph  $G = (V, E)$ , vertices  $s, t$ , capacity  $c_e$  on edges)

Variable  $x_e$  for each edge, equal to amt. of flow on edge

$$\max \sum_{e \text{ out of } s} x_e$$

$$\forall v \neq s, t \quad \sum_{e \text{ into } v} x_e - \sum_{e \text{ out of } v} x_e = 0$$

$$\forall e \quad x_e \leq c_e$$

$$\forall e \quad x_e \geq 0$$