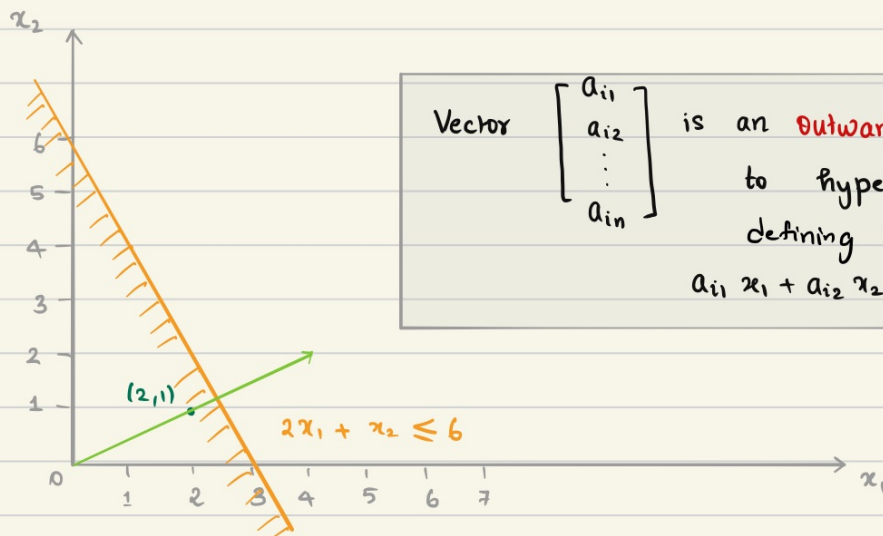


## A GEOMETRIC INTERPRETATION OF DUALITY - Part 1

REFERENCE: Lecture 11 from Prof. Sundar Vishwanathan's notes on Linear Optimization

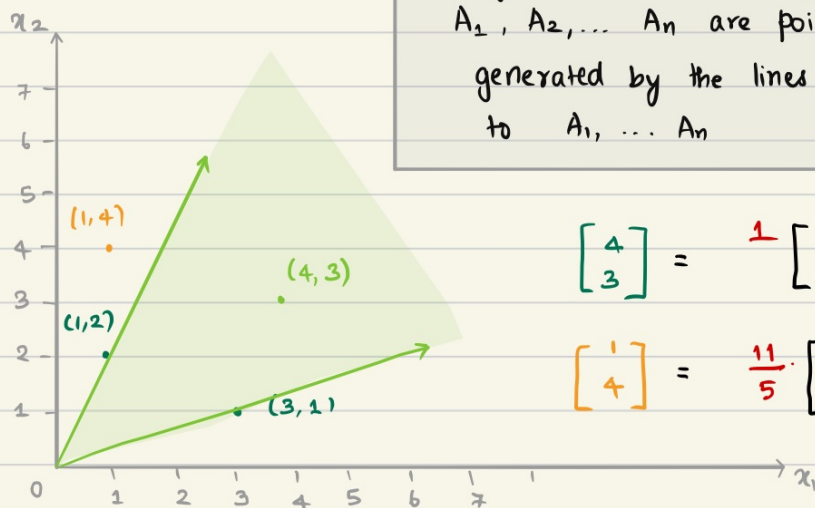
Some basic observations:

1)



Vector  $\begin{bmatrix} a_{i1} \\ a_{i2} \\ \vdots \\ a_{in} \end{bmatrix}$  is an **outward normal** to hyperplane defining the half-space  $a_{i1}x_1 + a_{i2}x_2 + \dots + a_{in}x_n \leq b_i$

2)



Non-negative combinations of vectors  $A_1, A_2, \dots, A_n$  are points in the **cone** generated by the lines joining origin to  $A_1, \dots, A_n$

$$\begin{bmatrix} 4 \\ 3 \end{bmatrix} = 1 \begin{bmatrix} 1 \\ 2 \end{bmatrix} + 1 \begin{bmatrix} 3 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} 1 \\ 4 \end{bmatrix} = \frac{11}{5} \begin{bmatrix} 1 \\ 2 \end{bmatrix} - \frac{2}{5} \begin{bmatrix} 3 \\ 1 \end{bmatrix}$$

Consider an LP:

$$\begin{array}{ll} \text{maximize} & c^T x \\ \text{subject to} & Ax \leq b \\ & x \text{ unrestricted} \end{array}$$

$$\begin{array}{l} A: m \times n \\ c: n \times 1 \\ x: n \times 1 \\ b: m \times 1 \end{array}$$

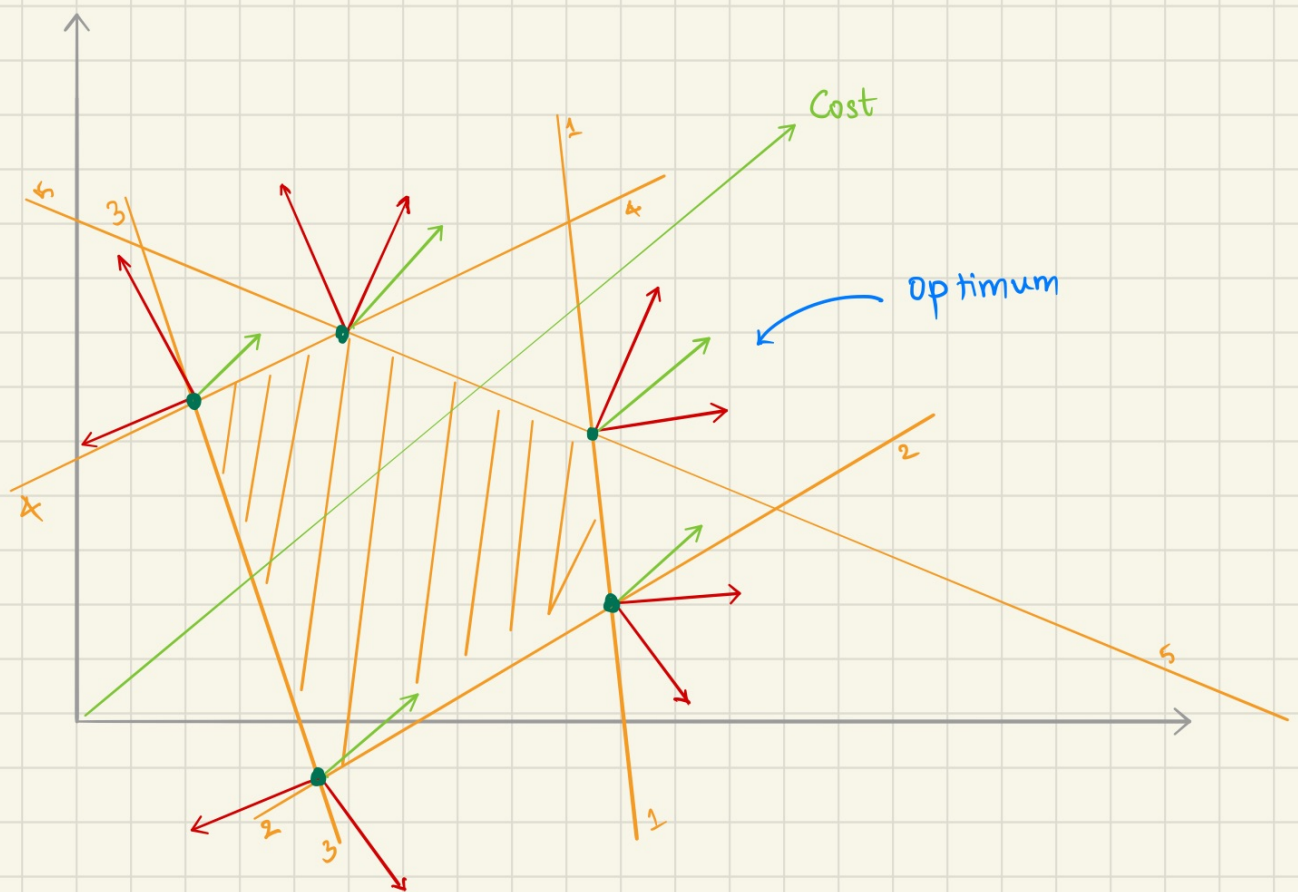
Assume that the LP is non-degenerate, and has an optimum

Extreme point: a feasible solution that:

- is obtained as the intersection of  $n$  linearly independent hyperplanes from  $A_1 x = b_1, A_2 x = b_2, \dots, A_m x = b_m$

$$\begin{array}{l} A' x = b' \quad (\text{the set of } n \text{ hyperplanes}) \\ A'' x < b'' \quad (\text{others}) \end{array}$$

Theorem: An extreme point defined by  $A' x = b', A'' x < b''$  is an optimum iff the cost vector 'c' can be written as a non-negative combination of  $A'_1, A'_2, \dots, A'_n$



Theorem: An extreme point defined by  $A'x = b'$ ,  $A''x < b''$  is an optimum iff the cost vector 'c' can be written as a non-negative combination of  $A'_1, A'_2, \dots, A'_n$

### KEY OBSERVATION

At optimum extreme point, cost decreases along all directions to the neighbouring extreme points.

## CHARACTERIZING NEIGHBOURING DIRECTIONS FROM AN EXTREME POINT:

$u_0$ : extreme point

$$A'x = b'$$

$$A''x < b''$$

Suppose  $u_i$  is a point such that:  $A'_j u_i = b_j \quad \forall j \neq i$

$$A'_i u_i < b_i$$

For example:  $u_1$  : 
$$\left. \begin{array}{l} A'_1 u_1 < b_1 \\ A'_2 u_1 = b_2 \\ \vdots \\ A'_m u_1 = b_m \end{array} \right\} \text{tight}$$

- From each extreme point, there are 'n' rays moving out to its neighbours.

Vectors  $u_1 - u_0$   $u_2 - u_0$   $\dots$   $u_n - u_0$  characterize these directions.

- Note that:

$$A'(u_1 - u_0) = \begin{bmatrix} A'_1 u_1 - A'_1 u_0 \\ A'_2 u_1 - A'_2 u_0 \\ \vdots \\ A'_m u_1 - A'_m u_0 \end{bmatrix} = \begin{bmatrix} \text{some negative value} \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

- By sufficient scaling, we can assume that  $A'_i (u_i - u_0) = -1$

Similarly  $A'_i (u_i - u_0) = -1$  
$$A'(u_i - u_0) = \begin{bmatrix} 0 \\ \vdots \\ -1 \\ \vdots \\ 0 \end{bmatrix} \leftarrow i^{\text{th}} \text{ place}$$

We have now 'n' vectors:

$$U = \begin{bmatrix} u_1 - u_0 & u_2 - u_0 & \dots & u_n - u_0 \end{bmatrix}$$

s.t.

$$A' U = \begin{bmatrix} -1 & 0 & \dots & 0 \\ 0 & -1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & -1 \end{bmatrix}$$

This implies:

$$U = -(A')^{-1}$$

Theorem: Directions to neighbours from an extreme point defined by  $A'x = b'$  are given by columns of  $-(A')^{-1}$ .  
 $A''x < b''$

At optimum, cost decreases along all its neighbours.

$$c^T (u_i - u_0) \leq 0$$

$$\therefore c^T \underbrace{[-(A')^{-1}]_i}_{i^{\text{th}} \text{ column of } -(A')^{-1}} \leq 0 \quad \forall i \in \{1, \dots, n\}$$

$$\therefore \boxed{c^T (A')^{-1}_i \geq 0 \quad \forall i \in \{1, \dots, n\}} \quad (*)$$

Writing the cost vector as a linear combination of rows of  $A'$ :

$A'x = b'$  contains 'n' linearly independent hyperplanes:

$$A'_1 x = b'_1$$

⋮

$$A'_n x = b'_n$$

- vectors:  $A'_1, \dots, A'_n$  are linearly independent.

∴ Cost  $c$  can be written as a linear combination of them

$$c = \alpha_1 \underbrace{A'_1}_{n \times 1} + \alpha_2 \underbrace{A'_2}_{n \times 1} + \dots + \alpha_n \underbrace{A'_n}_{n \times 1}$$

$n \times 1$ : column vectors.

Rewriting:  $c^T = \alpha_1 \underbrace{(A'_1)^T}_{1 \times n} + \alpha_2 A'_2{}^T + \dots + \alpha_n A'_n{}^T$

- Note that:  $c^T \cdot (A'_1)^{-1}_1 = \alpha_1$

⋮

$$c^T \cdot (A'_n)^{-1}_n = \alpha_n$$

$$\begin{matrix} A' \\ \vdots \end{matrix} (A')^{-1} = \begin{bmatrix} 0 & \dots & 0 \\ 1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 1 \end{bmatrix}$$

From (\*),  $\alpha_1, \alpha_2, \dots, \alpha_n \geq 0$

- Proves that at optimum, cost can be written as a non-negative linear combination of the outward normals of the 'n' hyperplanes defining the extreme point!