

March 31, 2020Today: Linear Programs.

eg. Min. $2x - 3y.$
 s.t. $x + y \leq 2$
 $x - y = 4$

General: Min $\vec{c}^T \vec{x}$
 s.t. $A\vec{x} \leq \vec{b}$

- Any equality constraint: $a_i^T x = b_i$ can be written as $a_i^T x \leq b_i$ and $a_i^T x \geq b_i$
- So equality constraints can be looped into inequality constraints.
- $a_i^T \vec{x} \geq b_i$ can be written as $-a_i^T \vec{x} \leq -b_i$

Standard Form:

Min $\vec{c}^T \vec{x}$
 s.t. $A\vec{x} = \vec{b}$
 $\vec{x} \geq 0.$

All LPs can be translated to standard form.

① Eliminate inequality constraints by introducing slack variables.

e.g. Consider a constraint of the form:

$$\sum_{j=1}^n a_{ij} x_j \leq b_i$$

Rewrite: $\sum_{j=1}^n a_{ij} x_j + s_i = b_i \quad ; \quad s_i \geq 0.$

s_i : slack variable.

② Eliminate free variables.

How do we get $x_i \geq 0$ for every variable?

If you have some x_j that is unconstrained, then

write $x_j = x_j^+ - x_j^-$, where $x_j^+ \geq 0$, $x_j^- \geq 0$.

Any real number can be written as the difference of two non-negative numbers.

Example:

$$\begin{aligned} \text{min.} \quad & 2x_1 + 4x_2. \\ \text{s.t.} \quad & x_1 + x_2 \geq 3. \\ & 3x_1 + 2x_2 = 14 \\ & x_1 \geq 0 \end{aligned}$$

$$\left. \begin{aligned} x_2 &= x_2^+ - x_2^- \\ x_2^+ &\geq 0, x_2^- \geq 0. \\ x_1 + x_2 + x_3 &= 3. \\ x_3 &\geq 0. \end{aligned} \right\}$$

→

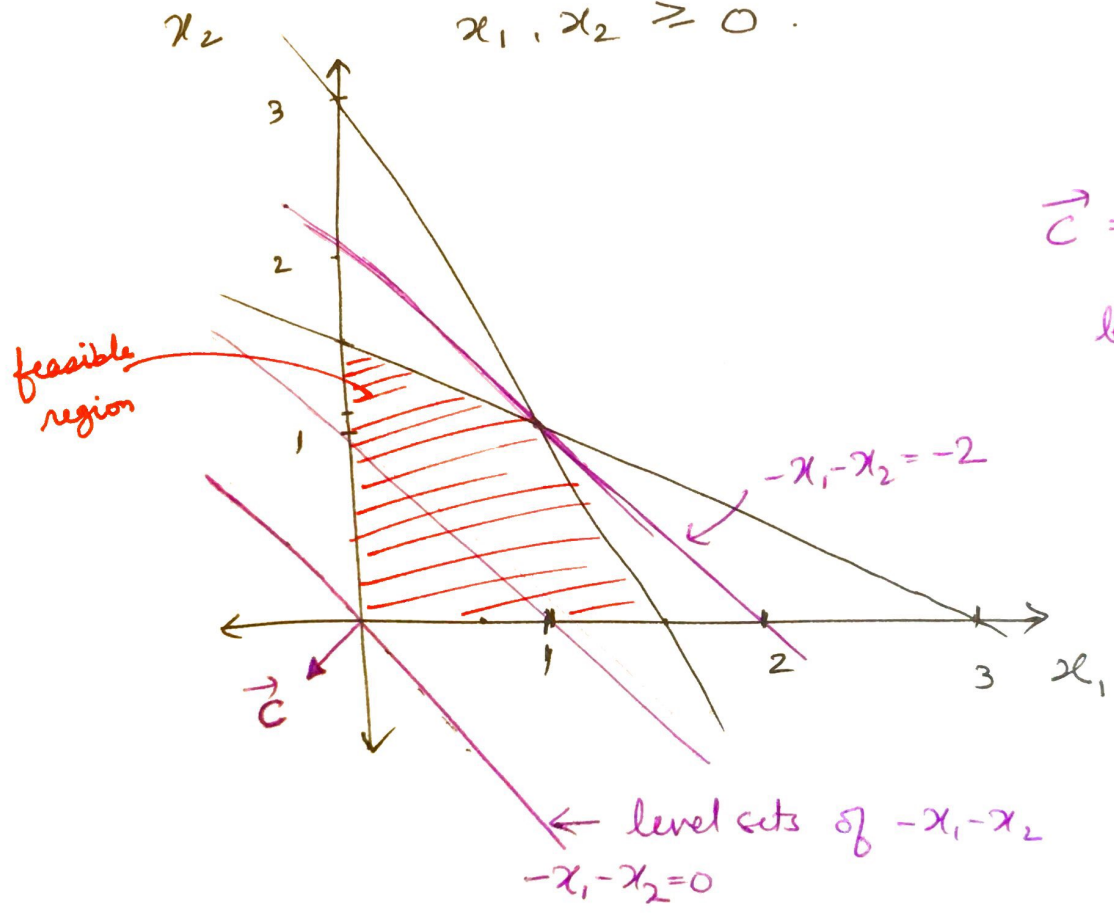
$$\begin{aligned} \text{min.} \quad & 2x_1 + 4x_2. \\ \text{s.t.} \quad & x_1 + x_2^+ - x_2^- + x_3 = 3. \\ & 3x_1 + 2x_2^+ - 2x_2^- = 14 \\ & x_1, x_2^+, x_2^-, x_3 \geq 0. \end{aligned}$$

Standard form is computationally more convenient.

Graphical Representation.

Example:

minimize. $-x_1 - x_2$
s.t. $x_1 + 2x_2 \leq 3$ (1)
 $2x_1 + x_2 \leq 3$ (2)
 $x_1, x_2 \geq 0$.



$\vec{c} = \begin{bmatrix} -1 \\ -1 \end{bmatrix}$
level sets are orthogonal to \vec{c}

We keep moving in the direction of $-\vec{c}$ until we can't.
We hit a 'corner'.

Defⁿ: Polyhedron:

Set: $\{x \in \mathbb{R}^n \mid Ax \geq b\}$. $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$

Can also be written in "standard form" with equality constraints:

set: $\{x \in \mathbb{R}^e \mid Cx = d, x \geq 0\}$.

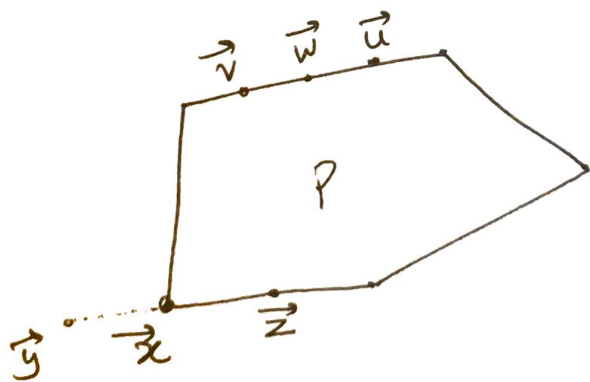
using earlier conversion. # of variables might change.

Defⁿ: Extreme point. P: Polyhedron. (Also vertex)

$x \in P$ is an extreme point of P if we cannot find two vectors $y, z \in P$ both different from x and a scalar $\lambda \in [0, 1]$, such that

$$x = \lambda y + (1-\lambda)z$$

x has to be a convex combination of $y, z \in P$ to not be extreme.

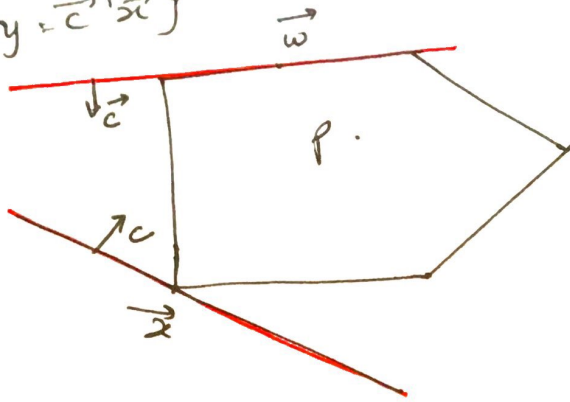


Defⁿ: Extreme point (Also vertex).

$x \in P$ is a vertex / extreme point of P if there exists some c such that $c^T x < c^T y$ for all $y \in P, y \neq x$

ie: All of P should be on "one side" of the hyperplane $\{y \mid c^T x = c^T y\}$. Hyperplane should meet P at only one point.

$$\{y \mid \vec{c}^T y = \vec{c}^T \vec{x}\}$$

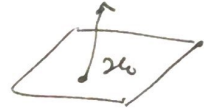


General form of hyperplane

$$\vec{c}^T (\vec{x} - \vec{x}_0) = 0$$

\vec{c} : normal vector

\vec{x}_0 : point on hyperplane.

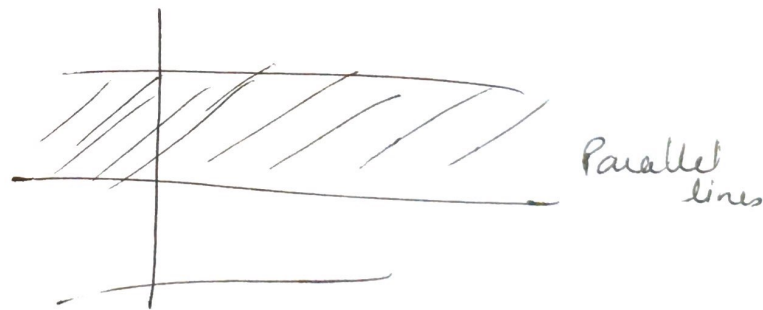
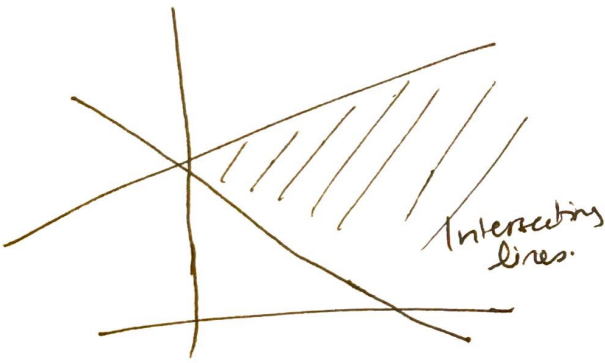


Fact:

If P has an extreme point, ~~then~~ P does not "contain a line"

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

Intuition in 2D.



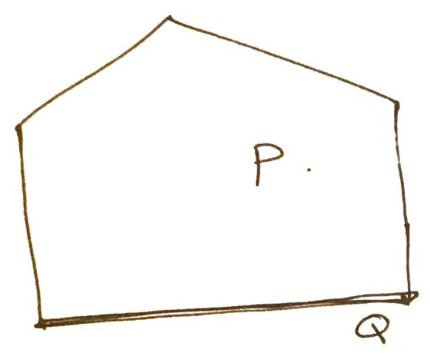
Thm: Consider a linear programming problem of minimizing $c^T x$ over poly. P .

$$\begin{aligned} \min c^T x. \\ \text{s.t. } Ax \leq b \end{aligned}$$

Suppose P has atleast one extreme point.
Suppose optimal solution exists and is finite
Then, there exists an optimal solution that is an extreme point of P .

Proof:

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



Let $v = c^T \bar{x}$ be the optimal value of $c^T \bar{x}$, $\bar{x} \in P$.

Let Q be the set of all optimal solutions i.e.

$$Q: \{\bar{x} \mid Ax \leq b, c^T \bar{x} = v\}.$$

Q is also a polyhedron.

$Q \subset P$, and P has no lines.
 $\Rightarrow Q$ has no lines.

Q also has an extreme point.

Let \bar{x}^* be an extreme point of Q . We will show that \bar{x}^* is also an extreme point of P .

If possible, \bar{x}^* is not an extreme point of P .

Then: $\exists \bar{y}, \bar{z} \in P, \bar{y} + \bar{z}, \bar{z} \neq \bar{x}^* \leq 4$.

$$\bar{x}^* = \lambda \cdot \bar{y} + (1-\lambda) \bar{z}.$$

Now,

$$\vec{c}^T \vec{x}^* = \theta.$$

$$\Rightarrow \vec{c}^T \cdot \lambda \vec{y} + \vec{c}^T \cdot (1-\lambda) \cdot \vec{z} = \theta$$

But θ is the optimal cost.

$$\Rightarrow \vec{c}^T \vec{y} \geq \theta \quad \text{and} \quad \vec{c}^T \vec{z} \geq \theta$$

$$\Rightarrow \vec{c}^T \vec{y} = \vec{c}^T \vec{z} = \theta.$$

$$\Rightarrow \vec{y} \in Q, \vec{z} \in Q.$$

$\Rightarrow \vec{x}^*$ cannot be an extreme point of Q .

~~Q~~ # contradiction! Our assumption was wrong.

$\Rightarrow \vec{x}^*$ must be an extreme point of P .

\therefore An extreme point of P is an optimal

QED

\rightarrow Foundations of the Simplex algorithm.