

LINEAR OPTIMIZATION

LECTURE 16

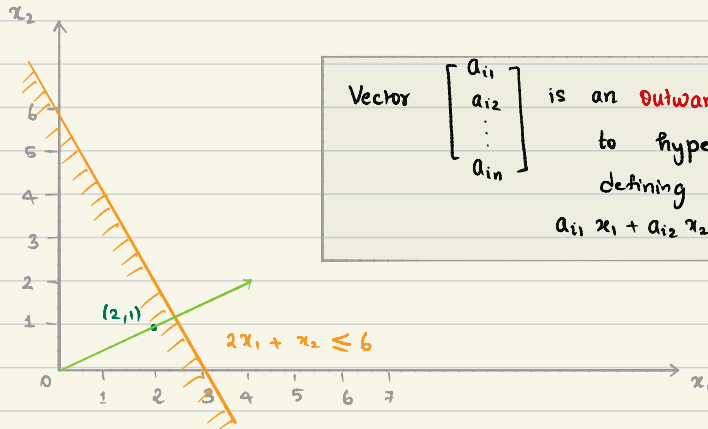
10/6/2021

A GEOMETRIC INTERPRETATION OF DUALITY

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

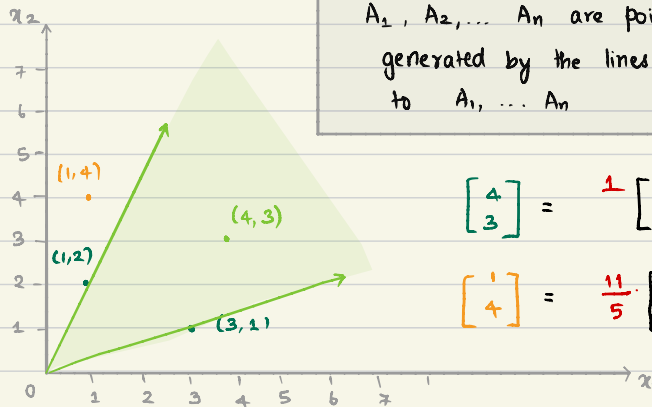
Some basic observations:

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

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

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

Consider an LP:

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

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

Assume that the LP is **non-degenerate**, and has an **optimum at an extreme point**.

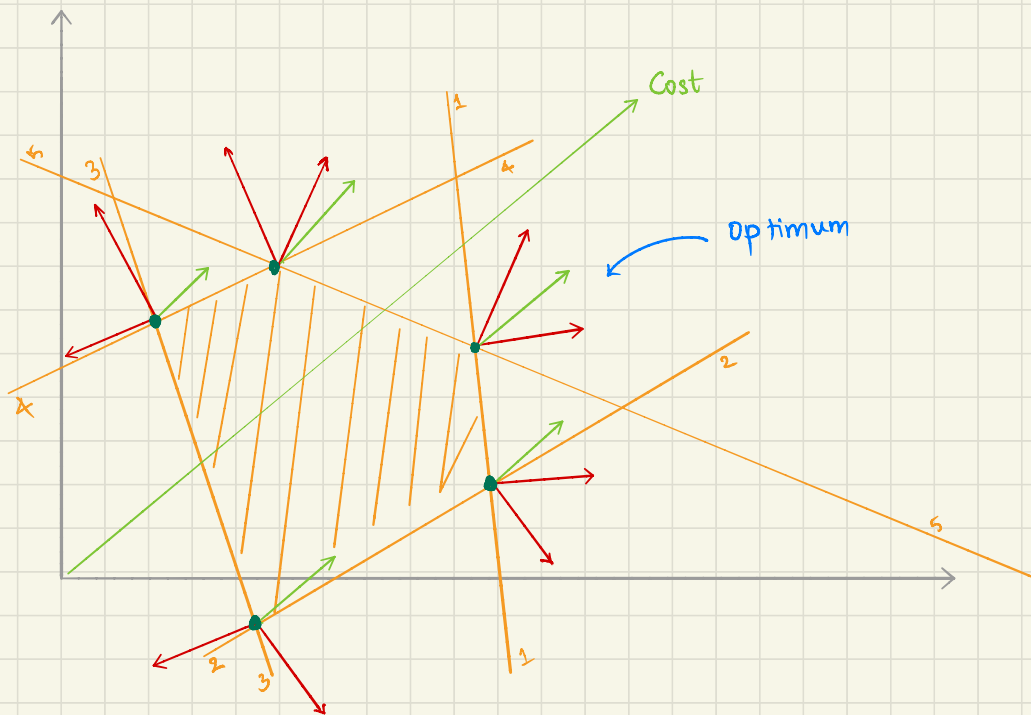
Extreme point: a feasible solution that:

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

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

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

$$A'x = b'$$

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

$$\begin{array}{cc} A'_1 & b'_1 \\ A'_2 & b'_2 \\ \vdots & \vdots \\ A'_n & b'_n \end{array}$$

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 :
$$\left. \begin{array}{l} A'_1 u_1 < b'_1 \\ A'_2 u_1 = b'_2 \\ \vdots \\ A'_n u_1 = b'_n \end{array} \right\} \text{tight}$$

- 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:

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

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

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

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.

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

This implies:

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

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

At optimum, cost decreases along all its neighbours.

suppose u_0 is optimum.

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

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

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

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

There is some t' s.t.

$u_0 + t(u_i - u_0)$ is an extreme point of $Ax \leq b$.

$$A_1' (u_i - u_0) = 0$$

$$A_2'$$

:

$$A_i' (u_i - u_0) = <$$

:

:

$$A_n'$$

$$A''$$

Consider the points: $u_0 + t(u_i - u_0)$

- At $t=0$, we get u_0 .
- On increasing t , what happens?
- We can find a $t > 0$ s.t. $u_0 + t(u_i - u_0)$ is feasible.
i.e., $A(u_0 + t(u_i - u_0)) \leq b$

- If $c^T (u_i - u_0) > 0$, then $c^T (u_0 + t(u_i - u_0)) > c^T u_0$
- contradiction that u_0 is optimum.

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: $c^T = \alpha_1 \underbrace{(A'_1)^T}_{\text{row vector}} + \alpha_2 A'_2{}^T + \dots + \alpha_n A'_n{}^T$

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

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

$$\vdots$$

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

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!

Rewriting: $c^T = \alpha_1 A_1'^T + \alpha_2 A_2'^T + \dots + \alpha_n A_n'^T$

Multiplying with $(A')^{-1}$ on both sides.

$$c^T (A')^{-1} = \alpha_1 A_1'^T (A')^{-1} + \dots + \alpha_n A_n'^T (A')^{-1}$$

$$c^T (A')^{-1} : (1 \times n) \times (n \times n)$$

$$= [\beta_1 \ \beta_2 \ \dots \ \beta_n]$$

where $\beta_i \geq 0 \quad \forall i \in \{1, \dots, n\}$

$$\alpha_1 (A_1')^T (A')^{-1} = A_1' [\dots] \left[(A')^{-1} \right]$$

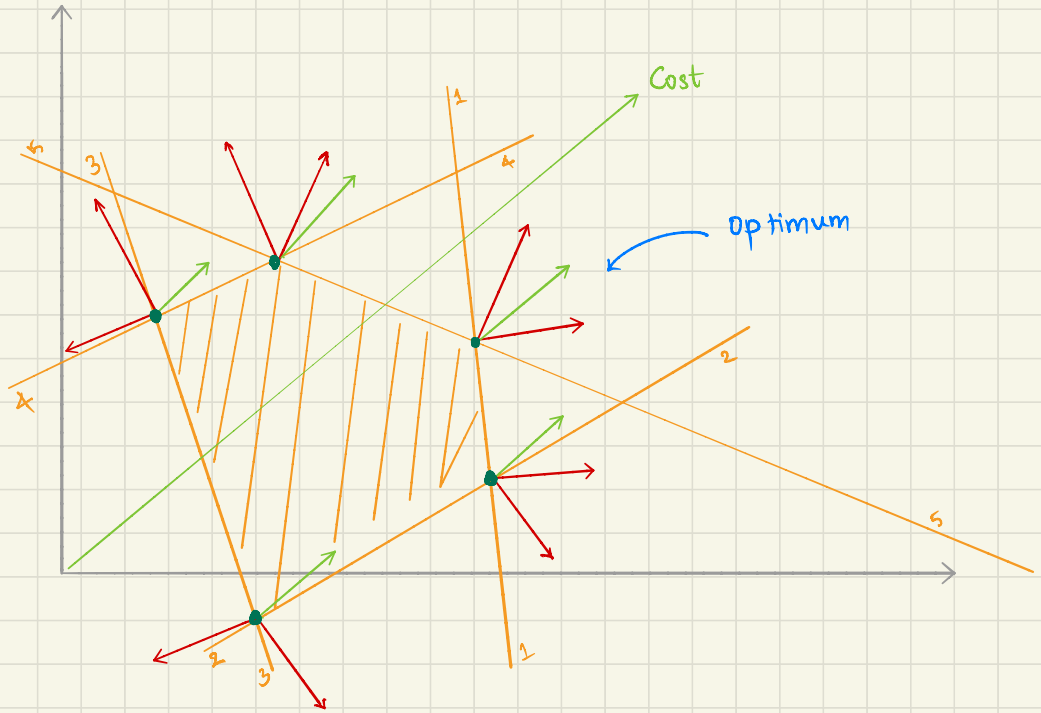
$$= \alpha_1 [1 \ 0 \ 0 \ \dots \ 0]$$

$$\vdots$$
$$\alpha_i (A_i')^T (A')^{-1} = \alpha_i [0 \ 0 \ \dots \ 1 \ \dots \ 0 \ 0]$$

\downarrow
ith place.

$$\therefore [\beta_1 \ \beta_2 \ \dots \ \beta_n] = [\alpha_1 \ \alpha_2 \ \dots \ \alpha_n]$$

GEOMETRIC INTERPRETATION OF DUALITY



Given LP maximize $C^T x$ subject to $Ax \leq b$

- non-degenerate, has optimum

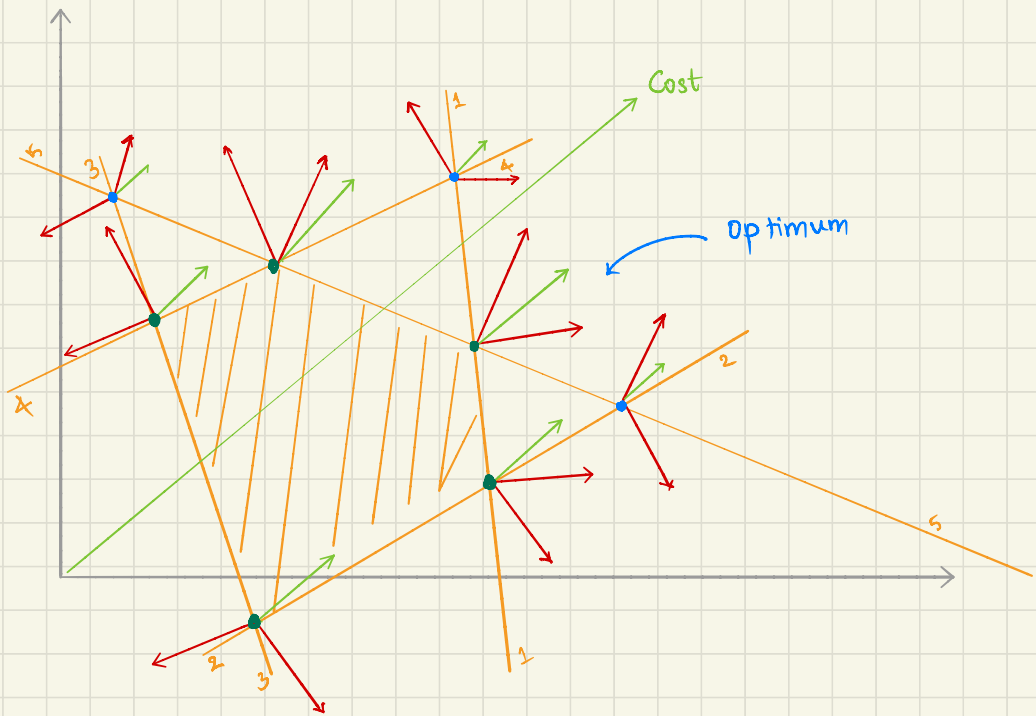
Intersection points: Points satisfying

$$\begin{aligned} A_{i_1} x &= b_{i_1} \\ A_{i_2} x &= b_{i_2} \\ &\vdots \\ A_{i_n} x &= b_{i_n} \end{aligned}$$

for some n linearly independent rows from $Ax \leq b$

- These points need not satisfy the other inequalities.

Extreme points: Intersection points that are also **feasible**.



Define $F :=$ set of intersection points such that cost vector 'c' is a non-negative combination of the outward normals of the defining hyperplanes

Point $x \in F$ satisfying
 $A_i x = b_i, \dots, A_n x = b_n$

$$c^T = \alpha_1 A_{i_1} + \alpha_2 A_{i_2} + \dots + \alpha_n A_{i_n}$$

$$\text{such that } \alpha_{i_1}, \alpha_{i_2}, \dots, \alpha_{i_n} \geq 0$$

Theorem: Optimum of LP is a point in F with minimum cost

To Prove: For every point $x \in F$, $c^T x \geq c^T x_0$, where x_0 is the optimum of the LP.

Proof: To show: $c^T(x - x_0) \geq 0$

Since $x \in F$: $c^T = \alpha_{i_1} A_{i_1} + \alpha_{i_2} A_{i_2} + \dots + \alpha_{i_n} A_{i_n}$, $\alpha_{i_1}, \dots, \alpha_{i_n} \geq 0$

A_{i_1}, \dots, A_{i_n} are hyperplanes defining x .

$$c^T(x - x_0) = \alpha_{i_1} A_{i_1}(x - x_0) + \alpha_{i_2} A_{i_2}(x - x_0) + \dots + \alpha_{i_n} A_{i_n}(x - x_0)$$

$$A_{i_j}(x) = b_{i_j}; \quad A_{i_j}(x_0) \leq b_{i_j} \Rightarrow A_{i_j}(x - x_0) \geq 0$$

$$\Rightarrow c^T(x - x_0) \geq 0$$

- For $x \in F$, with $A_{i_1}x = b_{i_1}, \dots, A_{i_n}x = b_{i_n}$

suppose $c^T = \alpha_{i_1} A_{i_1} + \alpha_{i_2} A_{i_2} + \dots + \alpha_{i_n} A_{i_n}$, $\alpha_{i_1}, \dots, \alpha_{i_n} \geq 0$

define $y \in \mathbb{R}^m$: $\langle y_1, y_2, \dots, y_m \rangle$

$$y_{i_1} = \alpha_{i_1}$$

$$y_j = 0 \quad \text{for } j \notin \{i_1, \dots, i_n\}$$

$$\vdots$$

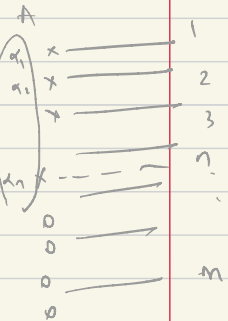
$$y_{i_n} = \alpha_{i_n}$$

Then:

$$c^T x = b^T y$$

define $\bar{F} = \{ \langle y_1, y_2, \dots, y_m \rangle \text{ as above} \mid \text{for each } x \in F \}$

Lemma: $\min \{ b^T y \mid y \in \bar{F} \} = \min \{ c^T x \mid x \in F \} = \text{optimum of primal}$



- For $x \in F$, with $A_{i_1} x = b_{i_1}, \dots, A_{i_n} x = b_{i_n}$

suppose $c^T = \alpha_{i_1} A_{i_1} + \alpha_{i_2} A_{i_2} + \dots + \alpha_{i_n} A_{i_n}$, $\alpha_{i_1}, \dots, \alpha_{i_n} \geq 0$

define $y \in \mathbb{R}^m$: $\langle y_1, y_2, \dots, y_m \rangle$

$$\begin{aligned} y_{i_1} &= \alpha_{i_1} \\ &\vdots \\ y_{i_n} &= \alpha_{i_n} \\ y_j &= 0 \quad \text{for } j \notin \{i_1, \dots, i_n\} \end{aligned}$$

$$\therefore c^T = y_1 A_1 + y_2 A_2 + \dots + y_n A_n, \quad y_i \geq 0$$

$$\begin{aligned} c^T x &= y_1 A_1 x + y_2 A_2 x + \dots + y_n A_n x \\ &= y_{i_1} A_{i_1} x + y_{i_2} A_{i_2} x + \dots + y_{i_n} A_{i_n} x + 0 \dots \\ &= b^T y. \end{aligned}$$

work $x \in F$

MOTIVATION FOR THE DUAL:

Now consider the LP:

Primal:
maximize $c^T x$
subj to $Ax \leq b$

$$\begin{array}{l} \text{minimize } b^T y \\ \text{subject to: } A^T y = c \\ y \geq 0 \end{array}$$

$$\begin{array}{l} Ax \leq b \\ y_1 x \quad \underline{A_1} \\ \vdots \\ y_m x \quad \underline{A_m} \end{array}$$

← cost is a non-negative combination of hyperplanes

→ Above LP is the dual of our considered primal.

Theorem: {Extreme points of dual} equals \bar{F}

Assuming this theorem: + fact that $c^T x_0 \leq b^T y \quad \forall y \text{ feasible (dual)}$

$$\text{Optimum (dual)} = \min \{ b^T y \mid y \in \bar{F} \} = \text{Optimum (Primal)}$$

- $F = \{ \langle x_1, x_2, \dots, x_n \rangle \in \mathbb{R}^n \mid \exists i_1, i_2, \dots, i_n. \}$
 - $A_{i_1} x = b_{i_1}$
 - \vdots
 - $A_{i_n} x = b_{i_n}$
 - A_{i_1}, \dots, A_{i_n} are lin. ind.
 - $c = \alpha_1 A_{i_1} + \dots + \alpha_{i_n} A_{i_n}$
 - $\alpha_{i_1}, \dots, \alpha_{i_n} \geq 0$ }

↓

for x given by , we have a y as follows:

$$\begin{aligned}
 &= y_{i_1} = \alpha_{i_1} \\
 &\quad \vdots \\
 & y_{i_n} = \alpha_{i_n} \\
 & \quad y_j = 0 \quad \forall \text{others.}
 \end{aligned}$$

- $\bar{F} = \{ \langle y_1, \dots, y_m \rangle \mid \text{obtained from each } x \in F \}$.
- Optimum of primal $x_0 \in F$. There will be a corresponding y_0 .
- \forall each $x \in F$, $c^T x = b^T y$ where y corresponds to x .
- $\min \{ c^T x \mid x \in F \} = \min \{ b^T y \mid y \in \bar{F} \} = \text{optimum (primal)}$
↖ follows because $c^T x_0 \leq c^T x$ for all $x \in F$.

Remains to show: \bar{F} is the set of extreme points of dual.

- Since dual is in equational form, this is equivalent to showing:
 \bar{F} is the set of all bfs of dual.

↳ (Exercise)

Summary:

- Consider all intersection points of primal such that cost is a non-negative combination of the rows corresponding to the defining hyperplanes.
- Optimum (primal) is a point with least cost in the above set.
- leads to the definition of dual, and duality theorem.