

# Linear Programming

A linear program is an optimization problem where  $f(\vec{x})$ ,  $\vec{g}(\vec{x})$ , and  $\vec{h}(\vec{x})$  are affine functions of  $\vec{x}$

## Example

Three goods:	$x_1, x_2, x_3$	$x_i \leq \bar{x}_i$
Volume per unit:	$v_1, v_2, v_3$	max volume $\bar{V}$
Price per unit:	$p_1, p_2, p_3$	
Weight per unit:	$w_1, w_2, w_3$	max weight $\bar{w}$

$$\begin{aligned} & \underset{\vec{x}}{\text{maximize}} && \sum_i p_i x_i \\ & \text{subject to} && \sum_i v_i x_i \leq \bar{V} \\ & && \sum_i w_i x_i \leq \bar{w} \end{aligned}$$

$$\begin{aligned} \underset{\vec{x}}{\text{minimize}} \quad & \|A\vec{x} - \vec{b}\|_1 \quad \Rightarrow \quad \underset{\vec{x}, \vec{s}}{\text{minimize}} \quad \sum_i s_i \\ & \text{subject to} \quad A\vec{x} - \vec{b} \leq \vec{s} \\ & \quad \quad \quad A\vec{x} - \vec{b} \geq -\vec{s} \end{aligned}$$

$$\begin{aligned} \underset{\vec{x}}{\text{minimize}} \quad & \|A\vec{x} - \vec{b}\|_\infty \quad \Rightarrow \quad \underset{\vec{x}, t}{\text{minimize}} \quad t \\ & \text{subject to} \quad A\vec{x} - \vec{b} \leq t\vec{1} \\ & \quad \quad \quad A\vec{x} - \vec{b} \geq -t\vec{1} \end{aligned}$$

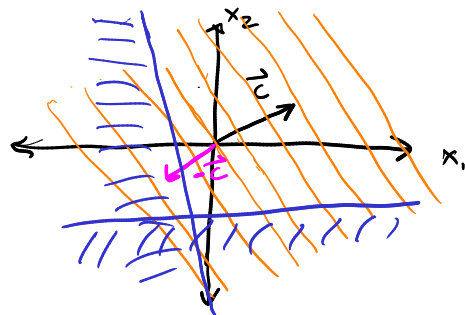
## Geometry

objective:  $\vec{c}^T \vec{x}$

constraints:  $h_i(\vec{x}) = \vec{a}_i^T \vec{x} + b_i$

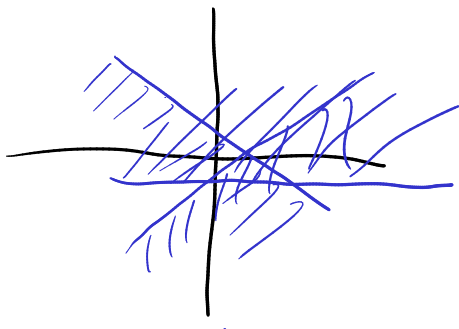
hyperplane  $\nearrow g_i(\vec{x}) = \vec{a}_i^T \vec{x} + b_i$

half space  $\nearrow$

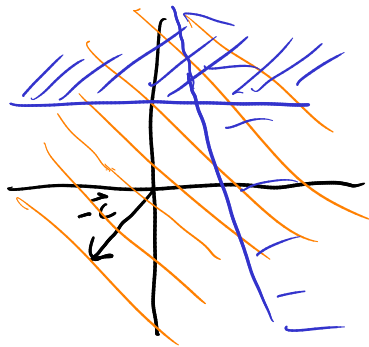


optimal

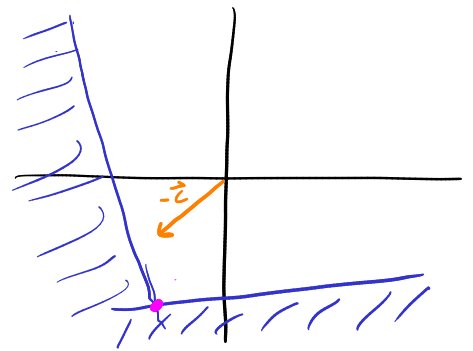
Break: If  $\vec{c} \neq \vec{0}$ , will there ever be  $\nabla$  solutions that are interior points?  
 and there are no equality constraints  $\nearrow$  no constraints are active



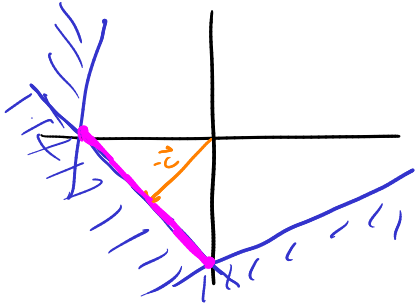
infeasible



unbounded



one solution at one vertex  
↑  
optimal

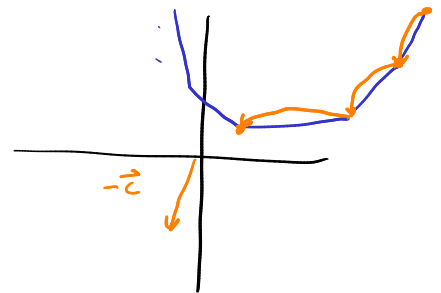
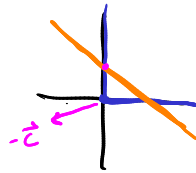


infinite number of optimal solutions on a face of the polytope

Except in degenerate cases, there is at least one vertex that is an optimal solution.

## Simplex Method

$$\begin{aligned} \underset{\vec{x}}{\text{minimize}} \quad & \vec{z}^T \vec{x} \\ \text{s.t.} \quad & A\vec{x} = \vec{b} \\ & \vec{x} \geq 0 \end{aligned}$$



Assume that  $A$  is an  $m \times n$  matrix all rows are linearly independent  
(preprocessing)  
 $m \leq n$

Design variable indices  $\{1, \dots, n\}$  partitioned into two sets:

$i \in V \Rightarrow x_i = 0$  "Active"  $n-m$  elements  
 $i \in B \Rightarrow x_i \geq 0$  "Inactive"  $m$  elements

$$\vec{x}_B, \vec{x}_V = 0$$

$$A_B \vec{x}_B = \vec{b} \rightarrow \vec{x}_B = A_B^{-1} \vec{b}$$

$A_B$  might be singular,  $\vec{x}_B$  might not be positive

Two phases

1. Initialization
2. Optimization

KKT conditions

$$\mathcal{L}(x, \lambda, \mu) = z^T \vec{x} - \vec{\mu}^T \vec{x} - \vec{\lambda}^T (A\vec{x} - \vec{b})$$

1. Feasibility:  $A\vec{x} = \vec{b}$ ,  $\vec{x} \geq 0$
- 2. Dual Feasibility:  $\vec{\mu} \geq 0$
3. Complementary Slackness:  $\vec{\mu} \odot \vec{x} = 0$
4. Stationarity:  $A^T \vec{\lambda} + \vec{\mu} = \vec{z}$

Since problem is convex

these are also sufficient conditions

$$A_B^T \vec{\lambda} + \underbrace{\vec{\mu}_B}_0 = \vec{z}_B \Rightarrow \vec{\lambda} = \overset{(A^T)^{-1}}{A_B^{-T}} \vec{z}_B$$

$$A_V^T \vec{\lambda} + \vec{\mu}_V = \vec{z}_V$$

$$\vec{\mu}_V = \vec{z}_V - (A_B^{-1} A_V)^T \vec{z}_B$$

if  $\vec{\mu}_V$  contains negative components, not optimal!

### Optimization Phase

Each step:  $\vec{x} \rightarrow \vec{x}'$  "pivot"

select "entering index"  $q \in V$

"leaving index"  $p \in B$

$\vec{x}'$  must satisfy

$$A\vec{x}' = \vec{b} = A_B \vec{x}'_B + A_q x'_q = A_B \vec{x}_B$$

$$\vec{x}'_B = \vec{x}_B - A_B^{-1} A_q x'_q$$

$p \in B$  becomes active when

$$(\vec{x}'_B)_p = 0 = (\vec{x}_B)_p - (A_B^{-1} A_q)_p x'_q$$

$$x'_q = \frac{(\vec{x}_B)_p}{(A_B^{-1} A_q)_p}$$

Choose  $p$  that minimizes this ratio (minimizes  $x'_q$ )

choose  $q$  based on the effect on objective

$$\vec{z}^T \vec{x}' = \vec{z}_B^T \vec{x}'_B + c_q x'_q$$