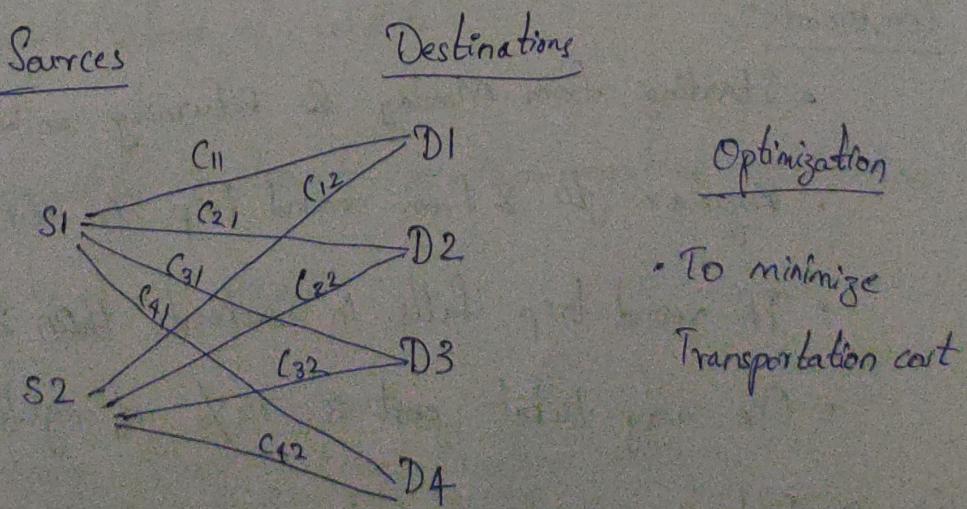


- Cost Function / Objective function / Risk function
 - Minimization or Maximization
 - 1. Cost (Depends on no. of gates) • No. of gates ↑ - Area ↑
 - 2. Delay Power consumption ↑
 - 3. Speed Cost ↑
 - for speed, Parallel processing - but it increases hardware
- DSP system : Adders, Multipliers, Delay elements }
Digital system : Logic gates
Analog System : R, C, Diodes, Transistors }
Building Blocks
- Minimizing cost, Maximizing Productivity
- 04/01/2023

Ex : Coalmine - Transportation



- Optimization always tries to optimize objective function.
(either maximization or minimization)

→ Optimizing or minimizing cost.

→ Optimizing or maximizing productivity.

- Consider constraints
 - Equality constraints
 - Non-equality constraints

- How to maximize or minimize objective function.

\Rightarrow Objective function & Constraints are based on "Decision variables"

Mathematical Modelling to Optimization Model:

- Abde to have alternatives.

Ex: VJA \rightleftarrows BNG for 5 weeks Starting from Jan 2023 to Feb 3rd 2023

Constraints:

- Starting from Monday & returning on Wednesday

- Regular to & from round trip is 10k/-

- If round trip falls in weekends then 20% discount

- One way ticket cost is 75% of regular fare

Q → Optimize cost of booking?

• Option 1: M

Option 2: I

Option 3: J

Ex: Garden-

Constraint:

To maximize

Objective function:

Decision Variable

Infinite no.

different

→ Inequal.

w

Linear

Option 1: Mon to Wed - for 5 weeks (round trip) $\Rightarrow 50K$

Option 2: 10 - one way tickets $\Rightarrow 37.5K$

Option 3: Jan 2nd - Feb 1st (round trip falls on weekends)
start end

$$\Rightarrow 5 \times 10K \times 0.20$$

Ex: Garden - Fencing • Length of fencing (fixed) is L'

Constraint: $2(w+h) = L$

To maximize/optimize the area

Objective function: $A = w \times h$

Decision Variables: w & h

Infinite no. of alternatives as we can choose different values of w & h.

\rightarrow Inequality constraint or Non-negative restriction

$$w > 0, h > 0$$

Linear Programming Problem \rightarrow

If objective function and constraints are linear in nature then that optimization is called as Linear Programming Problem (LPP)

- Q. A pharmaceutical company produces 3 types of medicines M₁, M₂, M₃. For manufacturing these medicines, 3 types of ingredients I₁, I₂, I₃ are required.
- 1 M₁ requires 3 units of I₁, 2 of I₂ and 1 M₂ requires 2 of I₁, 3 of I₂, 4 of I₃ and 1 M₃ requires 4 of I₁, 3 of I₂. Company has stock of 40 of I₁, 30 of I₂, 45 of I₃. Profit of M₁, M₂, M₃ are Rs 8, Rs 13, Rs 10. Formulate problem as an LPP so that company maximize the profit.

Sol:

	M ₁	M ₂	M ₃	Availability of Stock
I ₁	3	2	0	40
I ₂	2	3	0	30
I ₃	0	4	3	45

Decision Variables : x₁, x₂, x₃

No. of M_i manufactured } : x₁, x₂, x₃
 i = 1, 2, 3
 M₁ M₂ M₃

$$\text{Profit} : 8x_1 + 13x_2 + 10x_3$$

$$Z = f(x)$$

• Objective function: (which needs to be Maximized)

$$\text{Optimize / Maximize} : Z = 8x_1 + 13x_2 + 10x_3$$

$$\begin{aligned} & \text{Subject to} : \quad \left. \begin{aligned} & 3x_1 + 2x_2 + 4x_3 \leq 40 \\ & 2x_1 + 3x_2 \leq 80 \\ & 4x_2 + 3x_3 \leq 45 \\ & x_1, x_2, x_3 \geq 0 \end{aligned} \right\} \text{Constraints} \\ & \quad (I_1 \rightarrow 40) \\ & \quad (I_2 \rightarrow 30) \end{aligned}$$

• Constraints and Objective function Linear in nature
 \Rightarrow LPP

2 Problem : LPP to minimize total no. of waiters required.

• Hotel operates 24 hours

<u>Period</u>	<u>Time</u>	<u>minimum no. of waiters required</u>
1	7am - 11am	6
2	11am - 3pm	12
3	3pm - 7pm	8
4	7pm - 11pm	16
5	11pm - 3am	5
6	3am - 7am	3

$$\begin{aligned} x_1 + x_2 &\leq 6 \\ x_2 + x_3 &\leq 12 \\ x_3 + x_4 &\leq 8 \\ x_4 + x_5 &\geq 16 \end{aligned}$$

A waiter reports to the hotel manager at the beginning of the period and continues to work for 8 hours.

LPP - Linear Programming Problem

19/01/2023

- Objective function

- Constraints \rightarrow Inequality

- \rightarrow Non-negative restrictions

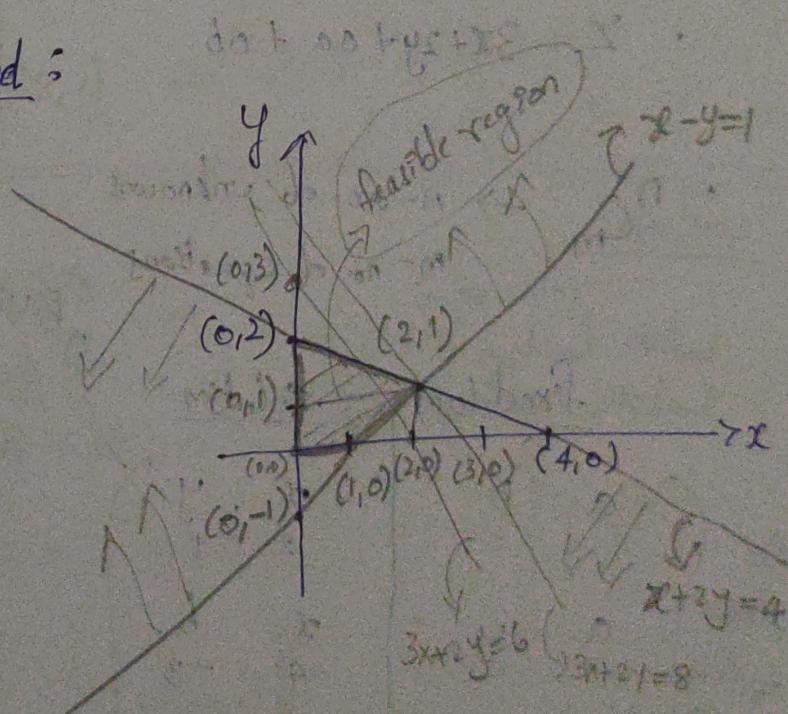
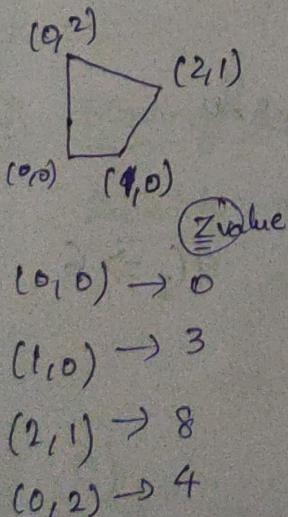
Ex: Objective function : $\underset{\text{Maximize}}{Z = 3x + 2y}$

Subject to : $x + 2y \leq 4$ } Inequality
 $x - y \leq 1$ } constraint

$x \geq 0, y \geq 0$ } Non-negative restrictions.

Using

Sol: Graphical Method:



- Maximization of objective function occurs at $(2,1) \equiv (x,y)$

$$\boxed{Z=8}$$

- Points on the line & in the region do not maximize (except the boundary points)

Sol: Using Algebraic Method : $Z = 3x + 2y$

$$x + 2y \leq 4$$

Introducing a new variable "a". $x + 2y + a = 4$; $a \geq 0$

$$x - y \leq 1$$

Introducing a new variable "b". $x - y + b = 1$; $b \geq 0$

- a, b are slack variables; as they do not contribute anything to the objective function.

$$Z = 3x + 2y + 0a + 0b$$

Fix non-basic variables
and solve for Basic variables

$n_m \rightarrow n - m$ no. of unknowns
 m - no. of equations

Basic Variables

		<u>Solution</u>		Z
		x	y	
<u>Non basic variables</u>		2	1	8
a	y	x	b	-
		= 4	-3	
a	x	b	y	4
		-3	2	
b	y	a	x	3
		3	1	
b	x	a	y	-
		6	-1	
x	y	a	b	0

Ex: Ma

Sob

Sol: (0)

(2, 3)

(0, 5)

(0, 0)

(4, 0)

$$a=0, x=0$$

$$z = 3x + 2y$$

$$z + 2y + a = 4$$

$$4a + ab$$

$$z - y + b = 1$$

$$\begin{cases} 2y = 4 \\ b - y = 1 \end{cases} \quad \begin{cases} y = 2 \\ b = 3 \end{cases}$$

$$z = 4$$

$$a=1, x=0$$

$$\begin{cases} 2y + 1 = 4 \\ b - y = 1 \end{cases} \quad \begin{cases} y = 1.5 \\ b = 2.5 \end{cases} \quad z = 3$$

$$a=0, x=1$$

$$\begin{cases} 2y + 1 = 4 \\ b - y = 1 \end{cases} \quad \begin{cases} y = 1.5 \\ b = 2.5 \end{cases} \quad z = 3$$

$$\therefore (x, y) = (2, 1) \Rightarrow z = 8$$

20/01/2023

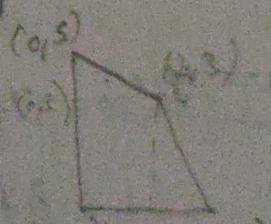
Ex: Maximize: $6x_1 + 5x_2$

Subject to: $x_1 + x_2 \leq 5$

$$3x_1 + 2x_2 \leq 12$$

and $x_1 \geq 0, x_2 \geq 0$

Solve using
 (i) Graphical Method
 (ii) Algebraic Method



$$\text{Sd: (i)} \quad z = 6x_1 + 5x_2$$

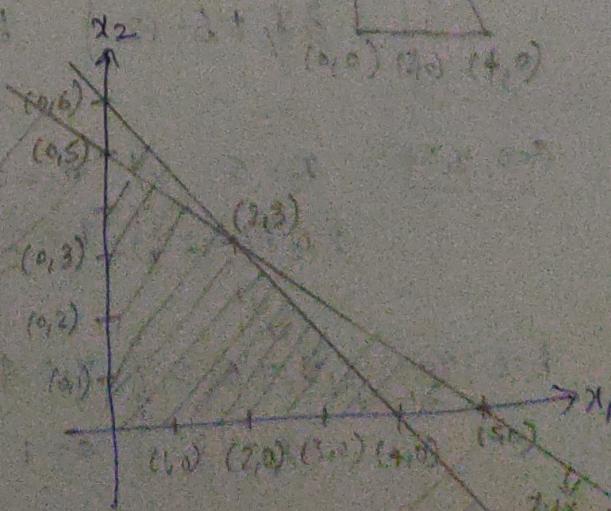
$$(2, 3) \Rightarrow z = 12 + 15 = 27$$

$$(0, 5) \Rightarrow z = 25$$

$$(0, 0) \Rightarrow z = 0$$

$$(4, 0) \Rightarrow z = 24$$

$$\therefore (x_1, x_2) = (2, 3)$$



$$3x_1 + 2x_2 = 12$$

(i) Algebraic Method

20/01/2023

$$Z = 6x_1 + 5x_2 + ax + ob$$

$$x_1 + x_2 \leq 5$$

$$2x_1 + 2x_2 \leq 12$$

$$x_1 + x_2 + a = 5 ; a \geq 0$$

$$3x_1 + 2x_2 + b = 12 ; b \geq 0$$

fixed (0,0)		Solution		Z
a	b	x_1	x_2	
0	0	2	3	27
a	x_2	x_1	b	-
0	0	5	-3	
a	x_1	b	x_2	
0	0	2	5	25
b	x_2	a	x_1	
0	0	1	4	24
b	x_1	a	x_2	
0	0	-1	6	-
x_1	x_2	a	b	0
0	0	5	12	

$$\therefore (x_1, x_2) \\ = (2, 3)$$

$$a=0, b=0 : \quad x_1 + x_2 = 5 \\ 3x_1 + 2x_2 = 12$$

$$\begin{cases} 3x_1 + 2x_2 = 12 \\ 2x_1 + 2x_2 = 10 \end{cases}$$

$$x_1 = 2$$

$$x_2 = 3$$

$$a=0, x_2=0 : \quad x_1 + a = 5 \\ 3x_1 + b = 12$$

$$x_1 = 5 \\ b = -3$$

$$b=0, x_1=0 : \quad x_2 + a = 5$$

$$a=0, x_1=0 : \quad x_2 = 5 \\ 2x_2 + b = 12$$

$$2x_2 = 12 \\ \Rightarrow x_2 = 6 \\ a = -1$$

$$b=0, x_2=0 : \quad x_1 + a = 5 \\ 3x_1 = 12$$

$$x_1 = 0, x_2 = 0 : \quad a = 5 \\ b = 12$$

- As n^T , no. of possible ways T
- $x_1 > x_2$, no need calculate x_2 iteration
- If x_1 is the max., then no need to move further.

Iteration-1 : $Z = 6x_1 + 5x_2 + 0a + 0b$

$$a = 5 - x_1 - x_2$$

$$b = 12 - 3x_1 - 2x_2$$

$$Z = 6x_1 + 5x_2$$

$$(x_1, x_2) = (0, 0) \Rightarrow Z = 0$$

$x_1 = 0$
$x_2 = 0$

$x_2 = 0$
$b = \emptyset$

Iteration-2 :

x_1, x_2 - Basic variables

$$3x_1 = 12 - 2x_2 - b$$

$$\Rightarrow x_1 = 4 - \frac{2}{3}x_2 - \frac{1}{3}b$$

$$b = 12 - 3x_1 \rightarrow x_1 = 4$$

(max)

$$\text{and } x_1 = 5 - x_2 - a$$

(0)

$$a = 5 - x_1 - x_2$$

$$\Rightarrow a = 5 - \left(4 - \frac{2}{3}x_2 - \frac{1}{3}b\right) - x_2$$

$$= 1 + \frac{2}{3}x_2 - x_2 + \frac{1}{3}b$$

$$= 1 - \frac{1}{3}x_2 + \frac{1}{3}b$$

$$= 1 - \frac{1}{3}x_2 + \frac{1}{3}(12 - 3x_1 - 2x_2)$$

$a = 5 - x_2 - x_1$

$$\therefore Z = 6x_1 + 5x_2 = 6\left(4 - \frac{2}{3}x_2 - \frac{1}{3}b\right) + 5x_2 \quad a = 1$$

$$Z = 24 + x_2 - 2b$$

$$(x_2, b) = (0, 0) \Rightarrow Z = 24$$

$x_1 = 4 - \frac{2}{3}x_2 - \frac{1}{3}b$

$a = 1 - \frac{1}{3}x_2 + \frac{b}{3}$
--

Disadvantages of Algebraic Method:

24/01/2023

- 1) As variables ↑, No. of possible combinations / ways solutions also increases.
- 2) Objective functions need to be calculated for all possible combinations.
- 3) We should be able to discard a combination whose solution is less than the existing optimized solution.
- 4) We should be able to terminate / stop the process, once we reach the optimized solution.
 - No. of iterations should be reduced.
 - Iterations which are not necessary, need to be discarded.
 - Process should be progressive towards optimized solution.

Iteration 3: $\mathbf{x}_3 = 0$ and x_1, x_2 are slack variables

$$x_1 + x_2 + a = 5 \quad \text{and} \quad 3x_1 + 2x_2 + b = 12$$

$$x_1 = 5 - x_2 - a$$

$$2x_2 = 12 - 3x_1 - b$$

$$x_2 = 6 - \frac{3}{2}x_1 - \frac{b}{2}$$

$$x_1 = 5 - 6 + \frac{3}{2}x_1 + \frac{b}{2} - a$$

$$a = 5 - x_1 - x_2$$

$$-\frac{1}{2}x_1 = -1 + \frac{b}{2} - a$$

$$a = 6 - x_1$$

$$x_1 = 2 - b + 2a$$

$$Z = 2x_1 + 5x_2$$

$$Z = 5x_1 + 5x_2$$

Solving for x_2 : $x_2 = 5 - a - x_1$

$$x_1 = 4 - \frac{2}{3}x_2 - \frac{1}{3}x_4 \rightarrow \max \text{ of } x_2 = 6$$

$$x_3 = 1 - \frac{1}{3}x_2 + \frac{1}{3}x_4 \rightarrow \max \text{ of } x_2 = 3$$

Non-basic Variables : $(a, b) = (0, 0)$ Basic Variables : x_1, x_2

$$a = 5 - x_2 - x_1$$

$$x_1 = 4 - \frac{2}{3}x_2 - \frac{1}{3}b$$

$$a = 1 - \frac{x_2}{3} + \frac{b}{3}$$

$$x_1 = 4 - \frac{2}{3}(3 + 6 - 3a) - \frac{1}{3}b$$

$$x_2 = 3 + b - 3a$$

$$x_1 = 4 - 2 - b + 2a$$

$$Z = 27 + 3a - b \rightarrow \max$$

$Z = 27$ cannot be further proceeded

① Simplex Algorithm in Algebraic form

Maximize: $Z = 6x_1 + 5x_2 + 0x_3 + 0x_4$

Subject to: $x_1 + x_2 \leq 5$, $3x_1 + 2x_2 \leq 12$, $x_1, x_2 \geq 0$

$$x_1 + x_2 + x_3 = 5, 3x_1 + 2x_2 + x_4 = 12, x_3, x_4 \geq 0$$

Iteration 1: $x_1, x_2 = 0, 0 \rightarrow$ Non basic variables & $x_3, x_4 \rightarrow$ Basic variables

$$x_3 = 5 - x_1 - x_2$$

$$x_4 = 12 - 3x_1 - 2x_2$$

$$\Rightarrow Z = 6x_1 + 5x_2 + 0x_3 + 0x_4$$

$$(x_1, x_2) = (0, 0) \Rightarrow Z = 0$$

As in Z, x_1 coefficient > x_2 coefficient, make x_1 as basic variable
 → Make x_2 & x_4 as non basic variables

$$\text{as } x_3 = 5 - x_1 - x_2 \rightarrow x_1(\max) = 5$$

$$x_4 = 12 - 3x_1 - 2x_2 \rightarrow x_1(\max) = 4 \rightarrow \min$$

Iteration 2: $x_2, x_4 = 0, 0$ and x_1, x_3 - Basic Variables

$$3x_1 + 2x_2 + x_4 = 12$$

$$x_1 = 4 - \frac{2}{3}x_2 - \frac{1}{3}x_4$$

$$\left| \begin{array}{l} x_3 = 5 - x_1 - x_2 \\ x_3 = 5 - \left(4 - \frac{2}{3}x_2 - \frac{1}{3}x_4\right) - x_2 \\ x_3 = 1 - \frac{1}{3}x_2 + \frac{1}{3}x_4 \end{array} \right.$$

$$\Rightarrow Z = 6\left(4 - \frac{2}{3}x_2 - \frac{1}{3}x_4\right) + 5x_2$$

$$Z = 24 + x_2 - 2x_4$$

$$\boxed{Z = 24}$$

Iteration 3: $x_3, x_4 \geq 0, 0$ and x_1, x_2 - Basis variables

, Make x_2 as basic variable as in Z, coefficient of x_2 is greater than x_4 .

, Make x_3 as non-basic variable as

$$x_1 = 4 - \frac{2}{3}x_2 - \frac{x_4}{3} \rightarrow x_2(\max) = 6$$

$$x_3 = 1 - \frac{1}{3}x_2 + \frac{1}{3}x_4 \rightarrow x_2(\max) = 3 \rightarrow \min$$

$$\Rightarrow x_3 = 5 - x_2 - x_1$$

$$x_3 = 1 - \frac{x_2}{3} + \frac{x_4}{3}$$

$$\Rightarrow x_2 = 3 + x_4 - 3x_3$$

$$x_1 = 4 - \frac{2}{3}x_2 - \frac{1}{3}x_4$$

$$x_1 = 4 - \frac{2}{3}(3 + x_4 - 3x_3) - \frac{1}{3}x_4$$

$$\Rightarrow x_1 = 2 - x_4 + 2x_3$$

$$\Rightarrow Z = 6(2 - x_4 + 2x_3) + 5(3 + x_4 - 3x_3)$$

$$\Rightarrow Z = 27 - 3x_3 - x_4$$

$$Z = 27$$

$$x_3 \geq 0, x_4 \geq 0$$

$$\therefore \text{Maximum } Z = 27$$

(2) Simplex Algorithm - Tabular form Method

25/01/2023

Maximize : $Z = 6x_1 + 5x_2 + 0x_3 + 0x_4$

Subject to : $x_1 + x_2 + x_3 = 5$

$3x_1 + 2x_2 + x_4 = 12$

- ① Initialization
- ② Iterations
- ③ Termination

Ex: Maximization
Subject to

C_j^0 (Basic variables)	x_1	x_2	x_3	x_4	R.H.S	θ
0 x_3	1	1	$\begin{bmatrix} 1 & 0 \end{bmatrix}$	5	$\frac{5}{1} = 5$	Set
0 x_4	3	2	$\begin{bmatrix} 0 & 1 \end{bmatrix}$	12	$\frac{12}{3} = 4$	Leave (min)
Z_j^0	$0x_1+0x_3 = 0$	$0x_1+0x_2 = 0$	$0x_1+0x_0 = 0$	$0x_0+0x_1 = 0$		
$C_j^0 - Z_j^0$	6 \uparrow (max)	5	0	0	$Z_j^0 = 0$	
0 x_3	0	$\frac{1}{3}$	1	$-\frac{1}{3}$	$\frac{1}{1/3} = 3$	Leave (min)
6 x_1	1	$\frac{2}{3}$	0	$\frac{1}{3}$	$\frac{4}{2/3} = 6$	
$C_j^0 - Z_j^0$	0	1 \uparrow (max)	0	-2	$Z_j^0 = 24$	
5 x_2	0	1	3	-1	$3 - (x_3 x_3) \Rightarrow x_3 x_3$	
6 x_1	1	0	$-2/3 x_3$ $= -2$	$\frac{1}{3} - (-1 \cdot \frac{2}{3}) = 1$	$4 - 3 \cdot \frac{2}{3} = 2 \Rightarrow x_1 - \frac{2}{3} x_2$	
$C_j^0 - Z_j^0$	0	0	$0 - (15 - 12) = -3$	$0 - (-5 + 6) = -1$	$5x_3 + 6x_2 = 27$	Maximum $\therefore Z = 27$

- Termination point : At which zeroes and -ve values are present

C_j^0	6
x_3	1
x_4	2
x_5	1
$C_j^0 - Z_j^0$	6
x_3	$\frac{4}{5}$
x_4	$2 - \frac{3}{5} = \frac{7}{5}$
x_2	$\frac{1}{5}$
$C_j^0 - Z_j^0$	$6 - \frac{8}{5} = 4.2$
x_3	0
x_1	1
x_2	0
$C_j^0 - Z_j^0$	0

01/2023

igation
tions
nation
OEx: Maximize: $6x_1 + 8x_2$ Subject to: $x_1 + x_2 \leq 10$ $2x_1 + 3x_2 \leq 25$ $x_1 + 5x_2 \leq 35$ $x_1, x_2 \geq 0$

$$Z = 6x_1 + 8x_2 + 0x_3 + 0x_4 + 0x_5$$

$$x_1 + x_2 + x_3 = 10$$

$$2x_1 + 3x_2 + x_4 = 25$$

$$x_1 + 5x_2 + x_5 = 35$$

$$x_1, x_2, x_3, x_4, x_5 \geq 0$$

θ

$$\frac{5}{1} = 5$$

$$\frac{12}{3} = 4 \xrightarrow{\text{leave min}}$$

$$\frac{1}{1/3} = 3 \xrightarrow{\text{leave min}}$$

$$\frac{4}{2/3} = 6$$

C_j^0	6	8	0	0	0	RHS	θ
x_1	1	2	x_3	x_4	x_5		
x_3	1	1	1	0	0	10	$\frac{10}{1}$
x_4	2	3	0	1	0	25	$\frac{25}{3} = 8\frac{1}{3}$
x_5	1	5	0	0	1	35	$\frac{35}{5} = 7 \xrightarrow{\text{leave}}$
$C_j - Z_j^0$	6	8	enter	0	0	0	
x_3	$\frac{4}{3}$	0	1	0	$-\frac{1}{5}$	$10 - 7 = 3$	$\frac{15}{4} = 3\frac{3}{4}$
x_4	$2 - \frac{3}{5} = \frac{7}{5}$	0	0	$\frac{1}{5}$	$-\frac{3}{5}$	$25 - 21 = 4$	$\frac{20}{7} = 2\frac{6}{7}$
x_2	$\frac{1}{5}$	1	0	0	$\frac{1}{5}$	7	35
$C_j - Z_j^0$	$6 - \frac{8}{5} = \frac{22}{5}$	0	0	0	$-\frac{8}{5} = -1.6$	56	

 $\Rightarrow x_3, x_3$

$$\Rightarrow x_1 - \frac{2}{3}x_2$$

Maximum

$$\therefore Z = 27$$

values are

$C_j - Z_j^0$	0	0	0	$-\frac{22}{7}$	$\frac{2}{7}$ enter	$\frac{480}{7}$	Y
x_3	0	0	1	$-\frac{4}{7}$	$-\frac{1}{5} + \frac{12}{35} = \frac{5}{35} = \frac{1}{7}$	$3 - \frac{80}{35} = \frac{5}{7}$	$\frac{5}{7} \xrightarrow{\text{leave}}$
x_1	1	0	0	$\frac{5}{7}$	$-\frac{3}{7}$	$\frac{20}{7}$	$\frac{-20}{3} \xrightarrow{\text{leave}}$
x_2	0	1	0	$-\frac{1}{7}$	$\frac{1}{5} + \frac{3}{35} = \frac{10}{35} = \frac{2}{7}$	$7 - \frac{4}{7} = \frac{45}{7}$	$\frac{45}{2} = 22.5$

C_j^o	x_1	x_2	x_3	x_4	x_5	RHS
$0 x_3$	$\frac{7}{3}x_1 - \frac{1}{7} = \frac{1}{3}$	0	1	$-\frac{4}{7} + \frac{5}{49} = \frac{-23}{49}$	0	$\frac{5}{7} + \frac{20}{21} = \frac{35}{21} = \frac{5}{3}$
$0 x_5$	$-\frac{7}{3}$	0	0	$-\frac{5}{7}$	1	$\frac{20}{7}x_1 - \frac{7}{3} = -\frac{20}{3}$
$8 x_2$	$\frac{7}{3}x_1 - \frac{2}{7} = \frac{2}{3}$	1	0	$-\frac{1}{7} + \frac{10}{49} = \frac{3}{49}$	0	$\frac{45}{7} + \frac{40}{21} - \frac{175}{21} = \frac{75}{21} = \frac{25}{2} = 12.5$
$C_j^o - Z_j^o$	$6 - \frac{16}{3}$ $= 2/3$	↑ enter	0	-24 $\frac{49}{49}$	0	$\frac{1400}{21} = \frac{200}{3}$ $= 66.67$
$0 x_3$	0	0	1	$-\frac{23}{49} - \frac{1}{3}x_1 - \frac{15}{49} = \frac{-28}{49}$	$\frac{3}{7}x_1 - \frac{1}{7} = \frac{1}{7}$	$\frac{5}{3} - \frac{20}{21} = \frac{15}{21}$
$6 x_1$	1	0	0	$-\frac{5}{7}x_1 - \frac{3}{7} = \frac{15}{49}$	$-\frac{3}{7}$	$\frac{15}{21}x_1 = 5$
$8 x_2$	0	1	0	$\frac{3}{49} - \frac{2}{3}x_1 - \frac{15}{49} = \frac{-7}{49}$ $= -\frac{1}{7}$	$\frac{-3}{7}x_1 - \frac{2}{7} = \frac{2}{7}$	$\frac{20}{7}$ $\frac{20}{7}x_1 - \frac{7}{3} = -\frac{20}{3}$
$C_j^o - Z_j^o$	0	0	0	$-\left(\frac{90}{49} - \frac{56}{49}\right)$ $= -\frac{34}{49}$	$-\left(\frac{-18}{7} + \frac{16}{7}\right)$ $= \frac{2}{7}$	$\frac{120}{7} + \frac{1080}{21}$ $= 68.57$

Standard form of Linear Programming

27/01/2023

Problem (LPP)

- (1) It's always a minimization problem.
- (2) (all constraints are linear equations.)
- (3) Decision variables are always non-negative.

Scalar form

Minimize : $f(x_1, x_2, \dots, x_n) = c_1 x_1 + c_2 x_2 + \dots + c_n x_n$

Objective function

Subject to the constraints :

$$a_{11} x_1 + a_{12} x_2 + \dots + a_{1n} x_n = b_1$$

$$a_{21} x_1 + a_{22} x_2 + \dots + a_{2n} x_n = b_2$$

$$a_{m1} x_1 + a_{m2} x_2 + \dots + a_{mn} x_n = b_m$$

and $x_1 \geq 0, x_2 \geq 0, \dots, x_n \geq 0$ (Non-negative restriction)

↳ (decision variables)

Vector / Matrix form

Minimize : $f(\vec{x}) = \vec{c}^T \cdot \vec{x}$

Subject to the constraints : $\vec{A} \vec{x} = \vec{B}$

and $\vec{x} \geq 0$ (non-negative restriction)

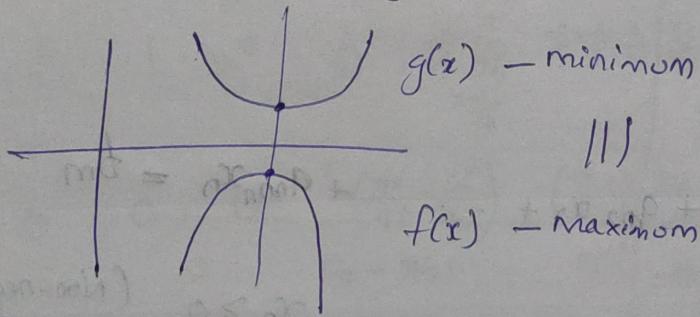
where

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \quad \vec{c} = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{bmatrix}$$

$$\vec{A} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix} \quad \vec{B} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}$$

and c_i, b_j, a_{ij} ($i=1, 2, \dots, n$ and $j=1, 2, \dots, m$)
are known constants.

- How to solve maximization problem



- We have 'm' equations and 'n' unknowns

Case 1: if $m=n$ - Algebraic problem (1-solution)

Case 2: if $m>n$ - Eqs. ~~are coincident~~ coincide

Case 3: if $m< n$ - Infinite solution \rightarrow The solution at which
given objective function ~~is~~ maximum or minimum

Problem: Minimize: $Z = 3x_1 + 4x_2$

Maximize: $Z' = -3x_1 - 4x_2$

Subject to: $2x_1 + 3x_2 \geq 8$

$5x_1 + 2x_2 \geq 12$

$x_1, x_2 \geq 0$

Sol: Using Simplex Algorithm:

Maximize:

Introducing slack variables: $Z = -3x_1 - 4x_2 - 0x_3 - 0x_4$

Subject to: $2x_1 + 3x_2 - x_3 = 8 ; x_3 \geq 0$

$5x_1 + 2x_2 - x_4 = 12 ; x_4 \geq 0$

C_j	-3	-4	0	0	RHS	θ
x_1	2	3	-1	0	8	
x_4	5	2	0	-1	12	
$C_j - Z_j$	-3	-4	0	0		

When nonbasic variables: $x_1, x_2 = 0, 0$

$x_3 = -8$ & $x_4 = -12$

Not a feasible solution

• It failed at the first step
i.e. Initialization step

• So introduce variables: Artificial (surplus) variables
(which does not have physical significance)

• Slack variables : has physical significance (the leftover materials)
Does not contribute to objective function

• Minimize :
Subject to :

• Artificial variables : has no physical significance
Does ~~not~~ contribute to objective function
(not?)

Maximizes: $Z^l = -3x_1 - 4x_2 - 0x_3 - 0x_4 - Ma_1 - Ma_2$

Subject to: $2x_1 + 3x_2 - x_3 + a_1 = 8$

$5x_1 + 2x_2 - x_4 + a_2 = 12$

~~X~~ Big M Method

C_j^0	-3	-4	0	0	-M	-M	RHS	Θ
	x_1	x_2	x_3	x_4	a_1	a_2		
$-Ma_1$	2	3	-1	0	1	0	8	4
$-Ma_2$	5	2	0	-1	0	1	12	$\frac{12}{5} = 2.4 \rightarrow$
$C_j^0 - Z_j^0$	$-3 + M$	$-4 + 5M$	-M	-M	0	0		
$-Ma_1$	0	$3 - \frac{4}{5} = \frac{11}{5}$	-1	$2/5$	1	$-2/5$	$\frac{8 - 4 \cdot 8}{5} = \frac{16}{5} = 3.2 \rightarrow$	$\frac{16}{11} \rightarrow$
$-3x_1$	1	$2/5$	0	$-4/5$	0	$1/5$	$2 \cdot 4 = \frac{12}{5}$	6
$C_j^0 - Z_j^0$	0	$\frac{11M - 14}{5}$	-M	$\frac{2M - 3}{5}$	0	$\frac{2M + 3}{5}$		
$-4x_2$	0	1	$-5/11$	$2/11$	$5/11$	$-2/11$	$\frac{16}{11}$	
$-3x_1$	1	0	$2/11$	$-\frac{15}{55} = -\frac{3}{11}$	$-2/11$	$\frac{15}{55} = \frac{3}{11}$	$\frac{20}{11}$	
$C_j^0 - Z_j^0$	0	$-\frac{20}{11} + \frac{6}{11} = -\frac{14}{11}$	$-\frac{9}{11} + \frac{6}{11} = -\frac{3}{11}$	$(-M + \frac{10 - 6}{11}) = -M + \frac{4}{11}$			$Z_j^0 = \frac{-64 - 60}{11} = -124/11$	

$\therefore \text{Maximum: } Z^l = -\frac{124}{11}$

$x_1 = 20/11$
 $x_2 = 16/11$

Minimum: $Z = \frac{124}{11}$

S.t: $2x_1 +$
 $5x_1 +$

Phase-0:

	0	
	x_1	
-1 a_1	2	
-1 a_2		
$C_j^0 - Z_j^0$		
-1 a_1		
0 x_1		
$C_j^0 - Z_j^0$		
0 x_2		
0 x_1		
$C_j^0 - Z_j^0$		

Minimize: $Z = 3x_1 + 4x_2$

Subject to: $2x_1 + 3x_2 \geq 8$

$5x_1 + 2x_2 \geq 12$, ($x_1, x_2 \geq 0$)

Primal LPP

31/01/2023

Two-Phase Method

S.T.:
 $2x_1 + 3x_2 - x_3 + a_1 = 8$

$5x_1 + 2x_2 - x_4 + a_2 = 12$

Maximize: $Z^1 = -3x_1 - 4x_2$

$-5x_3 - 2x_4$

$-Ma_1 - Ma_2$

Dual LPP: $Z^1 = 8y_1 + 12y_2$; S.T.: $2y_1 + 5y_2 \leq 3$
 Phase-01: Maximize $3y_1 + 2y_2 \leq 4$

	x_1	x_2	x_3	x_4	a_1	a_2	R.H.S	θ
-1 a_1	2	3	-1	0	1	0	8	$\frac{8}{2} = 4$
-1 a_2	5	2	0	-1	0	1	12	$\frac{12}{5} = 2.4$ → leave
$G_j - Z_j^1$	7	5	-1	-1	0	0		
-1 a_1	0	$\frac{3-4}{5} = \frac{11}{5}$	-1	$\frac{2}{5}$	1	$-\frac{2}{5}$	$\frac{8-24}{5} = \frac{16}{5}$	$\frac{16}{5} \times \frac{5}{11} = \frac{16}{11} = 1.4$
0 x_1	1	$\frac{2}{5}$	0	$-\frac{1}{5}$	0	$\frac{1}{5}$	$\frac{12}{5}$	$\frac{12}{5} \times \frac{5}{2} = 6$
$G_j - Z_j^1$	0	$\frac{11}{5}$	-1	$\frac{2}{5}$	0	$-\frac{7}{5}$		
0 x_2	0	1	$-\frac{5}{11}$	$\frac{2}{11}$	$\frac{5}{11}$	$-\frac{2}{11}$	$\frac{16}{5} \times \frac{5}{11} = \frac{16}{11}$	
0 x_1	1	0	$\frac{5 \times 2}{11} = \frac{2}{11}$	$-\frac{1}{3} - \frac{4}{55}$	$-\frac{5}{11} \times \frac{2}{3}$	$\frac{1}{5} + \frac{4}{55}$	$\frac{12-32}{5} = \frac{52}{55}$	$= \frac{100}{55} = \frac{20}{11}$
$G_j - Z_j^1$	0	0	0	0	-1	-1		

Termination step

Phase-02:

$$Z = -3x_1 + 4x_2 - 0x_3 - 0x_4$$

$$\text{Max}^e \\ \therefore Z = \frac{-124}{11}$$

$$\therefore Z_{\min} = \frac{-124}{11}$$

	-3	-4	0	0	
	x_1	x_2	x_3	x_4	RHS
$-4x_2$	0	1	$\frac{-9}{11}$	$\frac{2}{11}$	$\frac{16}{11}$
$-3x_1$	1	0	$\frac{2}{11}$	$\frac{-3}{11}$	$\frac{20}{11}$
$C_j - Z_j^*$	0	0	$\frac{-20+6}{11} = \frac{-14}{11}$	$\frac{8-9}{11} = \frac{-1}{11}$	$\frac{-64-60}{11} = \frac{-124}{11}$

Maximize: $Z'' = 8y_1 + 12y_2$; S.T: $2y_1 + 5y_2 \leq 3$ & $3y_1 + 2y_2 \leq 4$

Dual LPP

	8	12	0	0		
	y_1	y_2	s_1	s_2	RHS	Obj
0 s_1	2	5	1	0	3	$\frac{3}{2} = 1.5$
0 s_2	3	2 ↑	0	1	4	$\frac{4}{3} = 1.33 \rightarrow \text{Leave}$
$C_j - Z_j^*$	8	12	0	0		
0 s_1	$2 - \frac{15}{2} = -\frac{11}{2}$	0	1	$-5/2$	$3 - 10 = -7$	
12 y_2	$3/2$	1	0	y_2	2	
$C_j - Z_j^*$	8 - 18 = -10	0	0	0	24	

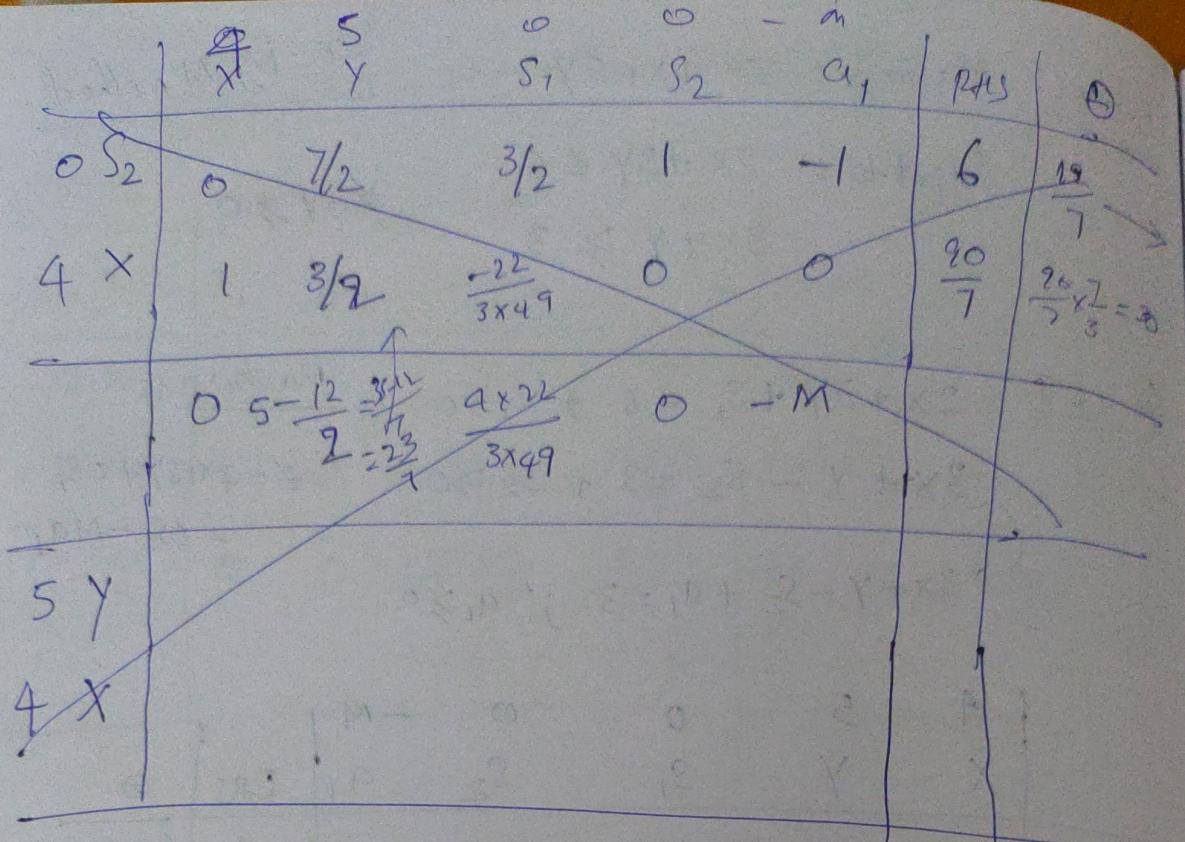
Problem: Maximize: $Z = 4x + 5y$ Use Big-M method

Subject to: $2x + 3y \leq 6$
 $x, y \geq 0$

$3x + y \geq 3$

Sol: ST: $2x + 3y + s_1 = 6, s_1 \geq 0$ Maximization:
 $3x + y - s_2 = 3, s_2 \geq 0$
 $Z = 4x + 5y + 0s_1 - 0s_2 - Ma_1$
 $\hookrightarrow 3x + y - s_2 + a_1 = 3, a_1 \geq 0$

	4	5	0	0	-M	RHS	
X	2	3	1	0	0	6	$\frac{6}{2} = 3$
-M a ₁	3	1	0	-1	1	3	$\frac{3}{3} = 1 \rightarrow$
G _j - Z _j	4+3M	5+M	0	M	$\frac{-M-(M)}{M} = 0$		
0 S ₁	0	$3 - \frac{2}{3} = \frac{7}{3}$	1	$0 - 2 \times \frac{1}{3} = \frac{2}{3}$	$-\frac{2}{3}$	$6 - \frac{2}{3} = 4$	$\frac{4 \times 3}{7} = \frac{12}{7} \rightarrow$
4 X	1	y_3	0	$-y_3$	y_3	1	$1 \times \frac{3}{1} = 3$
G _j - Z _j	0	$5 - \frac{4}{3} = \frac{11}{3}$	0	$\frac{4}{3}$	$\frac{-M - 4}{3}$		
5 Y	0	1	$\frac{3}{7}$	$\frac{2}{7}$	$-\frac{2}{7}$	$\frac{12}{7}$	$\frac{6}{7} \rightarrow$
4 X	1	0	$0 - \frac{1}{3} \times \frac{3}{7} = \frac{1}{7}$	$-\frac{1}{3} - \frac{2}{21} = \frac{1}{21}$	$\frac{1}{3} + \frac{2}{21} = \frac{7}{21}$	$1 - \frac{4}{7} = \frac{3}{7}$	$X - \frac{1}{3} Y$
G _j - Z _j	0	0	$-\frac{15}{7} + \frac{4}{7} = -\frac{11}{7}$	$-\frac{10}{7} + \frac{1}{7} = -\frac{9}{7} = -\frac{3}{7}$	$-\frac{M + 10}{7} = -\frac{12}{7}$	$\frac{60}{7} + \frac{12}{7} = \frac{72}{7}$	$(-\frac{1}{3}) - \frac{1}{3}(\frac{3}{7}) = -\frac{4}{21}$
0 S ₂	0	$\frac{7}{2}$	$\frac{3}{2}$	1	-1	6.	$\frac{14}{7} = 2$
4 X	1	$\frac{3}{4}$	$\frac{1}{4} + \frac{9}{14} = \frac{13}{14}$	0	$\frac{3}{7} - \frac{3}{8} = 0$	$\frac{20}{7} + \frac{18}{7} = \frac{38}{7}$	$\frac{27}{14} = \frac{3}{2}$



	x	y	s_1	s_2	a_1	RHS	
$0 s_2$	0	$7/2$	$3/2$	1	-1	6	
$4 x$	1	$3/2$	$+1/2$	0	0	3	
	$0 s_1 - \frac{12}{2} = -1$	-2	0	-M		12	

$\therefore \text{Maximum: } Z = 12$

$$(x, y) = (2, 1)$$

Q. (r) Maximization

S.T:

$$6x_1 + 10x_2 = 30$$

$$25x_1 + 10x_2 = 50$$

$$19x_1 = 20$$

$$3x_1 + 5x_2 = 15 \rightarrow (1)$$

$$5x_1 + 2x_2 = 10 \rightarrow (2)$$

Feasible region

$$(0, 0) \rightarrow$$

$$(0, 3) \rightarrow$$

$$(2, 0) \rightarrow$$

$$\left(\frac{20}{19}, \frac{45}{19}\right) \rightarrow$$

$$(2, 0) \text{ Min: } Z$$

$$\text{Extra } x_1 \leq 3$$

$$2x_1 + 2x_2 = 8$$

$$6x_1 + 2x_2 = 8$$

$$4x_1 = 0$$

$$(x_1, x_2) = (0, 4)$$

$$x_1 + x_2 = 4 \quad (4, 0) \text{ or } (0, 4)$$

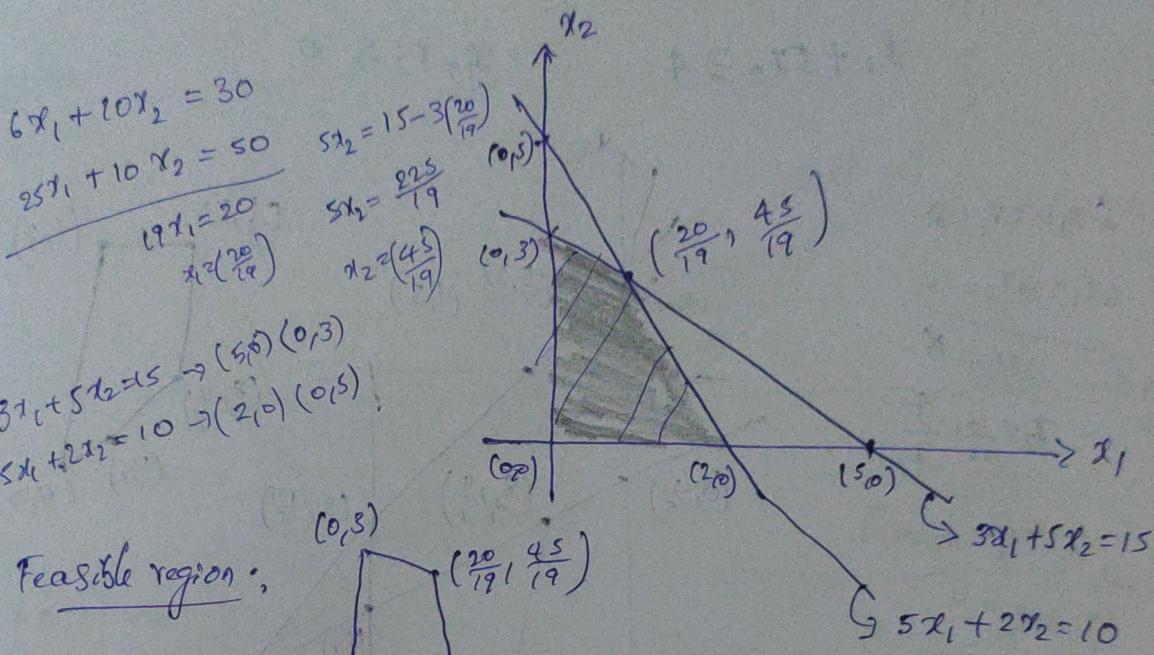
$$6x_1 + 2x_2 = 8 \quad \left(\frac{2}{3}, 0\right) \text{ or } (0, \frac{4}{3})$$

02/02/2023

Q. (i) Maximize: $Z = 5x_1 + 3x_2$

S.T: $3x_1 + 5x_2 \leq 15$ $x_1, x_2 \geq 0$

$5x_1 + 2x_2 \leq 10$



$(0,0) \rightarrow 0$

$(0,3) \rightarrow 9$

$(2,0) \rightarrow 10 \rightarrow \text{max.}$

$\left(\frac{20}{19}, \frac{45}{19}\right) \rightarrow \frac{100}{19} + \frac{135}{19} = \frac{235}{19} = 12.37 \rightarrow \text{max}$

$\left(\frac{20}{19}, \frac{45}{19}\right)$

$\therefore \text{Maximum: } Z = 12.37$

(ii) Min: $Z = 2x_1 + 3x_2$ S.T: $x_1 + x_2 \leq 4$, $6x_1 + 2x_2 \geq 8$

Extra: $x_1 \leq 3$, $x_2 \leq 3$, $x_1, x_2 \geq 0$

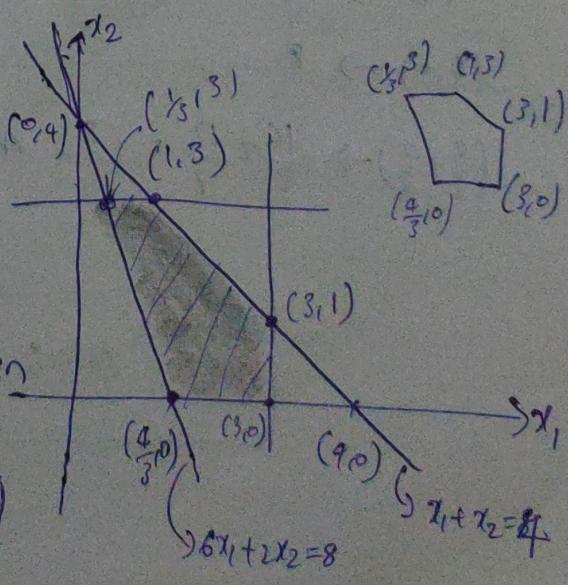
$2x_1 + 3x_2 = 8$
 $6x_1 + 2x_2 = 8$
 $4x_1 = 0$
 $x_1 = 0$

$(x_1, x_2) = (0, 4)$

$x_1 + x_2 = 4 \rightarrow (4,0), (0,4)$

$6x_1 + 2x_2 = 8 \rightarrow (\frac{4}{3}, 0), (0, 4), (\frac{1}{3}, 3)$

$\therefore \text{Min: } Z = 2.67$



$$(ii) \text{ Min: } Z = 2x_1 + 3x_2$$

$$\underline{\text{S.T:}} \quad x_1 + x_2 \leq 4 \quad x_1 \leq 3$$

$$6x_1 + 2x_2 \geq 8 \quad x_2 \leq 3$$

$$x_1 + 5x_2 \geq 4 \quad x_1, x_2 \geq 0$$

$$6x_1 + 2x_2 = 8$$

$$6x_1 + 3x_2 = 24$$

$$28x_2 = 16$$

$$x_2 = \frac{16}{28} = \frac{4}{7}$$

$$x_1 + 5x_2 = 4$$

$$x_1 + \frac{20}{7} = 4$$

$$x_1 = \frac{28 - 20}{7} = \frac{8}{7}$$

$$x_1 = \frac{8}{7}$$

$$(\frac{1}{3}, 3) \rightarrow 9.67$$

$$(1, 3) \rightarrow 10$$

$$(3, 1) \rightarrow 9$$

$$(4, 0) \rightarrow 8$$

$$(\frac{8}{7}, \frac{4}{7}) \rightarrow \frac{16}{7} + \frac{12}{7} = \frac{28}{7} = 4 \rightarrow \min$$

$$(i) (ii) \text{ Max: } Z$$

$$\underline{\text{S.T:}} \quad x_1 \leq 3$$

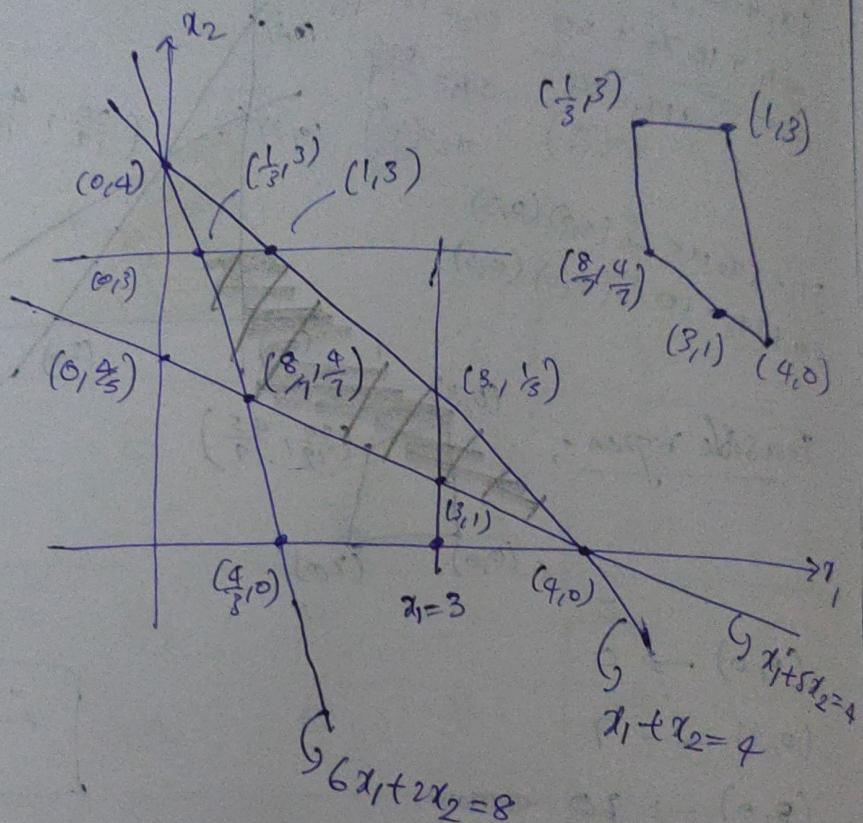
~~extra~~

$$x_1 - x_2 \leq 1 \rightarrow (1, 0)$$

$$-0.5x_1 + x_2 = 2 \rightarrow (0, 2)$$

$$0.5x_1 = 3$$

$$x_1 = 6$$



$$(iv) \text{ Max: } Z$$

$$\underline{\text{S.T:}} \quad x_1 \leq 3$$

$$x_1 < x_2$$

$$(0, 0) \rightarrow$$

$$(3, 3) \rightarrow$$

$$\therefore \text{Min: } Z = 4 \text{ at } (\frac{8}{7}, \frac{4}{7})$$

$$\text{i) (ii) Max: } Z = 2x_1 + 2x_2$$

S.T.: $x_1 - x_2 \geq 1$

$$x_1, x_2 \geq 0$$

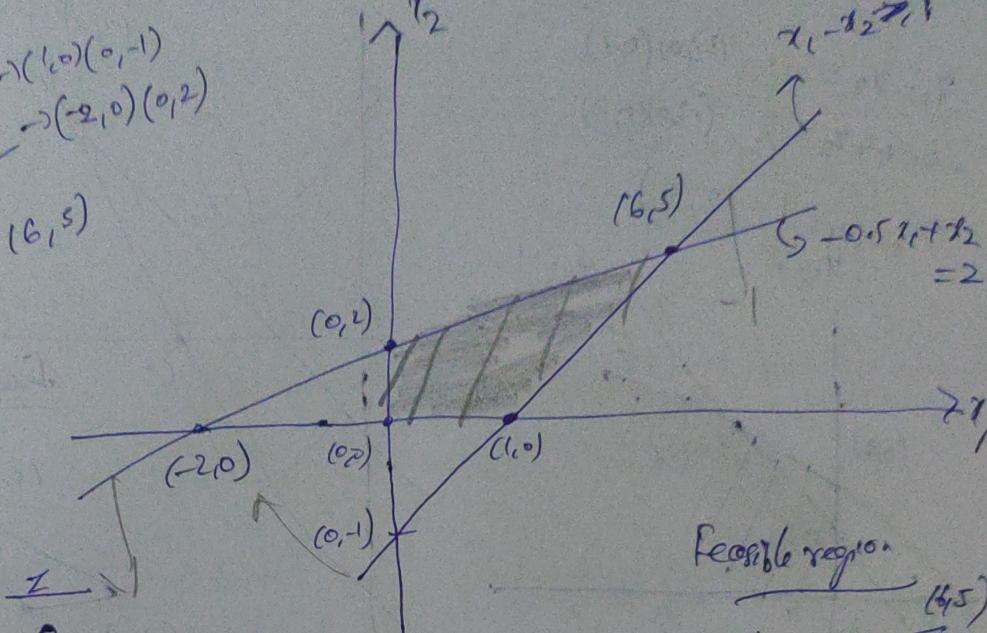
$$-0.5x_1 + x_2 \leq 2$$

Extra

$$x_1 - x_2 = 1 \rightarrow (1, 0), (0, -1)$$

$$-0.5x_1 + x_2 = 2 \rightarrow (-2, 0), (0, 2)$$

$$0.5x_1 = 3 \rightarrow x_1 = 6 \quad (6, 0)$$



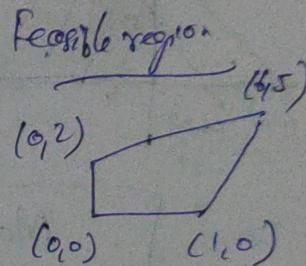
$$(0, 0) \rightarrow 0$$

$$(0, 2) \rightarrow 4$$

$$(1, 0) \rightarrow 2$$

$$(6, 5) \rightarrow 22 \rightarrow \max$$

$\therefore \text{Max: } Z = 22$
at $(6, 5)$



$$\text{(iv) Max: } Z = -3x_1 + 2x_2$$

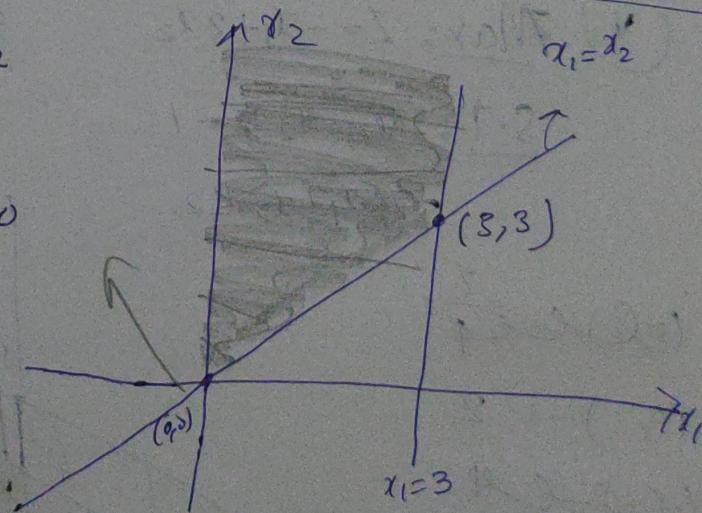
S.T.: $x_1 - x_2 \leq 0$

$$x_1 \leq 3, x_1, x_2 \geq 0$$

$$x_1 < x_2$$

$$(0, 0) \rightarrow 0$$

$$(3, 3) \rightarrow -9 + 6 = -3$$



$$(iii) \text{ Max: } Z = 2x_1 + 2x_2$$

$$\text{S.T: } x_1 - x_2 \geq 1$$

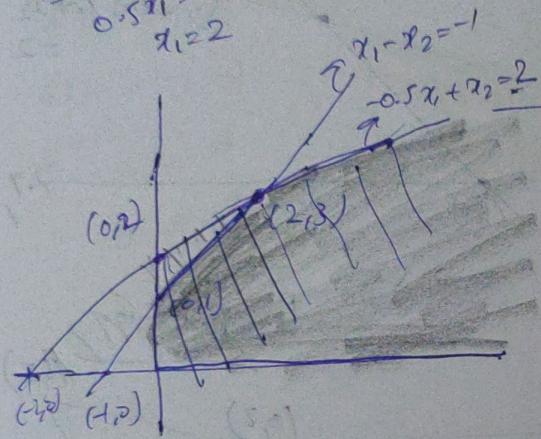
$$-0.5x_1 + x_2 \leq 2$$

$$x_1 - x_2 = -1 \quad (-1, 0), (0, 1)$$

$$-0.5x_1 + x_2 = 2 \quad (-2, 0), (0, 2)$$

$$0.5x_1 = 1 \quad (2, 3)$$

$$x_1 = 2$$



$\therefore \text{Max} = 10 \text{ at } (2, 3)$

$$(0, 2) \rightarrow 4$$

$$(0, 1) \rightarrow 2$$

$$(-2, 0) \rightarrow -4$$

$$(-1, 0) \rightarrow -2$$

$$(2, 0) \rightarrow 4+6=10$$

$$(vi) \text{ Max: } Z =$$

$$\text{S.T: } x_1$$

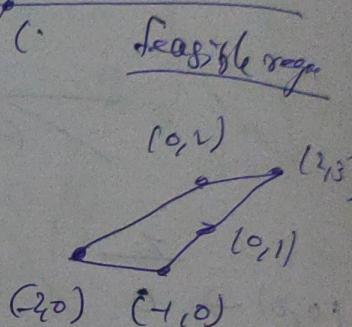
$$2x_1$$

$$x_2$$

$$2x_1 + x_2 = 2$$

$$x_1 + x_2 = 1$$

No feasible region



$$(vii) \text{ Max: } Z =$$

$$\text{S.T: }$$

$$x_1 - x_2 = 0$$

$$3x_1 - x_2 = 3 \rightarrow (1, 0)$$

$$-2x_1 + x_2 = -3$$

$$\frac{9}{2} + \frac{3}{2} = \frac{-6}{2} = -3$$

v

$$\text{Max: } Z = -2x_1 + 2x_2$$

$$x_1, x_2 \geq 0$$

$$\text{S.T: } x_1 - x_2 \geq -1$$

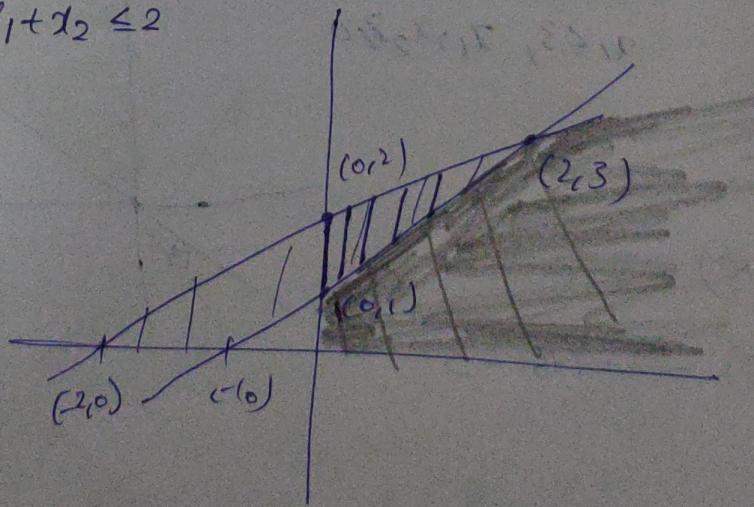
$$-0.5x_1 + x_2 \leq 2$$

$$(0, 2) \leftarrow \frac{7}{2}$$

$$(0, 1) \rightarrow 2$$

$$(2, 0) \leftarrow 2$$

$$(2, 3) \rightarrow -2+6=4$$



$$\left(-\frac{3}{2}, \frac{9}{2}\right)$$

$$(vi) \text{ Max: } Z = 3x_1 - 2x_2$$

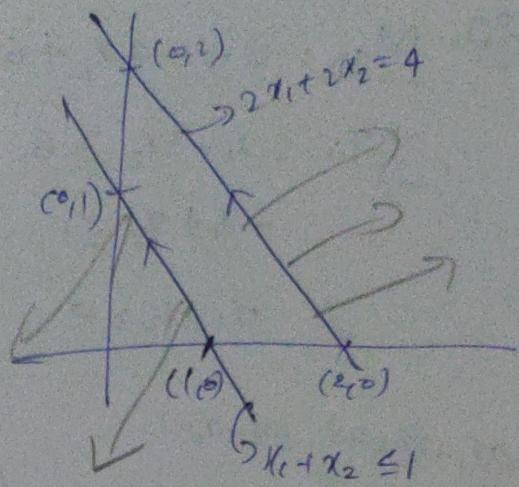
$$\underline{\text{S.T:}} \quad x_1 + x_2 \leq 1$$

$$2x_1 + 2x_2 \geq 4$$

$$x_1, x_2 \geq 0$$

$$\begin{aligned} 3x_1 - 2x_2 &\leq 2 \\ x_1 + x_2 &= 1 \end{aligned}$$

No feasible solution



$$(vii) \text{ Max: } Z = x_1 + x_2$$

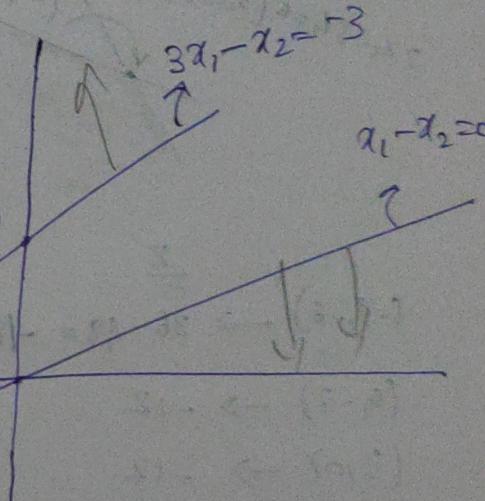
$$\underline{\text{S.T:}} \quad x_1 - x_2 \geq 0$$

$$3x_1 - x_2 \leq -3$$

$$x_1, x_2 \geq 0$$

$$\begin{aligned} x_1 - x_2 &= 0 \rightarrow (0,0) \\ 3x_1 - x_2 &= -3 \rightarrow (-1,0) \\ -3x_1 + x_2 &= 3 \rightarrow (0,3) \\ -2x_1 + x_2 &= -3 \rightarrow \left(-\frac{3}{2}, \frac{3}{2}\right) \\ -2x_1 + x_2 &= -3 \rightarrow \left(\frac{3}{2}, -\frac{3}{2}\right) \end{aligned}$$

$$\left(-\frac{3}{2}, \frac{3}{2}\right) \Rightarrow \underline{Z = -3}$$



$$\underline{20. \text{ Max: } z = -4x_1 + 6x_2}$$

$$\underline{\text{S.T: } 2x_1 - 3x_2 \geq 6}$$

$$-x_1 + x_2 \leq 1$$

$$-x_1 + x_2 = 1$$

$$x_1, x_2 \geq 0$$

$$-2x_1 + 3x_2 = 3 \quad (-x_1 + x_2 = 1)$$

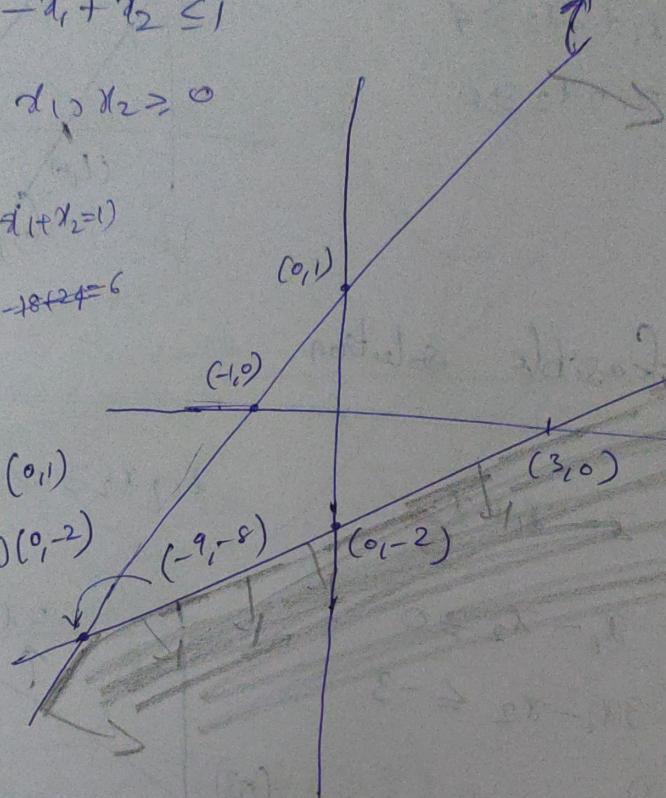
$$2x_1 - 3x_2 = 6 \quad -18 + 24 = 6$$

$$-x_1 = 9$$

$$(-9, -8)$$

$$-x_1 + x_2 = 1 \quad (-1, 0) (0, 1)$$

$$2x_1 - 3x_2 = 6 \quad (3, 0) (0, -2)$$



$$(-9, -8) \rightarrow \underline{z} = 36 - 48 = -12$$

$$(0, -2) \rightarrow -12$$

$$(3, 0) \rightarrow -12$$

$$(0, 3) \rightarrow -18$$

Max: $\underline{z = -12}$

07/02/2022

1. Solution is not altered even after any linear equation is multiplied with a scalar, from a given set of linear equations. $E_1, E_2 \Rightarrow 2E_1, 2E_2$

2. Solution is not altered, even after any equation is replaced by its linear combination with the same set of linear equations. $E_1, E_2 \Rightarrow E_1 + E_2, E_2$

Generalizing: $\begin{matrix} m=n \\ \downarrow \quad \downarrow \\ \text{No. of variables} \\ \text{No. of equations} \end{matrix}$

$$a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n = b_1 \rightarrow E_1$$

$$a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n = b_2 \rightarrow E_2$$

$$\begin{aligned} & a_{j1}x_1 + a_{j2}x_2 + \dots + a_{j,i-1}x_{i-1} + a_{ji}x_i \\ & + a_{ji+1}x_{i+1} + \dots + a_{jn}x_n = b_j \end{aligned} \rightarrow E_j$$

$$a_{n1}x_1 + a_{n2}x_2 + \dots + a_{nn}x_n = b_n \rightarrow E_n$$

→ Removing " x_i " from all the equations except from one equation, this operation is called as "Pivot Operation"

$$\cdot E'_1 = E_1 - \frac{a_{1i}}{a_{ji}} E_j^o$$

$$\cdot E'_2 = E_2 - \frac{a_{2i}}{a_{ji}} E_j^o$$

$$\cdot E'_n = E_n - \frac{a_{ni}}{a_{ji}} E_j^o$$

$$\Rightarrow \left\{ \begin{array}{l} a'_{11}x_1 + a'_{12}x_2 + \dots + a'_{1n}x_n = b'_1 \\ a'_{21}x_1 + a'_{22}x_2 + \dots + a'_{2n}x_n = b'_2 \\ \vdots \\ a'_{ji}x_1 + a'_{j2}x_2 + \dots + a'_{jn}x_n = b'_j \\ \vdots \\ a'_{nn}x_1 + a'_{n2}x_2 + \dots + a'_{nn}x_n = b'_n \end{array} \right.$$

By \Rightarrow

$$\Rightarrow \begin{cases} a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n = b_1 \\ a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n = b_2 \\ \vdots \\ a_{i1}x_1 + a_{i2}x_2 + \dots + a_{in}x_n = b_i \\ \vdots \\ a_{n1}x_1 + a_{n2}x_2 + \dots + a_{nn}x_n = b_n \end{cases}$$

Case 2: $n \geq m$ i.e., $n > m$

$$a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n = b_1$$

$$a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n = b_2$$

$$a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n = b_m$$

Applying Pivot Operation

$$\Rightarrow \begin{cases} 1x_1 + 0x_2 + \dots + 0x_m + a_{1,m+1}^n x_{m+1} + \dots + a_{1n}^n x_n = b_1 \\ 0x_1 + 1x_2 + \dots + 0x_m + a_{2,m+1}^n x_{m+1} + \dots + a_{2n}^n x_n = b_2 \\ \vdots \\ 0x_1 + 0x_2 + \dots + 1x_m + a_{m,m+1}^n x_{m+1} + \dots + a_{mn}^n x_n = b_m \end{cases}$$

Pivot Variables Non-pivot or independent Variables Constant

$$\therefore x_i^* = \begin{cases} b_i & , i=1, 2, \dots, m \\ 0 & , i=m+1, m+2, \dots, n \end{cases}$$

↓ This solution called as
(Basic Solution) as the solution vector contains
no more than 'm' nonzero terms.

→ Pivotal Variables / Basic Variables : x_i^* , $i=1, 2, \dots, m$

→ Non-Basic Variables : x_i^* , $i=m+1, m+2, \dots, n$

Problem : Find all basic feasible solutions corresponding to the
given system of linear equations. (BFSs)

$$2x_1 + 3x_2 - 2x_3 - 7x_4 = 1$$

$$x_1 + x_2 + x_3 + 3x_4 = 6$$

$$x_1 - x_2 + x_3 + 5x_4 = 4$$

Case 1:

Sol: Basic Variables : x_1, x_2, x_3

Non-Basic Variables : x_4

$$① \Rightarrow -x_1 - 5x_3 - 16x_4 = -17 \Rightarrow x_1 + 4x_4 = 2$$

$$② \Rightarrow x_1 + x_2 + 4x_4 = 6 \Rightarrow x_2 - x_4 = 1$$

$$③ \Rightarrow x_1 + x_2 + x_3 + 4x_4 = 4 \Rightarrow x_1 + x_3 + 4x_4 = 5 \Rightarrow -4x_3 - 12x_4 = -3$$

$$\Rightarrow \begin{cases} x_1 + x_4 = 2 \\ x_2 - x_4 = 1 \\ x_3 + 3x_4 = 3 \end{cases} \quad (x_1, x_2, x_3, x_4) = (2, 1, 3, 0)$$

Basic solution assumes zero value for non basic variables.

$$f = C_1 x_1 + C_2 x_2 + \dots + C_n x_n$$

$$\Rightarrow f_0' = C_1 x_1 + C_2 x_2 + \dots + C_n x_n - f_0$$

$$0x_1 + 0x_2 + \dots + 0x_m - f \\ + C_{m+1} x_{m+1} + \dots + C_n x_n = -f_0''$$

Feasible solution is the solution which satisfies all given constraints

\rightarrow BFS 1 $\Rightarrow x_4 = 0$ i.e. assuming x_4 as Non basic variable

BFS 2 $\Rightarrow x_1 = 0$ i.e. " x_1 "

BFS 3 $\Rightarrow x_2 = 0$ i.e. " x_2 "

BFS 4 $\Rightarrow x_3 = 0$ i.e. " x_3 "

No. of BFSs : n^m

Case 3: Basic Variable: x_1, x_3, x_4

Non-basic Variable: x_2

$$\textcircled{1} \Rightarrow 4x_1 + 5x_2 - x_4 = 13 \Rightarrow 4x_1 + 4x_2 = 12$$

$$4x_1 + 4x_2 = 12$$

$$\textcircled{2} \Rightarrow 4x_2 - 4x_4 = 7 \Rightarrow x_2 - x_4 = 1$$

$$\textcircled{3} \Rightarrow -5x_2 + 4x_3 + 7x_4 = 7 \Rightarrow 12x_2 + 4x_3 = 7 + 17x_4 = 24$$

$$\left\{ \begin{array}{l} 4x_1 + 2x_2 = 3 \\ x_2 - x_4 = 1 \\ 4x_2 + 2x_3 = 12 \end{array} \right.$$

BFS	I	II	III	IV
x_1	2	0	3	1
x_2	1	3	0	2
x_3	3	-3	6	0
x_4	0	2	-1	1

$\rightarrow \text{II \& III}$ solutions are not considered as $x_i \geq 0, i=1, 2, 3, 4$

x_1	x_2	x_3	x_4	RHS
2	3	-2	-7	1
1	1	1	3	6
1	-1	1	5	4

(R1)

(R2)

(R3)

Pivot operation 1
(Pivot element is x_1)

1	$\frac{3}{2}$	$-\frac{1}{2}$	$-\frac{7}{2}$	$\frac{1}{2}$
0	$1 - \frac{3}{2} = -\frac{1}{2}$	$1+1=2$	$3+7=\frac{13}{2}$	$6 - \frac{1}{2} = \frac{11}{2}$
0	$-1 - \frac{3}{2} = -\frac{5}{2}$	$1+1=2$	$5+7=\frac{17}{2}$	$4 - \frac{1}{2} = \frac{7}{2}$

$R_1' \rightarrow R_1 - \frac{3}{2}R_2$

$R_2' \rightarrow R_2 - R_1$

$R_3' \rightarrow R_3 - R_1$

Pivot operation 2

1	0	$-1 + 6 = 5$	$-\frac{7}{2} = 16$	-11
0	1	-4	-13	
0	0	0	0	
0	0	0	0	0

$$(x_1, x_2)_{f_0} = \left(\frac{1}{2}, \frac{1}{2} \right)$$

Ex 3.3 Find all the basic solutions corresponding to the system of linear equations

$$2x_1 + 3x_2 - 2x_3 - 7x_4 = 1$$

$$x_1 + x_2 + x_3 + 3x_4 = 6$$

$$x_1 - x_2 + x_3 + 5x_4 = 4.$$

	x_1	x_2	x_3	x_4	R.H.S
x_1	(2)	3	-2	-7	1
x_2	1	1	1	3	6
x_3	1	-1	1	5	4
	1	$\frac{3}{2}$	-1	$\frac{-7}{2}$	$\frac{1}{2}$
	0	($-\frac{1}{2}$)	2	$\frac{13}{2}$	$\frac{11}{2}$
	0	$-\frac{5}{2}$	2	$\frac{17}{2}$	$\frac{7}{2}$
	1	0	5	16	17
	0	+1	-4	-13	-11
	0	0	(-8)	-24	-24
x_4	1	0	0	1	$\frac{3}{2}$
x_2	0	1	0	-1	$\frac{3}{2}$ 1
x_3	0	0	1	(3)	+3
x_1	1	0	$-\frac{1}{3}$	0	1
x_2	0	1	($\frac{1}{3}$)	0	2
x_4	0	0	$\frac{1}{3}$	1	1
x_4	1	1	0	0	3
x_3	0	3	1	0	6
x_4	0	-1	0	1	-1

If $x_4 = 0$ then
the BFS is

$$[x_1=2; x_2=1; x_3=3]$$

If $x_3 = 0$ then
[1, 2, 1] is the
BFS

If $x_2 = 0$ then

$$[3, 6, -1]$$

BFS but not
feasible.

$$\rightarrow R_1$$

$$\rightarrow R_2$$

$$\rightarrow R_3$$

$$\rightarrow R_1/2 = R'_1$$

$$\rightarrow R_2 - R_1/2 = R'_2$$

$$\rightarrow R_3 - R_1/2 = R'_3$$

$$\rightarrow R''_1 = R'_1 - \frac{3}{2}R'_2$$

$$\rightarrow R''_2 = R'_2 \times (-2)$$

$$\rightarrow R''_3 = R'_3 + \frac{5}{2}R'_2$$

$$\rightarrow R'''_1 = R''_1 - 5R'''_2$$

$$\rightarrow R'''_2 = R''_2 + 4R'''_3$$

$$\rightarrow R'''_3 = R''_3 \times (-8)$$

$$\rightarrow R^{IV}_1 = R'''_1 - R'''_3$$

$$\rightarrow R^{IV}_2 = R'''_2 + R'''_3$$

$$\rightarrow R^{IV}_3 = R'''_3 / 3$$

$$\rightarrow R^V_1 = R^{IV}_1 + \frac{1}{3}R^{IV}_2$$

$$\rightarrow R^V_2 = 3R^{IV}_2$$

$$\rightarrow R^V_3 = R^{IV}_3 - \frac{1}{3}R^{IV}_2$$

Problem: Maximize : $Z = 2x + 5y$

S.T : $2x + y \leq 5$

$x + 2y \leq 4$

Use
Simplex Algorithm
Tabular Method
 $x \geq 0$
 $y \geq 0$

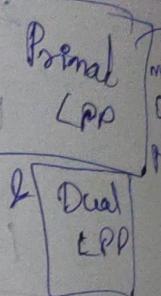
Dual LPP:

$Z' = 5y_1 + 4y_2$ S.T : $2y_1 + y_2 \geq 2$ & $y_1 + 2y_2 \geq 5$

Sd $Z = 2x + 5y + 0s_1 + 0s_2$

$2x + y + s_1 = 5$ $s_1 \geq 0$

$x + 2y + s_2 = 4$ $s_2 \geq 0$



	x	y	s_1	s_2	RHS	Θ
$0 s_1$	2	1	1	0	5	5
$0 s_2$	1	2	0	1	4	2 → leave
$C_j - Z_j^0$	2	5	0	0	0	
$0 s_1$	$\frac{3}{2}$	0	1	$-\frac{1}{2}$	3	
$0 y$	$\frac{1}{2}$	1	0	y_2	2	
$C_j - Z_j$	$2 - \frac{5}{2} = -\frac{1}{2}$	0	0	$-\frac{5}{2}$	10	

∴ Maximum: $Z = 10$

at $(x_1, y_1) = (0, 2)$

$x = 0$
 $y = 2$
 $s_1 = 3$
 $s_2 = 0$

Problem : Maximize : $Z = 4x + 5y$

Use Two Phase Method

S.T : $2x + 3y \leq 6$; $x, y \geq 0$

$$3x + y \geq 3$$

S.T : $2x + 3y + S_1 = 6$; $S_1 \geq 0$

$3x + y - S_2 + a_1 = 3$; $S_2, a_1 \geq 0$

Phase 1

	x	y	S_1	S_2	a_1	RHS	θ
0 S_1	2	3	1	0	0	6	3
-1 a_1	3	1	0	-1	1	3	1 → leave
$G - Z_0^0$	3	1	0	-1	0	-3	
0 S_1	0	$3 - 2/3 = 7/3$	1	$2/3$	$-2/3$	4	
0 X	1	$1/3$	0	$-1/3$	$1/3$	1	
$G - Z_0^0$	0	0	0	0	0		

Phase 2

	x	y	S_1	S_2	RHS	Θ
0 S_1	0	$7/3$	1	$2/3$	4	$4 \times 3/7 = \frac{12}{7}$
4 X_1	1	$1/3$	0	$-1/3$	1	3
$G - Z_0^0$	0	$\frac{S_4 - 11}{3} = \frac{11}{3}$	0	$4/3$	4	
5 y	0	1	$3/7$	$2/7$	$12/7$	6 → leave
4 x	1	0	$-1/7$	$-\frac{1}{3} \frac{2}{21} = \frac{-3}{21}$	$\frac{1-4}{7} = \frac{3}{7}$	-1
$G - Z_0^0$	0	0	$-\frac{15+4}{7} = \frac{-11}{7}$	$\frac{-10+12=2}{7} = \frac{2}{7}$		
						↑ after

	x	y	S_1	S_2	RHS
$0 S_2$	0	$7/2$	$3/2$	0	6
$4 x$	1	$3/2$	$\frac{-1+9}{7} = \frac{1}{2}$	0	$\frac{3+18}{7} = 3$
$C_1 - Z^0$	0	$\frac{s-12}{2} = -1$	-2	1	12

$\therefore \text{Maximum: } Z = 12$ at $(x, y) = (3, 0)$

$$\begin{aligned} x &= 3 \\ y &= 0 \\ S_1 &= 0 \\ S_2 &= 0 \end{aligned}$$

09/02/2022

Problem: Maximize: $Z = 3x + 2y$

$$S.T : 2x + y \leq 4$$

$$x + 2y \geq 9, x \geq 0, y \geq 0$$

Sol:

Maximize: $Z = 3x + 2y + 0S_1 - 0S_2 - Mq_1$

$$S.T : 2x + y + S_1 = 4, S_1 \geq 0$$

$$x + 2y - S_2 + q_1 = 9, S_2 \geq 0, q_1 \geq 0$$

(i) 2-Phase Method

(ii) Big-M Method

(iii) Graphical Method

Phase 1:

	σ	σ	σ	σ	a_1	RHS	σ
x	σ	σ	σ	σ	a_1	RHS	σ
s_1	2	1	1	0	0	4	4
a_1	-1	1	2	0	-1	9	$\frac{7}{2} = 4.5$
c_{j-2j}	1	2	10	-1	$\frac{-1+1}{2} = 0$	10	M
y	1	2	1	1	0	4	4
a_1	-3	0	0	-2	+1	1	$9-8=1$
c_{j-2j}	-3	10	-2	-1	$\frac{-1+1}{2} = 0$	10	M

Termination step

Phase-2:

3	2	0	0
x	y	s_1	s_2

$$x = x_1 + x_2 \quad y = y_1 + y_2$$

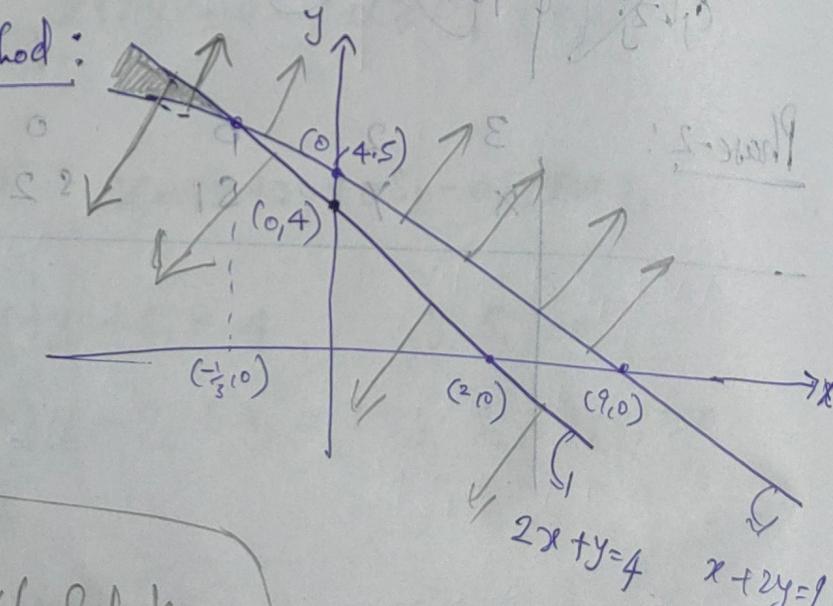
: basic feasible

Big-M Method:

		3	2	0	8	0	-M	RHS
	x	y	S_1	S_2	a_1			0
0	S_1	2	1	1	0	20	4	4
-M	a_1	1	-2	0	-1	1	9	$\frac{9}{2} = 4.5$
	$G_j - Z_j$	3+M	2+2M	0	-M	0		
2	4	2	1	1	80	0	8	4
-M	a_1	-3	0	-2	-1	1	9-8=1	
	$G_j - Z_j$	3-3M	0	2-2M	-M	0		
		+4						
		=-1-3M						

(Termination Step)

Graphical Method:



No feasible Solution

Duality in LPP

- Every LPP is associated with another LPP called the Dual LPP.
- The original is called as the Primal LPP.

In Dual Representation:

- No. of ^{decision} variables = No. of constraints in Primal.
- Objective function becomes Maximum if in Primal it is Minimum and vice versa.
- No. of constraints = No. of Decision variables in Primal.
- The problem has ($>$) type constraints, if in Primal it has (\leq) type and vice versa.
- RHS constants of the constraints have the objective coefficients in the Primal and vice versa.
- Coefficients of constraints of original Primal problem which appear from left to right are placed from top to bottom in the constraints of the dual problem and vice versa.
- If the i^{th} primal variable is unrestricted in sign, the the j^{th} dual constraint is = type & vice versa.

Problem: Primal:

$$\text{Max: } Z = 6x_1 + 5x_2$$

$$\text{S.T.: } x_1 + x_2 \leq 5$$

$$3x_1 + 2x_2 \leq 72$$

$$x_1, x_2 \geq 0$$

Problem: Primal:

$$\text{Max: } Z = -5x_1 + 2x_2$$

$$\text{S.T.: } -x_1 + x_2 \leq -2$$

$$2x_1 + 3x_2 \leq 5$$

$$x_1, x_2 \geq 0$$

$$\text{Sol: Max: } Z = -5x_1 + 2x_2$$

$$\text{S.T.: } x_1 - x_2 \geq 2$$

$$x_1, x_2 \geq 0 \quad 2x_1 + 3x_2 \leq 5$$

Dual: (Refer Table)

$$\text{Min: } W = 2y_1 + 5y_2$$

$$\text{S.T.: } y_1 + 2y_2 \geq -5$$

$$-y_1 + 3y_2 \leq 2$$

$$y_1 \leq 0, y_2 \geq 0$$

Problem: Primal:

$$\text{Max: } Z = 3x_1 + 2x_2$$

$$\text{S.T.: } 3x_1 + 4x_2 \leq 12$$

$$3x_1 + 2x_2 \leq 16$$

$$x_1 + x_2 \leq 3$$

$$x_1, x_2 \geq 0$$

Dual:

$$\text{Min: } W = 12y_1 + 16y_2 + 3y_3$$

$$3y_1 + 2y_2 + 0y_3 \geq 3$$

$$4y_1 + 2y_2 + y_3 \geq 2$$

$$y_1, y_2, y_3 \geq 0$$

Problem: Primal

$$\text{Max: } Z = -5x_1 + 2x_2$$

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

$$2x_1 + 3x_2 \leq 5$$

$$x_1, x_2 \geq 0$$

$$\text{Sd: Max: } Z = -5x_1 + 2x_2$$

$$\text{s.t.: } x_1 - x_2 \geq 2$$

$$x_1, x_2 \geq 0 \quad 2x_1 + 3x_2 \leq 5$$

Dual: (Refer Table)

$$\text{Min: } W = 2y_1 + 5y_2$$

$$\text{s.t.: } y_1 + 2y_2 \geq -5$$

$$-y_1 + 3y_2 \geq 2$$

$$y_1 \leq 0, y_2 \geq 0$$

ab:

$$\therefore W = 12y_1 + 16y_2 + 3y_3$$

$$3y_1 + 3y_2 + 0y_3 \geq 3$$

$$4y_1 + 2y_2 + y_3 \geq 2$$

$$y_1, y_2, y_3 \geq 0$$

Problem: Primal

$$\text{Max: } Z = x_1 + x_2$$

$$\text{s.t.: } 2x_1 + x_2 = 5$$

$$3x_1 - x_2 = 6$$

x_1, x_2 (unrestricted)
(urs)

Dual

$$\text{Min: } W = 5y_1 + 6y_2$$

$$\text{s.t.: } 2y_1 + 3y_2 = 1$$

$$y_1 - y_2 = 1$$

y_1, y_2 (urs)

$$20 + 180 + 28 + 12 = 220$$

Problem: Primal

$$\text{Max: } Z = x_1 - 2x_2 + 3x_3$$

$$\text{s.t.: } -2x_1 + x_2 + 3x_3 = 2$$

$$2x_1 + 3x_2 + 4x_3 = 1$$

$$x_1, x_2, x_3 \geq 0$$

Dual

$$\text{Min: } W = 2y_1 + y_2$$

$$-2y_1 + 2y_2 \geq 1$$

$$y_1 + 3y_2 \geq -2$$

$$3y_1 + 4y_2 \geq 3$$

y_1, y_2 (urs)

~~Diagram~~

	Primal	Dual	
Constraints	$\geq \leftrightarrow \leq$		Variables
Variables	$\leq \leftrightarrow \geq$		Constraints
	$\geq \leftrightarrow \geq$		
	$\leq \leftrightarrow \leq$		
	unrestricted		
Objective function	Max	Min	Objective function

Maximize: $Z = 4x_1 + 3x_2$

10/02/2023

S.T.: $x_1 + 3x_2 \leq 8$

$3x_1 + 2x_2 \leq 12$

$x_1, x_2 \geq 0$

$Z = 4x_1 + 3x_2 + 0s_1 + 0s_2$

$2x_1 + 3x_2 + s_1 = 8$; $s_1 \geq 0, x_1 \geq 0, x_2 \geq 0$

$3x_1 + 2x_2 + s_2 = 12$; $s_2 \geq 0, x_1 \geq 0, x_2 \geq 0$

	4	3	0	0	RHS	Q
x_1	2	3	1	0	8	$\frac{8}{2} = 4$
s_1	3	2	0	1	12	$\frac{12}{3} = 4$
$Z_j - Z_p$	4	3	0	0		
x_1	1	$\frac{3}{2}$	$\frac{1}{2}$	0	4	
s_2	0	$2 - \frac{9}{2} = -\frac{5}{2}$	$-\frac{3}{2}$	1	$12 - 12 = 0$	
$Z_j - Z_p$	0	$3 - \frac{12}{2} = -3$	-2	0	16	

Solution: $x_1 = 4, x_2 = 0, s_1 = 0, s_2 = 0$

Case(i)

$Z = 16$

Solution: $x_1 = 4, x_2 = 0, s_1 = 0, s_2 = 0$

Case(ii)

	x_1	x_2	s_1	s_2	RHS	θ
θs_1	2	3	1	0	8	4
θs_2	3	2	0	1	12	4 →
$C_j - Z_j^o$	4	3	0	0		
θs_1	0	$\frac{3-4}{3} = \frac{-1}{3}$	1	$-2/3$	$8-4x2=0$	0 <u>Leave</u>
$4 x_1$	1	$2/3$	0	y_3	$\frac{12}{3} = 4$	6 Max
$C_j - Z_j^o$	0	$3 - \frac{8}{3} = \frac{1}{3}$	0	$-\frac{4}{3}$	16	
θs_1	$\frac{-3}{2}x_1 - \frac{5}{2}$	0	1	$\frac{2}{3} - \frac{5}{3}x_1$	$0 - 6x_1 = -10$	
$3 x_2$	$3/2$	1	0	$1/2$	$9x_2/2 = 6$	
$C_j - Z_j^o$	$4 - \frac{9}{2} = \frac{1}{2}$	0	0	$-3/2$	18	
$3 x_2$	0	1	$3/5$	$-2/5$	0	
$4 x_1$	1	0	$-2/5$	$3/5$	4	
$C_j - Z_j^o$	0	0	$-4/5$	$-6/5$	16	

Degeneracy

Book: SS Rao (Opt. Theory)

Infimum

↳ 1.4 (Ex. 1.6)

↳ 2 (rough idea)

↳ # 3 ~~#~~

→ Why in Simplex algorithm

↳ 4.3

We consider linear objective f(x) = Gx
and min. value is θ .

Minor-1

Image processing

- Signal processing

- VLSI

- Digital

- Bio - Signal Proc

Course Project

Abstract

problem

solution

Minor-2

③ OT problem related to E.C. Infra. tone

Contact : faculty

Unconstrained Optimization :-

Minimize : $f(x)$

$x \in F$ (Field)

$F \subset R^n$

(feasible region) (n -dimensional vector space)

$$x = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}$$

$f: R^n \rightarrow R$

(1-dimensional space)

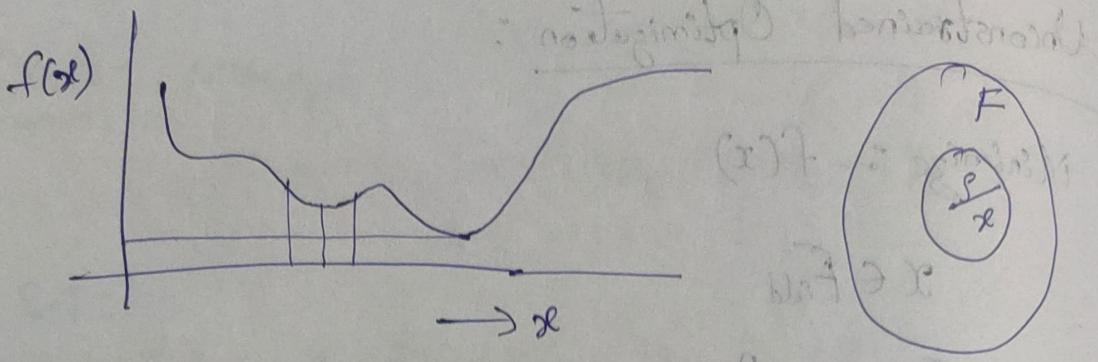
- Global minimum, Strictly global min., Local min,
strict local min.

→ A $x \in F$ is said to be Global minimum if
 $f(x) \leq f(y) ; \forall y \in F$

→ A $x \in F$, then $f(x)$ is said to be Strictly global minimum
 if $f(x) < f(y) ; \forall y \in F$ and $y \neq x$

→ A $x \in F$, then $f(x)$ is said to be Local Minimum
 $\exists \rho > 0, f(x) \leq f(y), \forall y \in F$ and $\|y-x\|_2 \leq \rho$

- Local minimum defined for a given interval.

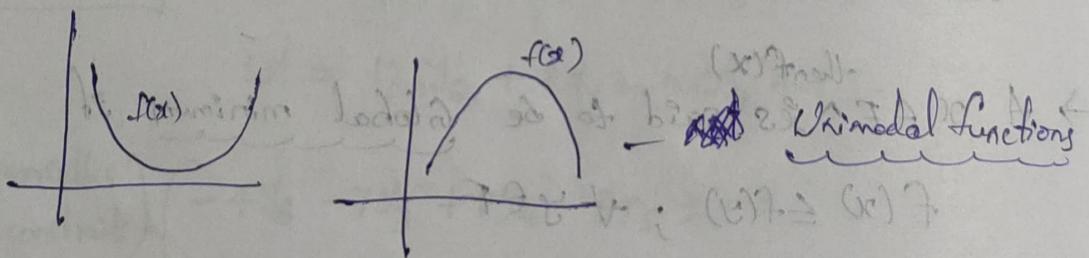


$\rightarrow \forall x \in F, f(x)$ is said to be strictly local minimum if $\exists r > 0, f(x) < f(y); \forall y \in F, y \neq x$ and $|x-y| < r$

Unimodal Function:

(at keeping) (increasing) or (keeps on decreasing)

- Either only increase or only decrease.



Search algorithm - used if $f(x)$ is a unimodal function.

Linear Search Algorithm:

Initially, Guess x_1

Step size s

$$x_2 = x_1 + s ; f(x_1) \quad f(x_2)$$

- (Case 1) if $f(x_1) < f(x_2) \Rightarrow$ min. available from $(-\infty, x_1)$
 Search region is $(-\infty, x_1)$
- (Case 2) if $f(x_1) > f(x_2) \Rightarrow$ $x_3 = x_1 + s$,
 $x_3 = x_2 + s$. \therefore search region is $(-\infty, x_2)$.
 $x_3 = x_1 + 2s$. \therefore search region is $(-\infty, x_1)$.

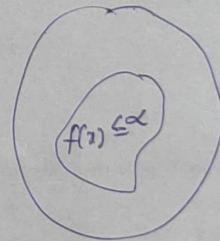
The above method for 1-dimension

For n-dimension, as it is difficult to calculate

objective function for each & every problem, we go for
 progressive step-size.

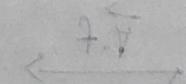
Compact set - means closed region

* Level set :- $L(\alpha) = \{x : f(x) \leq \alpha\}$



Derivative of a function gives the rate at which function is growing.

More slope \rightarrow High rate



Gradient : $\nabla f = i \frac{\partial}{\partial x} + j \frac{\partial}{\partial y} + k \frac{\partial}{\partial z}$

Divergence : $\nabla \cdot \vec{F} = \frac{\partial F_x}{\partial x} + \frac{\partial F_y}{\partial y} + \frac{\partial F_z}{\partial z}$; $\vec{F} = F_x \hat{i}_x + F_y \hat{j}_y + F_z \hat{k}_z$

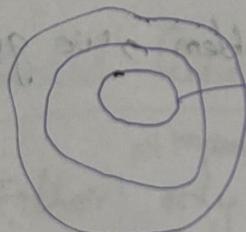
Curl : $\nabla \times \vec{F} = \begin{vmatrix} i & j & k \\ \frac{\partial}{\partial x} & \frac{\partial}{\partial y} & \frac{\partial}{\partial z} \\ F_x & F_y & F_z \end{vmatrix}$

→ it is a local property
 → Gradient gives us the direction of rate at which function is growing "rapidly" and its magnitude gives the rate value, it's always \perp to the surface i.e. tangent

- Gradient calculated for scalar fields.

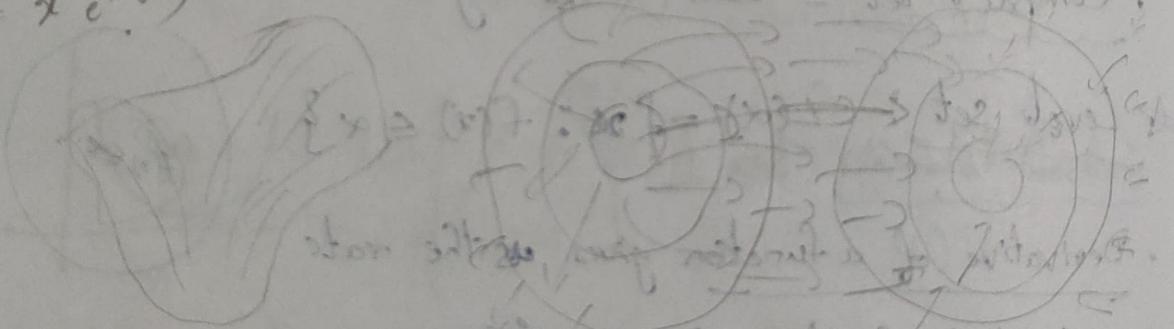
- Gradient gives a vector as op.

- Contour - Each contour represents different elevations



This contour has high elevation value.

$$(f = x e^{x^2+y^2})$$



$$\begin{array}{c} \vec{\nabla} f \\ \swarrow \quad \searrow \\ d \end{array} \quad \vec{\nabla} f \cdot \vec{d} \leftarrow \text{Directional derivative}$$

$$\boxed{\vec{\nabla} f^T \cdot \vec{d}}$$

~~By column vector~~
 $(\vec{\nabla} f^T \text{- column vector})$

- Rate at which f growing in specified (\vec{d}) direction

2/03/2023

$$\text{Ex: } f(x, y) = xy^2 + x^3y$$

Find $\vec{i} \cdot \vec{\nabla} f$

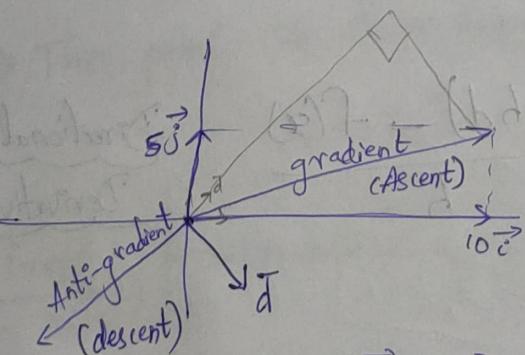
$$\text{Sol: } \vec{\nabla} f = i \frac{\partial f}{\partial x} + j \frac{\partial f}{\partial y}$$

$$= \left(i \frac{\partial}{\partial x} + j \frac{\partial}{\partial y} \right) (xy^2 + x^3y)$$

$$= \vec{i} (y^2 + 3x^2y) + \vec{j} (2xy + x^3)$$

$$\text{At } (1, 2) \quad \vec{\nabla} f(x, y) = ?$$

$$\begin{aligned} \vec{\nabla} f(1, 2) &= (4+6)\vec{i} + (4+1)\vec{j} \\ &= 10\vec{i} + 5\vec{j} \end{aligned}$$



Gradient gives direction of point at which its growing rapidly. (with max. rate)

$$\vec{F} = \frac{1}{\sqrt{2}}\vec{i} + \frac{1}{\sqrt{2}}\vec{j}$$

Anti-gradient - The direction at which point descending rapidly. (max. rate).

Directional Derivative: $\vec{\nabla} f \cdot \vec{d}$

$$(10\vec{i} + 5\vec{j}) \cdot \left(\frac{1}{\sqrt{2}}\vec{i} + \frac{1}{\sqrt{2}}\vec{j} \right) = \frac{10}{\sqrt{2}} + \frac{5}{\sqrt{2}} = \frac{15}{\sqrt{2}}$$

* rate at which growing in \vec{d} (1, 2)

Usually, vectors representation as column vectors

$$\vec{\nabla} f = \begin{bmatrix} \frac{\partial}{\partial x} f \\ \frac{\partial}{\partial y} f \end{bmatrix} = \begin{bmatrix} y^2 + 8x^2y \\ 2xy + x^3 \end{bmatrix} \quad \vec{d} = \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}$$

$$\vec{\nabla} f_{(1,2)}^T \cdot \vec{d} = \begin{bmatrix} 10 & 5 \end{bmatrix}_{1 \times 2} \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}_{2 \times 1} = \frac{15}{\sqrt{2}}$$

$$\frac{df}{dx} = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h} \quad \begin{array}{l} \text{Definition of} \\ \text{Derivative} \end{array}$$

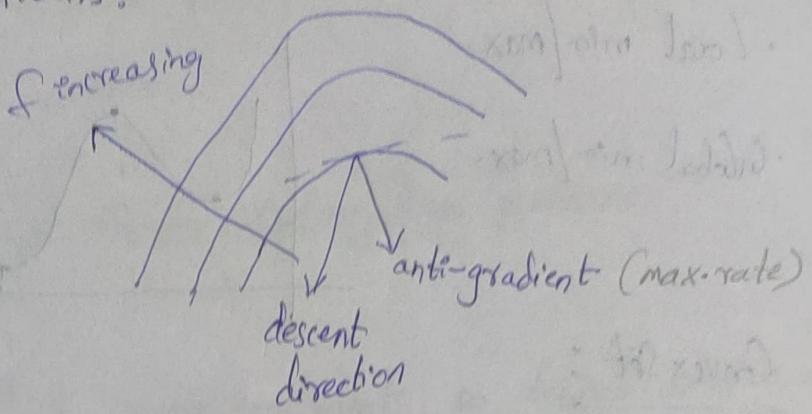
$$\vec{\nabla} f' \cdot \vec{d} = \lim_{h \rightarrow 0} \frac{f(x+hd) - f(x)}{h} \quad \begin{array}{l} \text{Directional} \\ \text{Derivative} \end{array}$$

→ Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$. A vector $d \in \mathbb{R}^n$ is said to be a descent direction for f at x_0 , if $\exists \delta > 0$ such that

$$f(x_0 + dd) < f(x_0); \quad (d \text{-constant}, d \in \mathbb{R}^n)$$

If ∇f exists & is continuous, if $\vec{\nabla} f(x_0)^T \vec{d} < 0$ then direction d is a descent direction for f at x_0 .

equally contours:



→ The gradient $\nabla f(x_0)$ is a direction orthogonal (!) to the level surface and it is a direction of ascent and hence the anti-gradient $-\nabla f(x_0)$ is a descent direction.

$$\cos \theta = \frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \|\mathbf{b}\|}$$

→ The point x_0 is a local minimum of f , iff $\vec{\nabla} f(x_0) = 0$ (when ∇f exists)

Proof: (by contradiction)

$$(\text{Anti-gradient}) \quad \vec{d} = -\vec{\nabla} f(x_0)$$

if x_0 is not a local minimum point then

$$f(x_0 + \lambda \vec{d}) < f(x_0)$$

$$f(x_0 - \lambda \vec{d}) < f(x_0)$$

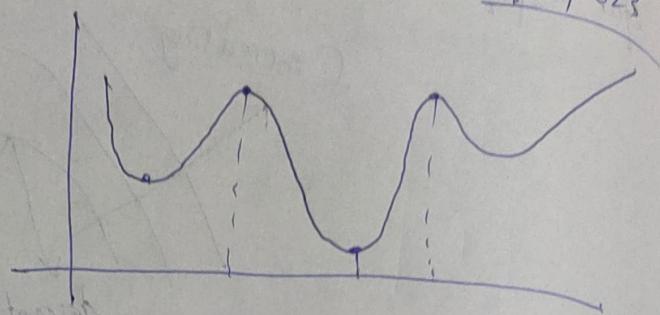
This contradicts the hypothesis and so x_0 is a local minimum

Hence Proved

03/03/2023

• Local min./max.

• Global min./max.



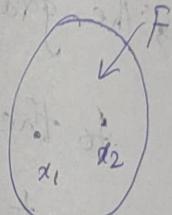
Convex Set:

∴ A set is said to be Convex.

$f:$

$d_1, d_2 \text{ if } d_1 x_1 + d_2 x_2 \in F$

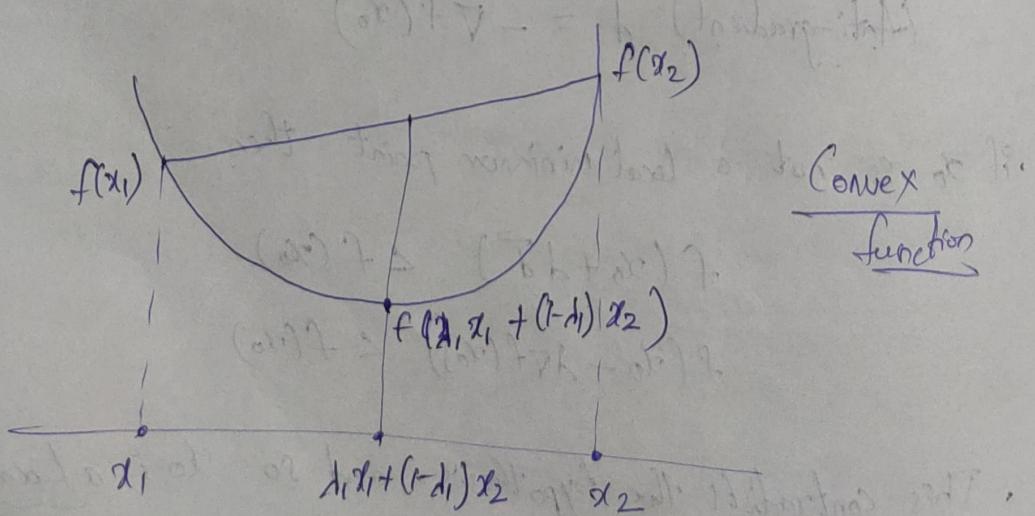
then $d_1 + d_2 = 1$ has



$$y = d_1 x_1 + (1-d_1)x_2 ; \quad 0 \leq d_1 \leq 1$$

• f defined on Convex set is Convex function.

Condition: $f(d_1 x_1 + (1-d_1)x_2) \leq d_1 f(x_1) + (1-d_1)f(x_2)$



→ If not convex, it is Concave.

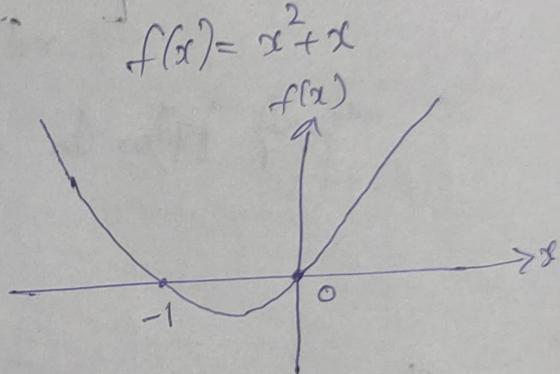
All LPP deals with convex function i.e. Convex Optimization problem.

LPPs are always Convex Optimization problems.

Ex: $f(x) = x^2 + x$ no constraints, so defined over $(-\infty, \infty)$

Find minimum value?

Sol:
At $x=3$: $f(3) = 9 + 3 = 12$



Methods: Gradient descent ✓

Steepest descent ✓

Steepest Ascent

Gradient Ascent

Gradient Descent Algorithm:

$$f(x), -\vec{\nabla}f, \frac{\vec{\nabla}f}{\|\vec{\nabla}f\|}$$

Ex: $f(x,y) = 4x^2 - 4xy + 2y^2$ min value?

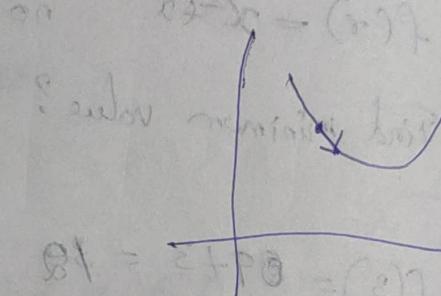
Sol: $\vec{\nabla}f = \vec{i}(8x - 4y) + \vec{j}(-4x + 4y)$

$$= \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} = \begin{bmatrix} 8x - 4y \\ -4x + 4y \end{bmatrix}$$

Sol: Assume initial guess $(2, 3)$

$$\vec{\nabla} f = \begin{bmatrix} 8x - 4y \\ -4x + 4y \end{bmatrix} \quad \vec{\nabla} f(2, 3) = \begin{bmatrix} 4 \\ 4 \end{bmatrix}$$

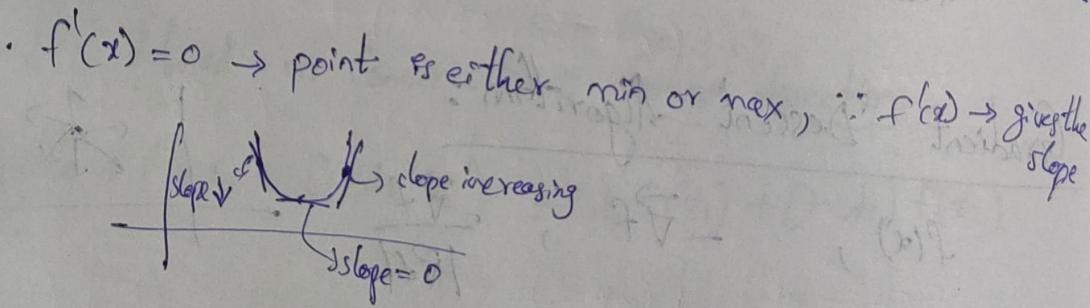
$$\frac{-\vec{\nabla} f(2, 3)}{\|\vec{\nabla} f\|} = \begin{bmatrix} -4/\sqrt{2} \\ -1/\sqrt{2} \end{bmatrix}$$



$$f(\bar{x} - t\bar{d})$$

07/08/2023

- $f'(x) > 0$ - function is increasing \rightarrow it has min. point & so $f''(x) > 0$
- $f'(x) < 0$ - is decreasing \rightarrow it has max. point & so $f''(x) < 0$



- FONC - First order Necessary condition
- SONC - Second Order Necessary condition
- SOSC - Second Order Sufficient Condition

$$\text{Ex: Minimize } f(x,y) = 4x^2 - 4xy + 2y^2, \quad f: \mathbb{R}^2 \rightarrow \mathbb{R}$$

Sol: Steepest Descent method:

$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} = \begin{bmatrix} 8x - 4y \\ 4y - 4x \end{bmatrix}$$



- Gradient always gives a vector
- Gradient gives the direction at which function is growing rapidly.
- Gradient is a local property.
- Step value changes after every iteration.

• Initial guess $(2, 3) = (x_0, y_0)$

$$\nabla f(x_0, y_0) = \begin{bmatrix} 4 \\ 4 \end{bmatrix}$$

Unconstrained
Non-LPP
Optimized problems

$$f(\bar{x} + \alpha \bar{d}) \leq f(\bar{x}) \quad ; \quad \alpha \geq 0$$

$$\bar{d} = -\vec{\nabla} f$$

$$\alpha^* = \arg \min_{\alpha} f(\bar{x} - \alpha \vec{\nabla} f)$$

$$\alpha = \phi'(\alpha)$$

$$\boxed{\vec{\nabla} f(x_0, y_0) - \alpha \vec{\nabla} f(x_0, y_0)} \cdot \vec{\nabla} f(x_0, y_0) = 0$$

$$\text{Sol: } f(\underline{x}^*) - \alpha(\underline{g} + \underline{A}\underline{\beta}) = f(\underline{x}^* - \alpha\underline{A}\underline{\beta})$$

$$\text{Let } \phi(\alpha) = f(\underline{x}^* - \alpha\underline{A}\underline{\beta})$$

$$f(\underline{x}^* - \alpha\underline{A}\underline{\beta})$$

$$\cancel{\phi(\alpha)} = \cancel{\begin{bmatrix} -16\alpha + 4\alpha \\ -4\alpha + 8\alpha \end{bmatrix}} = \cancel{\begin{bmatrix} -12\alpha \\ 4\alpha \end{bmatrix}}$$

$$\rightarrow f((x_0, y_0) - \alpha \nabla f(x_0, y_0)) = \cancel{f(x_0, y_0) - \alpha \cancel{\nabla f(x_0, y_0)}}$$

$$= f\left(\begin{bmatrix} 2 & 3 \end{bmatrix}^T \alpha \begin{bmatrix} 4 & 4 \end{bmatrix}^T\right)$$

$$= f\left(\begin{bmatrix} 2-4\alpha & 3-4\alpha \end{bmatrix}^T\right)$$

$$= f(2-4\alpha, 3-4\alpha)$$

$$\text{let } \phi(\alpha) = f(2-4\alpha, 3-4\alpha)$$

$$\nabla \phi(\alpha) = \begin{bmatrix} 8(2-4\alpha) - 4(3-4\alpha) \\ 4(3-4\alpha) - 4(2-4\alpha) \end{bmatrix} = \begin{bmatrix} 16 - 32\alpha - 12 + 16\alpha \\ 12 - 16\alpha - 8 + 16\alpha \end{bmatrix}$$

$$= \begin{bmatrix} 4-16\alpha \\ 4 \end{bmatrix}$$

$$(4-16\alpha) + 4 = 8$$

$$\stackrel{W.k.T}{\Rightarrow} \vec{\nabla} f(\vec{x}_0 - \alpha \vec{\nabla} f(x_0, y_0)) \cdot \vec{\nabla} f(x_0, y_0) = 0$$

$$\Rightarrow (4 - 16\alpha)(4) + (4)(4) = 0$$

$$\Rightarrow 4 - 16\alpha + 4 = 0$$

$$\Rightarrow 16\alpha = 8$$

$$\Rightarrow \alpha = \frac{1}{2}$$

New guess: $\vec{x}_1 = \vec{x}_0 + \alpha \vec{d}$

$$\vec{x}_0 = (2, 3)$$

$$\begin{bmatrix} 2 \\ 3 \\ 2 \\ 3 \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} 2 \\ 3 \end{bmatrix} - \frac{1}{2} \begin{bmatrix} 4 \\ 4 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\vec{x}_1 = (0, 1)$$

$$\vec{\nabla} f = \begin{bmatrix} 8x - 4y \\ 4y - 4x \end{bmatrix}$$

$$\vec{\nabla} f(0, 1) = \begin{bmatrix} -4 \\ 4 \end{bmatrix}$$

$$\rightarrow f((0, 1) - \alpha(-4, 4)) = f([4\alpha \ 1 - 4\alpha]^T)$$

$$\vec{\nabla} f([4\alpha \ 1 - 4\alpha]^T) = \begin{bmatrix} 8(4\alpha) - 4(1 - 4\alpha) \\ 4(1 - 4\alpha) - 4(4\alpha) \end{bmatrix} = \begin{bmatrix} 32\alpha - 4 + 16\alpha \\ 4 - 16\alpha - 16\alpha \end{bmatrix}$$

$$= \begin{bmatrix} 48\alpha - 4 \\ 4 - 32\alpha \end{bmatrix}$$

$$\therefore \vec{\nabla} f([4\alpha \ 1 - 4\alpha]^T) \cdot \vec{\nabla} f(0, 1) = 0 \quad \text{→}$$

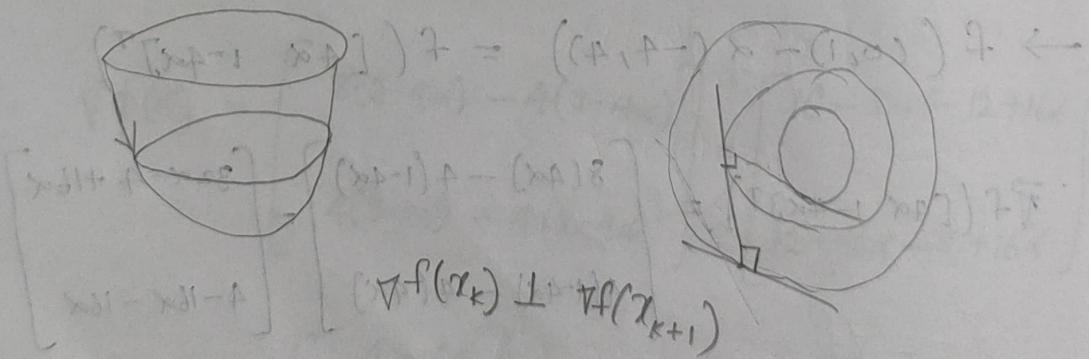
$$\Rightarrow (48\alpha - 4)f(4) + (4 - 32\alpha)(4) = 0$$

$$\Rightarrow 4 - 48\alpha + 4 - 32\alpha = 0 \Rightarrow 1 - 12\alpha + 1 - 8\alpha = 0$$

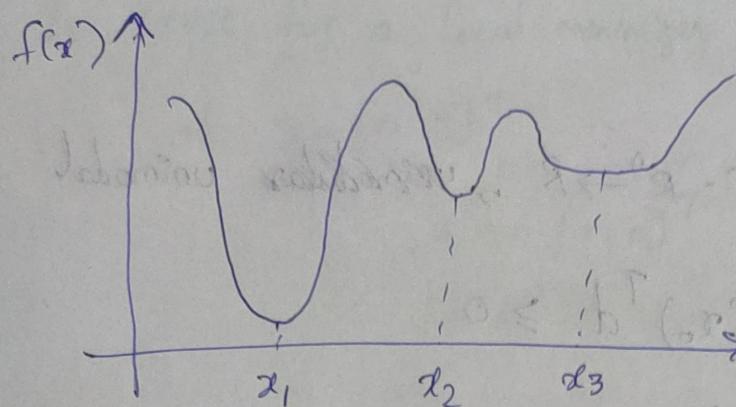
$$\Rightarrow 2 - 20\alpha = 0 \Rightarrow \alpha = \frac{1}{10}$$

$$\Rightarrow 80\alpha = 8 \Rightarrow \alpha = \frac{1}{10}$$

	<u>Descent direction</u>	<u>Step value</u>	<u>New estimate</u>
I ₁	$\begin{bmatrix} 2 \\ 3 \end{bmatrix}$	$\begin{bmatrix} 4 \\ 4 \end{bmatrix}$	$\alpha = \frac{1}{2}$ $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$
I ₂	$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$	$\begin{bmatrix} -4 \\ 4 \end{bmatrix}$	$\alpha = \frac{1}{10}$ $\begin{bmatrix} 2/5 \\ 3/5 \end{bmatrix}$
I ₃	$\begin{bmatrix} 2/5 \\ 3/5 \end{bmatrix}$		$\begin{bmatrix} 0 \\ 2/10 \end{bmatrix}$

$$\vec{x}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} - \frac{1}{10} \begin{bmatrix} -4 \\ 4 \end{bmatrix} = \begin{bmatrix} 2/5 \\ 3/5 \end{bmatrix}$$


The value of \vec{x} , at which the function takes minimum value, that \vec{x} is defined as Minimizer.



• x_1 - Global minimizer

• x_2 - Strict Local minimizer

$\vec{x}_3 \rightarrow$ Local minimizers such that it is not strict.

$$f(\vec{x}) = f(x_1, x_2, \dots, x_n)$$

Gradient: $\vec{\nabla} f = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{bmatrix}$

Hessian

$$\vec{\nabla}^2 f = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_2 \partial x_1} & \cdots & \frac{\partial^2 f}{\partial x_n \partial x_1} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & & \frac{\partial^2 f}{\partial x_n \partial x_2} \\ \vdots & & \ddots & \\ \frac{\partial^2 f}{\partial x_1 \partial x_n} & \frac{\partial^2 f}{\partial x_2 \partial x_n} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{bmatrix}$$

FONC:

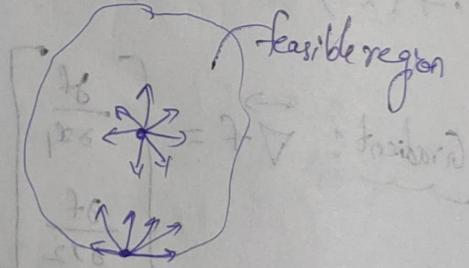
- A function: $f: \mathbb{R}^n \rightarrow \mathbb{R}$ \rightarrow unimodal

$$\text{FONC: } \vec{\nabla} f(x_0)^T d \geq 0$$

(directional derivative) $d^T \vec{\nabla} f(x_0) \geq 0$

then x_0 is local minimizer. (x_0 is a boundary point)

- $f \in C^1 \rightarrow$ function is first order differentiable and continuous
- $f \in C^2 \rightarrow$ function is 2nd order differentiable & continuous
- $S/F \subset \mathbb{R}^n$



For Interior points case:

$$\left. \begin{array}{l} \vec{\nabla} f(x_0)^T d \geq 0 \\ \vec{\nabla} f(x_0)^T d \leq 0 \end{array} \right\}$$

$$\Rightarrow \vec{\nabla} f(x_0) = 0 ; x_0 - \text{is an interior point}$$

Example: minimize $\therefore x_1^2 + 0.5x_2^2 + 3x_2 + 4.5$

6.3
(in K.P.Chong book)

Subject to: $x_1, x_2 \geq 0$ (Feasible region)

- (a) Is the FONC for a local minimizer satisfied at

$$x = [1 \ 3]^T$$

(b) Is FONC for a local minimizer satisfied at $x = [0 \ 3]^T$

(c) " at $x = [1, 0]^T$

(d) " at $x = [0, 0]^T$

Sol: $f(x) = x_1^2 + 0.5x_2^2 + 3x_2 + 4.5$; $x_1, x_2 \geq 0$

(a)

Point: $(1, 3)$ $\vec{\nabla} f = \begin{bmatrix} 2x_1 \\ x_2 + 3 \end{bmatrix}$ $\vec{\nabla} f(1, 3) = \begin{bmatrix} 2 \\ 6 \end{bmatrix} \neq \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

(Interior point)

(b)

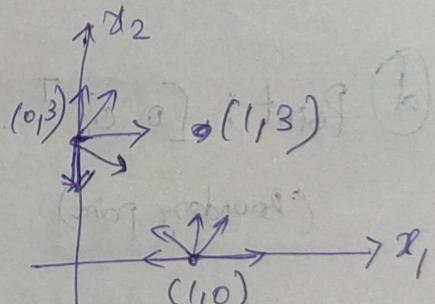
Point: $(0, 3)$ $\vec{\nabla} f = \begin{bmatrix} 2x_1 \\ x_2 + 3 \end{bmatrix}$ $\vec{\nabla} f(0, 3) = \begin{bmatrix} 0 \\ 6 \end{bmatrix}$ satisfies for (i, e) imp.

(Boundary point)

~~$d = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} = \begin{bmatrix} 1.5 \\ 6 \end{bmatrix}$~~

from graph: $d_1 \geq 0$

$d_2 \leq 0$ s.s. : App. $0 \leq 6$



Necessary Condition $\vec{\nabla} f(0, 3) \cdot d \geq 0 \Rightarrow 6d_2 \geq 0 \Rightarrow d_2 \geq 0$ is not always greater than zero

FONC is not satisfied for $[0 \ 3]^T$

FONC is not satisfied for $[1 \ 3]^T$

① Point: $[1 \ 0]^T$ (Boundary point) $\vec{\nabla}^2 f = \begin{bmatrix} 2x_1 & \\ & 1 \end{bmatrix}$ $\vec{\nabla}^2 f(1,0) = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$

$$d = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix}$$

From graph: $d_1 \geq 0$ \rightarrow limited to $-1 \leq d_1 \leq 0$
 $d_2 \geq 0$ \rightarrow $d_2 \geq 0$

FONC to be satisfied: $\vec{\nabla}^2 f(1,0)^T d = 2d_1 + 3d_2 \geq 0$ $\text{not always greater than zero}$

• FONC is not satisfied at $[1 \ 0]^T$ (misunderstand)

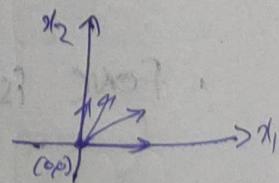
② Point: $[0 \ 0]^T$ (Boundary point) $\vec{\nabla}^2 f = \begin{bmatrix} 2x_1 & \\ & 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$

$$d = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix}$$

From graph: $d_1 \geq 0$
 $d_2 \geq 0$

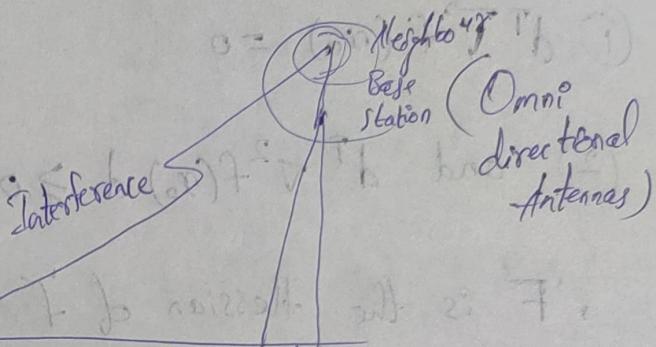
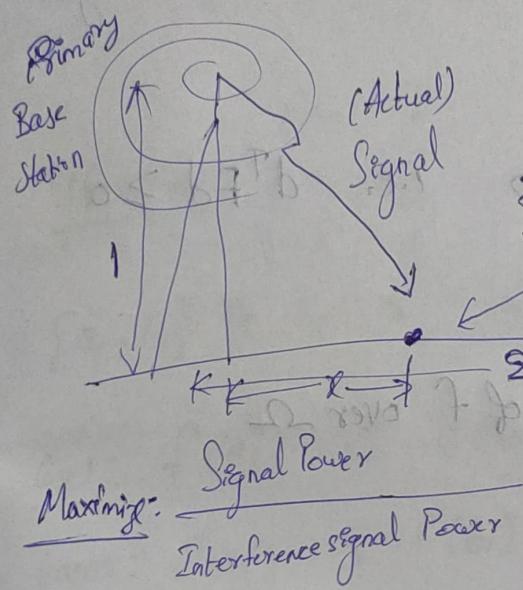
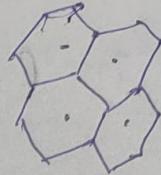
FONC to be satisfied: $\vec{\nabla}^2 f(0,0)^T d = 3d_2 \geq 0$ (True)

\therefore FONC is satisfied at $[0 \ 0]^T$



Q. Two antennas
Cell site (hexagonal shape)

Example 6.4



Maximize: $\frac{\text{Signal Power}}{\text{Interference signal Power}}$

Find $x = ?$

$$\cdot \text{Signal Power} \propto \frac{1}{(\sqrt{1+x^2})^2}$$

$$(\because \text{Power} \propto \frac{1}{d^2})$$

$$\cdot \text{Interference Signal Power} \propto \frac{1}{(\sqrt{1+(2-x)^2})^2}$$

Therefore,

$$\text{Maximize: } f(x) = \frac{1+(2-x)^2}{1+x^2} = \frac{5-4x+x^2}{1+x^2}$$

$$\text{Using FONC: } f'(x) = 0 \Rightarrow f'(x) = \frac{4(x^2-2x-1)}{(1+x^2)^2} = 0$$

$(x_0 \rightarrow \text{interior point})$
 $\text{Boundary point - both same}$

$$\Rightarrow x_0 = 1 \pm \sqrt{2}$$

Here, function
is one dimensional

$$\boxed{\therefore x_0 = 1 \pm \sqrt{2}}$$

(As $1+\sqrt{2}$ is beyond 2)

SOSC: $f: \mathbb{R}^n \rightarrow \mathbb{R}$, $f \in C^2$, $\Omega \subset \mathbb{R}^n$
 \downarrow feasible region

$$\textcircled{1} \quad d^T \nabla f(x_0) = 0$$

$$\textcircled{2} \quad \text{and } d^T \nabla^2 f(x_0) d \geq 0 \quad \text{i.e. } d^T F d \geq 0$$

'F' is the Hessian of 'f'

x_0 - is a local minimizer of f over Ω

SOSC: $f \in C^2$

$$\textcircled{1} \quad \nabla f(x_0) = 0$$

$$\textcircled{2} \quad F(x_0) > 0$$

Line Search algorithms : searching in a single line. 09/03/2023

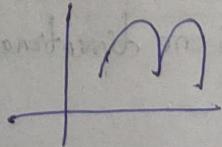
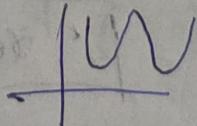
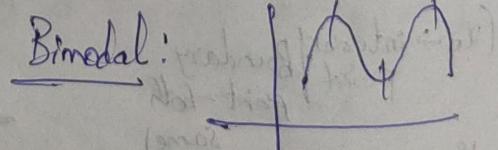
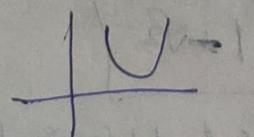
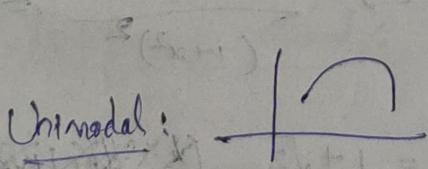
1. Golden-section search (Unimodal)

2. Fibonacci method

3. Newton's method

4. Secant method

5. Bisection method



09/08/2023

1. Golden - Section Search

$$f(x) \in [a_0, b_0]$$

$$[a_0, b_0]$$

$$\text{Iteration 1: } [a_1, b_1]$$

$$[a_1, b_1] \ni a_1 - a_0 = b_0 - b_1 = P(b_0 - a_0); P < \frac{1}{2}$$

Case 1: $f(a_1) < f(b_1)$ P -shorter length
Case 2: $f(a_1) > f(b_1)$ $(1-P)$ -longer length

For a minimizing problem:

$$(1-P)P = 1 - 1$$

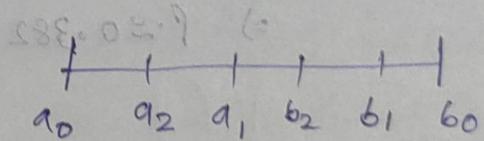
In Case 1 i.e. $f(a_1) < f(b_1)$ then minimizer is $x_0 \in [a_0, b_1]$

In Case 2 i.e. $f(a_1) > f(b_1)$ then minimizer is $x_0 \in [a_1, b_0]$

$$\text{Iteration 2: } [a_2, b_2]$$

$$\text{Case 1: } [a_0, b_1]$$

$$a_2 - a_0 = b_1 - b_2 = P(b_1 - a_0)$$



To reduce computational calculations, make points b_2 and a_1 as symmetric, i.e. $b_2 = a_1$

$$[a_2, b_2] = [a_2, a_1]$$

$$a_2 - q_0 = b_1 - b_2 = p_k(b_1 - q_0) \quad ; \quad p_k = P \text{ value of } k^{\text{th}} \text{ iteration}$$

In Golden-section search, $p_k = p_{k+1}$ i.e. P value is same for all iterations

In Fibonacci method, different values of P is considered for different iterations

In Golden-section search

$$\Rightarrow 1-2p = p(1-p)$$

$$\Rightarrow 1-2p = p-p^2$$

$$\Rightarrow p^2 - 3p + 1 = 0$$

$$\Rightarrow p = \frac{3 \pm \sqrt{9-4}}{2} = \frac{3-\sqrt{5}}{2}$$

$$\Rightarrow p \approx 0.382$$

Length of the interval in n^{th} iteration is $(1-p)^n$

$$1-p = 1 - \left(\frac{3-\sqrt{5}}{2}\right) = \frac{\sqrt{5}-1}{2} \quad ; \quad \frac{p}{1-p} = \frac{3-\sqrt{5}}{\sqrt{5}-1} = \frac{\sqrt{5}-1}{2} = 1-p$$

$\therefore \frac{p}{1-p} = \frac{1-p}{1}$; the ratio of shorter segment to longer equals to ratio of longer to sum of two.

This rule was referred to by ancient Greek geometers as the Golden section

Example 7:1

$$f(x) = x^4 - 14x^3 + 60x^2 - 70x \text{ defined over } [0, 2]$$

Value of x that minimizes $f(x)$? (use Golden-section Search method)

- locate x value to within a range of 0.3

$$\left[\frac{\varphi}{\varphi-1} - 1 = \frac{1}{1+\varphi} \right]$$

$(n+1) \dots (d-1) (l-1) :$ Downside of the digits.

$$x = d, \quad \varepsilon = d, \quad s = d, \quad l = d, \quad t = d, \quad 0 = d$$

2. Fibonacci Method :

$$P_{k+1} = \frac{F_{k+1}}{F_k}$$

$$P_{k+1} = \frac{1 - 2P_k}{1 - P_k}$$

$$\therefore P_{k+1} = 1 - \frac{P_k}{1 - P_k}$$

Length of the intervals : $(1 - P_1) (1 - P_2) \dots (1 - P_N)$

$$P_1 = 0, P_0 = 1, P_1 = 1, P_2 = 2, P_3 = 3, P_4 = 5 \\ 8, 13, 21, 34, \dots$$

The rate at which the interval length narrows down is much faster in Fibonacci Method than in Golden-section Search algorithm.

$$P_1 = 1 - \frac{F_N}{F_{N+1}}, \dots, P_N = 1 - \frac{F_1}{F_2}$$

3. Bisection Method :

$$[a_0, b_0]$$

Iteration 1 :

$$\therefore x_0 = \frac{a_0 + b_0}{2}, f'(x_0) > 0 \Rightarrow [a_0, \frac{a_0 + b_0}{2}]$$

$$f'(x_0) < 0 \Rightarrow [\frac{a_0 + b_0}{2}, b_0]$$

Rate at which interval gets narrower & narrower is $(0.5)^n$ in Bisection Method i.e. $(0.5)^N$

4. Newton's Method :

$$f(x+h) = f(x) + h f'(x) + \frac{h^2}{2!} f''(x) + \dots$$

~~$$\rightarrow x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}$$~~

$$Q(x) = f(x^k) + f'(x^k)(x-x^k) + \frac{1}{2} f''(x^k) (x-x^k)^2$$

$$Q'(x)=0 \Rightarrow f'(x^k) + f''(x^k)(x-x^k) = 0$$

$$\text{Setting } x = x^{k+1} \Rightarrow x^{k+1} = x^k - \frac{f'(x^k)}{f''(x^k)}$$

4. Newton's Method :

$$\{ f(x+h) = f(x) + hf'(x) + \frac{h^2}{2!} f''(x) + \dots \}$$

$$\Rightarrow x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}$$

Taylor series :

$$g(x) = f(x^k) + f'(x^k)(x - x^k) + \frac{1}{2} f''(x^k) (x - x^k)^2$$

$$g'(x) = 0 \Rightarrow f'(x^k) + f''(x^k)(x - x^k) = 0$$

$f(x_k)$ is a constant

$$\text{Setting } x = x^{k+1} \Rightarrow x^{k+1} = x^k - \frac{f'(x^k)}{f''(x^k)}$$

10/08/2023

Line-Search Algorithms

1. Golden-section Search / No. use of

2. Fibonacci method / $f(x)$ & $f'(x)$

3. Bisection / $f(x)$ is used

4. Newton's method / Both $f(x)$ & $f'(x)$ are used

5. Secant method /

A. Newton's Method:

$$\text{Let } g(x) = f(x_k) + (x - x_k)f'(x_k) + \frac{(x - x_k)^2}{2!} f''(x_k) + \dots$$

FONC : $g'(x) = 0 \Rightarrow g'(x) = f'(x_k) + \frac{2(x - x_k)}{2!} f''(x_k) = 0$

$$\Rightarrow f'(x_k) + (x - x_k) f''(x_k) = 0$$

$$\Rightarrow (x - x_k) f''(x_k) = -f'(x_k)$$

$$\Rightarrow x - x_k = \frac{-f'(x_k)}{f''(x_k)}$$

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}$$

$$\boxed{x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}}$$

$$, f'(x_k) > 0 , f'(x_{k+1}) < 0$$

If $f''(x_k)$ is not available

5. Secant Method:

$$f''(x_k) \approx \frac{f'(x_k) - f'(x_{k-1})}{x_k - x_{k-1}}$$

$$x_{k+1} = x_k - \frac{(x_k - x_{k-1}) f'(x_k)}{f'(x_k) - f'(x_{k-1})}$$

$$\boxed{x_{k+1} = \frac{x_{k-1} f'(x_k) - x_k f'(x_{k-1})}{f'(x_k) - f'(x_{k-1})}}$$

Example 1.4: $f(x) = \frac{1}{2}x^2 - \sin x$, find the minimizer x_* ?

Sol: $f'(x) = x - \cos x$

$f''(x) = 1 + \sin x$

Let $x_0 = 0.5$

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}$$

$$\begin{aligned}x_1 &= 0.5 - \frac{[0.5 - \cos(0.5)]}{[1 + \sin(0.5)]} \\&= 0.7552\end{aligned}$$

$$\begin{aligned}x_2 &= x_1 - \frac{f'(x_1)}{f''(x_1)} = 0.7552 - \frac{[0.7552 - \cos(0.7552)]}{[1 + \sin(0.7552)]} \\&= 0.7391\end{aligned}$$

$$x_3 = x_2 - \frac{f'(x_2)}{f''(x_2)} = 0.7390$$

$$x_4 = x_3 - \frac{f'(x_3)}{f''(x_3)} = 0.7390$$

$$f(x)$$

$$f'(x)$$

$$f(x_1, x_2, \dots, x_n) = f(\vec{x})$$

$\nabla f(\vec{x})$ — gradient

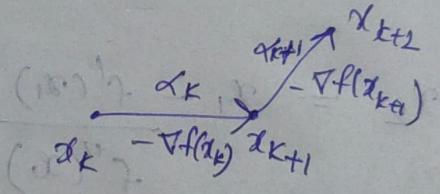
$$f(\vec{x} + \alpha \vec{d})$$

$\nabla f(x + \alpha d)^T d$ — Directional Derivative

If $\{x_k\}_{k=0}^{\infty}$ is a steepest descent sequence for a given function $f: \mathbb{R}^n \rightarrow \mathbb{R}$, then for each k the vector $x_{k+1} - x_k$ is orthogonal to the vector $x_{k+2} - x_{k+1}$.

Proof:

$$x_{k+1} - d_k = ?$$



$$\Rightarrow x_{k+1} - d_k = -\alpha_k \nabla f(d_k)$$

; α_k — magnitude (step-size)
 $-\nabla f(x_k)$ → descent direction

$$\Rightarrow x_{k+2} - d_{k+1} = -\alpha_{k+1} \nabla f(x_{k+1})$$

RTP: $(x_{k+1} - x_k)$ orthogonal to $(x_{k+2} - x_{k+1})$

$$\Rightarrow \langle \nabla f(x_k), \nabla f(x_{k+1}) \rangle = 0 \quad (\text{RTP condition})$$

$$\phi_k(\alpha) = f(x_k - \alpha \nabla f(x_k))$$

Generalized Newton's Method

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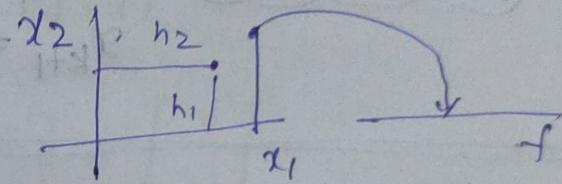
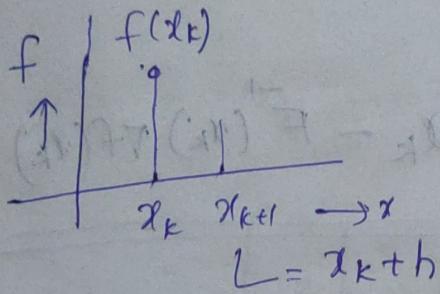
14/08/2023

Taylor series of a function:

$$f(x+h) = f(x) + h \cdot f'(x) + \frac{h^2}{2!} f''(x) + \dots$$

$$f(x_{k+1}) = g(x) \approx f(x_k) + (x - x_k) \cdot f'(x_k)$$

$$+ \frac{(x - x_k)^2}{2!} f''(x_k) + \dots$$



N-dimensional case:

$$\nabla f(x_{k+1}) = g(x) \approx f(x_k) + (x - x_k)^T \nabla f(x_k) + \frac{1}{2!} (x - x_k)^T F(x - x_k)$$

$$\therefore f(x+h) \approx f(x) + h^T \nabla f(x) + \frac{1}{2!} h^T F(h)$$

$$F = \nabla^2 f \quad \text{Hessian}$$

$$\rightarrow f(x_k) = f(x_1, x_2, \dots, x_n)$$

$$\rightarrow x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)} \quad \left(\text{from } g'(x) = 0 \right)$$

$$g'(x) = f'(x_k) + (x - x_k) f''(x_k)$$

$$\text{Newton's Method} : x = x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}$$

$$\text{Steepest Descent Method} : x_{k+1} = x_k - \alpha \nabla f(x_k)$$

In N-Dimension case:

Newton's Method:

$$x_{k+1} = x_k - F^{-1}(x_k) \nabla f(x_k)$$

$$\text{Ex: } f(x, y) = 4x^2 - 4xy + 2y^2$$

$$x = [2, 3]$$

$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} = \begin{bmatrix} 8x - 4y \\ 4y - 4x \end{bmatrix} \quad \nabla f(x) = \begin{bmatrix} 4 \\ 4 \end{bmatrix}$$

$$\nabla^2 f = F = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial y \partial x} & \frac{\partial^2 f}{\partial y^2} \end{bmatrix} = \begin{bmatrix} 8 & -4 \\ -4 & 4 \end{bmatrix}$$

$$F^{-1} = \frac{1}{(8-16)} \begin{bmatrix} 4 & 4 \\ 4 & 8 \end{bmatrix}^T = \frac{1}{16} \begin{bmatrix} 4 & 4 \\ 4 & 8 \end{bmatrix}$$

$$F^{-1} \nabla f(\vec{x}) = \frac{1}{16} \begin{bmatrix} 4 & 4 \\ 4 & 8 \end{bmatrix} \begin{bmatrix} 4 \\ 4 \end{bmatrix}$$

$$= \frac{1}{4} \begin{bmatrix} 4 & 4 \\ 4 & 8 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\stackrel{(c) \rightarrow (b)}{=} \frac{1}{4} \begin{bmatrix} 8 \\ 12 \end{bmatrix} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$$

$$\cdot \quad x_{k+1} = x_k - F^{-1} \nabla f(\vec{x})$$

$$= \begin{bmatrix} 2 \\ 3 \end{bmatrix} - \begin{bmatrix} 2 \\ 3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\cdot \quad f(\vec{x}) = 4(4) - 4(2)(3) + 2(9)$$

$$= 16 - 24 + 18$$

$$= 10$$

$$\cdot \quad f(\vec{x}') = 4(0) - 4(0)(0) + 2(0)$$

$$= 0$$

1. Solve for $d^{(k)}$ in

$$F(\vec{x}^k) d^k = -g^k$$

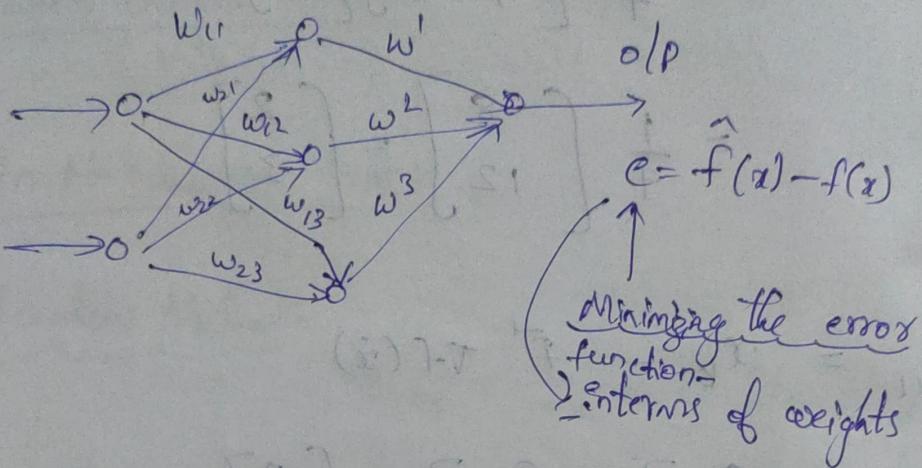
$$\Rightarrow d^k = -F^{-1}(\vec{x}_k) g_k$$

$$\boxed{\begin{aligned} F &= \nabla^2 f \\ g &= \nabla f \end{aligned}}$$

$$2. \text{ Set } \cdot \quad x_{k+1} = x_k + d_k$$

OT in ML/AI

MLP - Multi-layer perceptron



- Dual role application, Machine learning problem
- 5-weight problem

$$\star f(x) = E[x] = \sum_{i=1}^m w_i [e_i(x)]^p \quad \text{(Weighted summation)}$$

$$w_i [e_i(x)]^p \rightarrow [e_i(x)]^p$$

$$\rightarrow E[x] = \sum_i e_i^p - \underbrace{\text{least } p^{\text{th}} \text{ optimization technique}}$$

$$\rightarrow \text{if, } p=2 \therefore E = \sum_i e_i^2 - \underbrace{\text{least square optimization technique}}$$

$$E(x_1, x_2) = \sum_i e_i^2 (d_i, x_2) \quad (\text{min}, p=2)$$

(2-dimensional)

FONC : x^* , $\nabla f(x^*) = 0$

$$\nabla E(x) = 0$$

for $P=2$

$$\nabla E(x) = \begin{bmatrix} \frac{\partial}{\partial x_1} E \\ \frac{\partial}{\partial x_2} E \\ \vdots \\ \frac{\partial}{\partial x_n} E \end{bmatrix} = \begin{bmatrix} 2 \sum_i e_i \cdot \frac{\partial e_i}{\partial x_1} \\ 2 \sum_i e_i \cdot \frac{\partial e_i}{\partial x_2} \\ \vdots \\ 2 \sum_i e_i \cdot \frac{\partial e_i}{\partial x_n} \end{bmatrix}$$

$$\Rightarrow \nabla E(x) = 2 \begin{bmatrix} \sum_i (e_i \cdot \frac{\partial e_i}{\partial x_1}) \\ \sum_i (e_i \cdot \frac{\partial e_i}{\partial x_2}) \\ \vdots \\ \sum_i (e_i \cdot \frac{\partial e_i}{\partial x_n}) \end{bmatrix}$$

for P

$$\nabla E(x) = P \begin{bmatrix} \sum_i e_i^{P-1} \cdot \frac{\partial e_i}{\partial x_1} \\ \sum_i e_i^{P-1} \cdot \frac{\partial e_i}{\partial x_2} \\ \vdots \\ \sum_i e_i^{P-1} \cdot \frac{\partial e_i}{\partial x_n} \end{bmatrix}$$

$$(x_1 + x_2)^P \rightarrow (x_1 + x_2)^{P-1} \cdot q \rightarrow (x_1 + x_2)^{P-1}$$

$$x_1^{P-1} \cdot x_2^{P-1} \cdot (x_1 + x_2)^P = (x_1 + x_2)^{P-1}$$

$$J(x) = \begin{bmatrix} \frac{\partial e_1}{\partial x_1} & \frac{\partial e_1}{\partial x_2} & \cdots & \frac{\partial e_1}{\partial x_n} \\ \frac{\partial e_2}{\partial x_1} & \frac{\partial e_2}{\partial x_2} & \cdots & \frac{\partial e_2}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial e_m}{\partial x_1} & \frac{\partial e_m}{\partial x_2} & \cdots & \frac{\partial e_m}{\partial x_n} \end{bmatrix}_{m \times n}$$

$$= \left[\frac{\partial e_i}{\partial x_k} \right]$$

Jacobian Matrix

$$e = \begin{bmatrix} e_1(x) \\ e_2(x) \\ \vdots \\ e_m(x) \end{bmatrix}$$

$$\boxed{\nabla E(x) = 2 J^T e(x)} \quad \text{for } p=2$$

for Least p^{th} method

$$\boxed{\nabla E(x) = p J^T(x) e^{p-1}(x)}$$

FONC: ~~if~~ $\nabla E(x') \leq \nabla E(x^\circ)$

$$x' = x^\circ + \delta$$

$$\boxed{\nabla E(x+\delta x) = p J^T(x+\delta x) e^{p-1}(x+\delta x)}$$

$$\nabla E(x+\delta x) = 2 J^T(x+\delta x) e(x+\delta x)$$

→ The initial parameter vector will usually not be at the minimum thus $\nabla E(x)$ will not be zero.

→ However, $\nabla E(x) = P J^T(x) e^{P^{-1}}(x)$ can be used to obtain a change δx such that the magnitude of gradient is reduced.

→ The increment δx can be found by using above expression to express the gradient at $x + \delta x$.

$$\text{as } \nabla E(x + \delta x) = 2 J^T(x + \delta x) e(x + \delta x)$$

$$\nabla E(x + \delta x) = P J^T(x + \delta x) e^{P^{-1}}(x + \delta x)$$

Approximation

$$\nabla E(x + \delta x) \approx 2 J^T(x) e(x + \delta x)$$

$$\nabla E(x + \delta x) \approx P J^T(x) e^{P^{-1}}(x + \delta x)$$

As Jacobian does not vary very much, it will be true as the minimum is approached.

$$e(x + \delta x) \approx e(x) + \nabla e(x)^T \delta(x) + \frac{1}{2!} \delta(x)^T \nabla^2 e(x) \delta(x)$$

16/03/2023

Least P^{th} optimization

$$E(x) = \sum_{i=1}^m [e_i(x)]^P$$

$$\bar{x} = [x_1, x_2, \dots, x_n]_{1 \times n}^T$$

$$E(x) = \sum_{i=1}^m e_i^2(x)$$

$$e = [e_1, e_2, \dots, e_m]_{1 \times m}^T$$

$$J = \begin{bmatrix} \frac{\partial e_1}{\partial x_1} & \frac{\partial e_1}{\partial x_2} & \dots & \frac{\partial e_1}{\partial x_n} \\ \frac{\partial e_2}{\partial x_1} & \frac{\partial e_2}{\partial x_2} & \dots & \frac{\partial e_2}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial e_m}{\partial x_1} & \frac{\partial e_m}{\partial x_2} & \dots & \frac{\partial e_m}{\partial x_n} \end{bmatrix}_{m \times n}$$

$$\nabla E = \begin{bmatrix} \frac{\partial E}{\partial x_1} \\ \frac{\partial E}{\partial x_2} \\ \vdots \\ \frac{\partial E}{\partial x_n} \end{bmatrix} = \frac{\partial}{\partial} \begin{bmatrix} \sum_i e_i \frac{\partial e_i}{\partial x_1} \\ \sum_i e_i \frac{\partial e_i}{\partial x_2} \\ \vdots \\ \sum_i e_i \frac{\partial e_i}{\partial x_n} \end{bmatrix}$$

$$\nabla E = \frac{\partial}{\partial} J^T e$$

$$\nabla E(x) = P \cdot J^T e^{P-1}$$

$$\nabla E(x + \delta x) = \frac{\partial}{\partial} J(x + \delta x) e$$

$$\Rightarrow \nabla E(x + \delta x) \approx 2 J^T(x) e(x + \delta x)$$

$$\text{FONC: } \nabla E(x^*) = 0$$

Initial guess: x^* , $\nabla E(x^*) \neq 0$

$$x_1 = x^* + \delta x$$

$$\nabla E(x + \delta x) \rightarrow 0$$

$$\nabla E(x + \delta x) = P \cdot J^T(x + \delta x) e^{(P-1)}_{(x + \delta x)}$$

$$\Rightarrow \nabla E(x + \delta x) \approx P J^T(x) e^{P^{-1}}(x + \delta x)$$

for least squares method :

$$\# e(x + \delta x) \approx e(x) + \delta x \cdot e'(x + \delta x)$$

$$\Rightarrow e(x + \delta x) \approx e(x) + \nabla e^T(x + \delta x) \cdot \delta x$$

$$\nabla e^T(x + \delta x) = \left[\frac{\partial e}{\partial x_1} \frac{\partial e}{\partial x_2} \dots \frac{\partial e}{\partial x_n} \right]_{m \times n}$$

$$\delta x = \begin{bmatrix} \delta x_1 \\ \delta x_2 \\ \vdots \\ \delta x_n \end{bmatrix}_{n \times 1}$$

$$= J(x + \delta x)$$

$$\frac{\partial e}{\partial x_i} = \begin{bmatrix} \frac{\partial e_1}{\partial x_1} \\ \frac{\partial e_2}{\partial x_2} \\ \vdots \\ \frac{\partial e_m}{\partial x_n} \end{bmatrix}_{m \times 1}$$

$$\Rightarrow e(x + \delta x) \approx e(x) + J(x + \delta x) \delta(x)$$

$$\approx e(x) + J(x) \delta(x)$$

$$\approx e(x) + J(x) \delta(x)$$

$$(x) \rightarrow C (1) + (2) \rightarrow ①$$

FONC:

$$2 J^T(x) e(x + \delta x) = 0 \quad \text{from eq ①}$$

$$\Rightarrow 2 J^T(x) [e(x) + J(x) \delta(x)] = 0$$

$$\Rightarrow J^T e(x) + J^T J \delta(x) = 0$$

$$\Rightarrow J^T J \delta(x) = -J^T e(x)$$

$$\Rightarrow J^T(x) J(x) \delta(x) = -J^T(x) e(x)$$

∴ For least squares method

$$\mathbf{J}^T(\mathbf{x}) \mathbf{J}(\mathbf{x}) \mathbf{s}(\mathbf{x}) = -\mathbf{J}^T(\mathbf{x}) \mathbf{e}(\mathbf{x})$$

$$\mathbf{x}^{(1)} = \mathbf{x}^{(0)} + \mathbf{s}(\mathbf{x})$$

For least p^{th} method

$$\nabla e(\mathbf{x} + \delta \mathbf{x}) \approx p \mathbf{J}^T(\mathbf{x}) e^{p-1}(\mathbf{x} + \delta \mathbf{x}) = 0$$

$$e^{p-1}(\mathbf{x} + \delta \mathbf{x}) \approx e^{p-1}(\mathbf{x}) + s(\mathbf{x})(p-1) e^{p-2}(\mathbf{x}) \frac{de}{d\mathbf{x}}$$

$$\approx e^{p-1}(\mathbf{x}) + (p-1) e^{p-2}(\mathbf{x}) \nabla e(\mathbf{x}) s(\mathbf{x})$$

$$\approx e^{p-1}(\mathbf{x}) + (p-1) D \mathbf{J} s(\mathbf{x})$$

$$D = \text{diag.} [e_1^{p-2}(\mathbf{x}), e_2^{p-2}(\mathbf{x}), \dots, e_m^{p-2}(\mathbf{x})]$$

$$\mathbf{e} = [(\mathbf{x})^T (\mathbf{x})^T + (\mathbf{x})^T] (\mathbf{x})^T$$

Therefore:

$$\mathbf{J}^T(\mathbf{x} + \delta \mathbf{x}) = p \mathbf{J}^T(\mathbf{x}) e^{p-1}(\mathbf{x} + \delta \mathbf{x}) = 0$$

$$\Rightarrow p \mathbf{J}^T(\mathbf{x}) [e^{p-1}(\mathbf{x}) + (p-1) D \mathbf{J} s(\mathbf{x})] = 0$$

$$\Rightarrow \mathbf{J}^T D \mathbf{J} s(\mathbf{x}) = -\frac{1}{p-1} \mathbf{J}^T e^{p-1}$$

For least p th method

$$J^T D J S(x) = -\frac{1}{p-1} J^T e^{p-1}$$

Problem: $E(x) = (x_1^2 + x_2^2 + x_1 x_2 - 4)^2 + 4x_1^2 x_2^2 + 9x_1^2 x_2^4$

Sol: Initial guess: $(x_1, x_2) = (1, 1)$

$$\vec{x} = [1 \ 1]^T$$

$$e_1 = x_1^2 + x_2^2 + x_1 x_2 - 4$$

$$E(x) = \sum_{i=1}^3 e_i^2$$

$$e_2 = 2x_1 x_2$$

$$e_3 = 3x_1 x_2^2$$

Least Squares Method

$$J = \begin{bmatrix} \frac{\partial e_1}{\partial x_1} & \frac{\partial e_1}{\partial x_2} \\ \frac{\partial e_2}{\partial x_1} & \frac{\partial e_2}{\partial x_2} \\ \frac{\partial e_3}{\partial x_1} & \frac{\partial e_3}{\partial x_2} \end{bmatrix} = \begin{bmatrix} 2x_1 + x_2 & 2x_2 + x_1 \\ 2x_2 & 2x_1 \\ 3x_2^2 & 6x_1 x_2 \end{bmatrix}$$

$$e = \begin{bmatrix} x_1^2 + x_2^2 + x_1 x_2 - 4 \\ 2x_1 x_2 \\ 3x_1 x_2^2 \end{bmatrix} \Rightarrow e(\vec{x}) = \begin{bmatrix} -1 \\ 2 \\ 3 \end{bmatrix}$$

$$J(\vec{x}) = \begin{bmatrix} 3 & 3 \\ 2 & 2 \\ 3 & 6 \end{bmatrix}$$

WKT. $J^T(\vec{x}) J(\vec{x}) \delta(x) = -J^T(\vec{x}) e(\vec{x})$

$$\begin{bmatrix} 3 & 2 & 3 \\ 3 & 2 & 6 \end{bmatrix}_{3 \times 3} \begin{bmatrix} 3 & 3 \\ 2 & 2 \\ 3 & 6 \end{bmatrix}_{3 \times 2} \delta(x) = -\begin{bmatrix} 3 & 2 & 3 \\ 3 & 2 & 6 \end{bmatrix}_{3 \times 3} \begin{bmatrix} -1 \\ 2 \\ 3 \end{bmatrix}_{3 \times 1}$$

$$\begin{bmatrix} 9+4+9 & 7+4+18 \\ 9+4+18 & 9+4+36 \end{bmatrix} \delta(x) = -\begin{bmatrix} -3+4+9 \\ -3+4+18 \end{bmatrix}$$

$$\begin{bmatrix} 22 & 31 \\ 31 & 49 \end{bmatrix} \delta(x) = -\begin{bmatrix} 10 \\ 19 \end{bmatrix}$$

$$\Rightarrow \delta(x) = -\begin{bmatrix} 22 & 31 \\ 31 & 49 \end{bmatrix}^{-1} \begin{bmatrix} 10 \\ 19 \end{bmatrix}$$

$$= -\frac{1}{(22 \times 49 - 31^2)} \begin{bmatrix} 49 & -31 \\ -31 & 22 \end{bmatrix}^T \begin{bmatrix} 10 \\ 19 \end{bmatrix}$$

$$\Rightarrow s(x) = -\frac{1}{117} \begin{bmatrix} 49 & -31 \\ -31 & 22 \end{bmatrix} \begin{bmatrix} 10 \\ 19 \end{bmatrix}$$

$$= -\frac{1}{117} \begin{bmatrix} 490 - 31 \times 19 \\ -310 + 22 \times 19 \end{bmatrix}$$

$$\therefore s(x) = -\frac{1}{117} \begin{bmatrix} 1 - 99 \\ 108 \end{bmatrix} = \begin{bmatrix} 0.8462 \\ -0.9231 \end{bmatrix}$$

$$\therefore s(x) = \begin{bmatrix} 0.8462 \\ -0.9231 \end{bmatrix}$$

$$x^{(1)} = x^{(0)} + s(x) = \begin{bmatrix} 1 \\ 8 \\ 52 \end{bmatrix} + \begin{bmatrix} 0.8462 \\ -0.9231 \end{bmatrix}$$

$$= \begin{bmatrix} 1.8462 \\ 0.0769 \end{bmatrix}$$

$$\begin{bmatrix} 1 \\ 8 \\ 52 \end{bmatrix} = (x)^{(1)}$$

$$e = \begin{bmatrix} x_1^2 + x_2^2 + x_1 x_2 - 4 \\ 2x_1 x_2 \\ 3x_1 x_2^2 \end{bmatrix} \Rightarrow e(x^{(1)}) = \begin{bmatrix} -0.4434 \\ 0.28394 \\ 0.03275 \end{bmatrix}$$

$$E(\hat{x}) = 14$$

$$E(\hat{x}') = 0.2784 \approx 0.279$$

$$E(x) = e_1^4 + e_2^4 + e_3^4$$

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$$e_1 = x_1^2 + x_2^2 + x_1 x_2 - 4$$

$$e_2 = 2x_1 x_2$$

$$e_3 = 3x_1 x_2^2$$

$$J^T D J \delta(x) = \frac{-1}{P-1} [J^T e^{P-1}(x)] ; D = \text{diag}(e_1^{P-1}, e_2^{P-1}, \dots, e_m^{P-1})$$

$$J^T J \delta(x) = -J^T e(x)$$

Sol:

$$e^{P-1}(x) = \begin{bmatrix} e_1^{P-1}(x) \\ e_2^{P-1}(x) \\ e_3^{P-1}(x) \end{bmatrix}$$

$$e(i) = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$$

P=4:

$$e^3(x) = \begin{bmatrix} -1 \\ 8 \\ 27 \end{bmatrix}$$

$$D = \begin{bmatrix} e_1^2 & 0 & 0 \\ 0 & e_2^2 & 0 \\ 0 & 0 & e_3^2 \end{bmatrix}_{3 \times 3} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 4 & 0 \\ 0 & 0 & 9 \end{bmatrix}_{3 \times 3}$$

$$J = \begin{bmatrix} \frac{\partial e_1}{\partial x_1} & \frac{\partial e_1}{\partial x_2} \\ \frac{\partial e_2}{\partial x_1} & \frac{\partial e_2}{\partial x_2} \\ \frac{\partial e_3}{\partial x_1} & \frac{\partial e_3}{\partial x_2} \end{bmatrix} = \begin{bmatrix} 3 & 3 \\ 2 & 2 \\ 3 & 6 \end{bmatrix}_{3 \times 2}$$

$$\therefore J^T D J \ s(x) = \frac{-1}{p-1} J^T e^{p-1}(x)$$

$$\stackrel{P=4}{=} J^T D J \ s(x) = \frac{-1}{(4-1)} J^T e^3(x)$$

$$\begin{bmatrix} 3 & 2 & 3 \\ 3 & 2 & 6 \\ 3 & 2 & 6 \end{bmatrix}_{2 \times 3} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 4 & 0 \\ 0 & 0 & 9 \end{bmatrix}_{3 \times 3} \begin{bmatrix} 3 & 3 \\ 2 & 2 \\ 3 & 6 \end{bmatrix}_{3 \times 2} s(x)$$

$$= -\frac{1}{3} \begin{bmatrix} 3 & 2 & 3 \\ 3 & 2 & 6 \\ 3 & 2 & 6 \end{bmatrix}_{2 \times 3} \begin{bmatrix} -1 \\ 8 \\ 27 \end{bmatrix}_{3 \times 1}$$

$$\begin{bmatrix} 3 & 2 & 3 \\ 3 & 2 & 6 \\ 3 & 2 & 6 \end{bmatrix} \begin{bmatrix} 3 & 3 \\ 8 & 8 \\ 27 & 54 \end{bmatrix} s(x) = -\frac{1}{3} \begin{bmatrix} -3+16+81 \\ -3+16+162 \\ 0+0+0 \end{bmatrix}$$

$$h = sh + rh \quad ; \quad e^{\alpha} h + \beta s h = b$$

$$0 \leq rh \quad ; \quad (\alpha - \beta e^{\alpha}) h + \beta e^{\alpha} =$$

$$\beta e^{\alpha} + h(\alpha e^{\alpha} - \beta) =$$

$$h = (\alpha e^{\alpha} - \beta) \text{ and } ; \quad (\alpha - \beta e^{\alpha}) h + \beta e^{\alpha} = b$$

$$\frac{(\alpha - \beta e^{\alpha})}{\beta e^{\alpha}} +$$

• MAE: Mean absolute error

$$E = |e_1| + |e_2| + |e_3|$$

* A general property of least- p^{th} optimization technique is that the larger the power p , the slower the rate of convergence.

Convex Set: $S \in \mathbb{R}^n$, x_1 & x_2 , $y = \lambda x_1 + (1-\lambda)x_2$, if yes then ' S ' is a convex set.

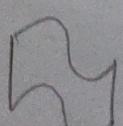
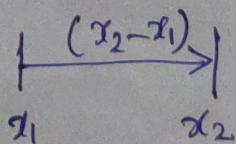
$$\begin{array}{c} \left[\begin{matrix} x_1 + x_2 \\ \lambda x_1 + (1-\lambda)x_2 \end{matrix} \right] \xrightarrow{\quad} \left(\begin{matrix} x_1 \\ x_2 \end{matrix} \right) \xrightarrow{\quad} \left[\begin{matrix} x_1 \\ x_2 \end{matrix} \right] \xrightarrow{\quad} \left[\begin{matrix} x_1 \\ x_2 \end{matrix} \right] \\ \lambda_1 \leq 1 \quad \left| \begin{matrix} \xrightarrow{\quad} \\ \lambda_1 \geq 1 \end{matrix} \right. \\ \lambda_1 x_1 \end{array} \quad \begin{array}{c} \left[\begin{matrix} x_1 \\ x_2 \end{matrix} \right] \xrightarrow{\quad} \left[\begin{matrix} x_1 \\ x_2 \end{matrix} \right] \xrightarrow{\quad} \left[\begin{matrix} x_1 \\ x_2 \end{matrix} \right] \\ \lambda_2 \leq 1 \quad \left| \begin{matrix} \xrightarrow{\quad} \\ \lambda_2 \geq 1 \end{matrix} \right. \\ \lambda_2 x_2 \end{array}$$

$$y = \lambda_1 x_1 + \lambda_2 x_2 \quad ; \quad \lambda_1 + \lambda_2 = 1$$

$$= x_1 + \lambda_2 (x_2 - x_1) \quad ; \quad \lambda_2 \geq 0$$

$$= (x_2 - x_1) \lambda_1 + x_2$$

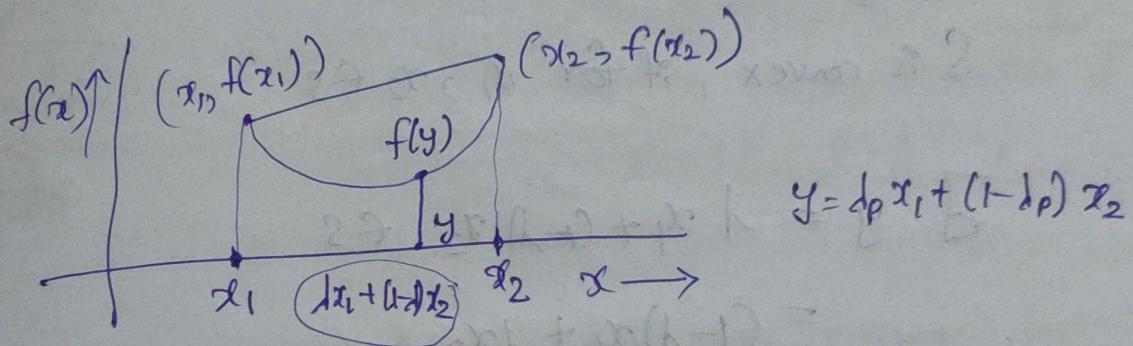
$$y = x_1 + \theta (x_2 - x_1) \quad ; \quad \text{here } (x_2 - x_1) \text{ is a vector}$$



Convex function:

A function f is convex on a convex set S if it satisfies $f(\alpha x + (1-\alpha)y) \leq \alpha f(x) + (1-\alpha)f(y)$

$$f(y) = f(\lambda x_1 + (1-\lambda)x_2) \leq \lambda f(x_1) + (1-\lambda)f(x_2)$$



$$y = \lambda x_1 + (1-\lambda)x_2$$

Concave: $f(\alpha x + (1-\alpha)y) \geq \alpha f(x) + (1-\alpha)f(y)$

Condition for Convexity:

→ A function is convex if and only if $f''(x) \geq 0 \forall x \in S$

→ For des, $d^T \nabla^2 f d \geq 0 \Rightarrow d^T F d \geq 0$

F - Hessian matrix : $F = \nabla^2 f$

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First order condition for Convexity

Convex function: $f(x) : R^n \rightarrow R'$

domain f is convex

(i) $\forall x \in S$, S is convex

S is convex, if for $x_1, x_2 \in S$

First order condition for convexity

21/03/2023

Convex function: $f(x) : f: \mathbb{R}^n \rightarrow \mathbb{R}$ & domain f is convex

(i) $\forall x \in S, S \text{ is convex} \Leftrightarrow (x_1 + x_2) \in S$

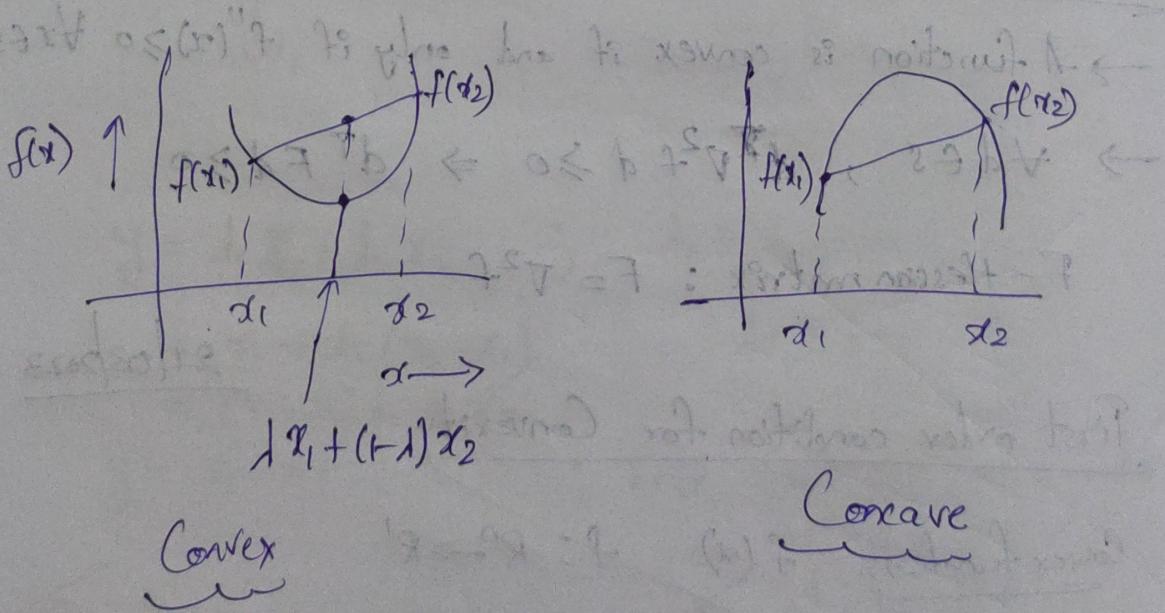
S is convex, if for $x_1, x_2 \in S$

$$y = \lambda x_1 + (1-\lambda)x_2 \in S$$

$$= (1-\lambda)x_1 + \lambda x_2$$

Lecture notes
3rd chapter
Linear &
non-linear
optimization

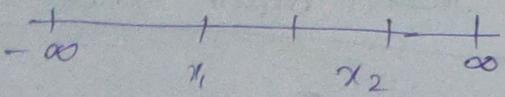
(ii) $f(\lambda x_1 + (1-\lambda)x_2) \leq \lambda f(x_1) + (1-\lambda)f(x_2)$



Strictly Convex: $f(\lambda x_1 + (1-\lambda)x_2) < \lambda f(x_1) + (1-\lambda)f(x_2)$

Strictly Concave: $\lambda f(x_1) + (1-\lambda)f(x_2) < f(\lambda x_1 + (1-\lambda)x_2)$

• Real line is a convex set :



First Order Condition:

As, it is difficult to check for all points, we have come up with First order & second order conditions.

$$f(y) \geq f(x) + \nabla f(x)^T (y-x) \quad \begin{matrix} \text{represents a vector} \\ \text{like } \vec{v} \end{matrix}$$

Proof: If f is convex then

$$f(\lambda x_2 + (1-\lambda)x_1) \leq \lambda f(x_2) + (1-\lambda) f(x_1)$$

$$f(\lambda x_2 + x_1 - \lambda x_1) \leq \lambda f(x_2) + f(x_1) - \lambda f(x_1)$$

$$f(x_1 + \lambda(x_2 - x_1)) \leq f(x_1) + \lambda [f(x_2) - f(x_1)]$$

$$\frac{f(x_1 + \lambda(x_2 - x_1)) - f(x_1)}{\lambda} \leq f(x_2) - f(x_1)$$

$$\lim_{\lambda \rightarrow 0} \frac{f(x_1 + \lambda(x_2 - x_1)) - f(x_1)}{\lambda(x_2 - x_1)} \leq f(x_2) - f(x_1)$$

$$\Rightarrow (x_2 - x_1)^T \nabla f(x_1) = \nabla f(x_1)^T (x_2 - x_1) \leq f(x_2) - f(x_1)$$

$$\Rightarrow f(x_2) \geq f(x_1) + \nabla f(x_1)^T (x_2 - x_1)$$

Hence, Proved

Second order Condition for Convexity : $f \in C^2$

$$\nabla^T \nabla^2 f(x) \nabla \geq 0 \quad \Leftrightarrow f''(x) \geq 0 \text{ on } 1D$$

First order condition

$$f(y) \geq f(x) + \nabla f^T(x)(y-x)$$

function growing in the given specified direction

Example: 3.2 Let $S_1 = \{x : x_1 + x_2 \leq 1, x_1 \geq 0\}$ and

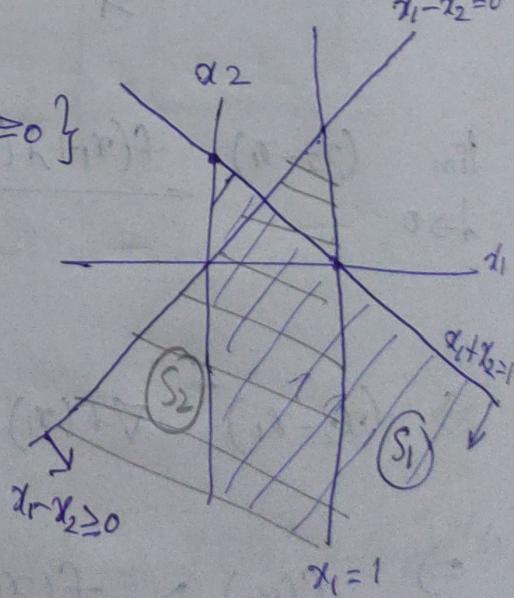
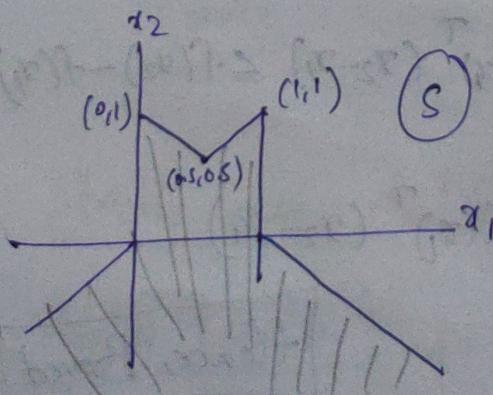
$S_2 = \{x : x_1 - x_2 \geq 0, x_1 \leq 1\}$ and let $S = S_1 \cup S_2$.

Prove that S_1 & S_2 are both convex sets but S is not a convex set.

→ This shows that union of convex sets is not necessarily convex.

So. $S_1 = \{x : x_1 + x_2 \leq 1, x_1 \geq 0\}$

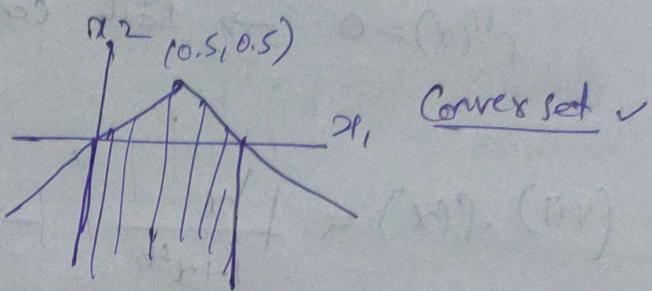
$$S_2 = \{x : x_1 - x_2 \geq 0, x_1 \leq 1\}$$



$S_1 \text{ & } S_2$ are convex sets

But their union S i.e. $S_1 \cup S_2$ is not a convex set.

$$S''' = S \cap S_2$$



Their intersection is a convex set.

Ex: 3.19

Check whether convex, concave or both even strictly or not

$$(v) f(x) = 4 - 5x + 3x^2$$

$$f'(x) = -5 + 6x$$

$$f''(x) = 6 > 0 \rightarrow \text{Strictly convex set}$$

$$(vi) f(x) = 2x^4 + 3x^3 + 4x^2$$

$$f'(x) = 8x^3 + 9x^2 + 8x$$

$$f''(x) = 24x^2 + 18x + 8 > 0 \rightarrow \text{strictly convex set}$$

$$(vii) f(x) = \sqrt{1+x^2}$$

$$f'(x) = \frac{x}{\sqrt{1+x^2}}$$

$$f''(x) = \frac{(\sqrt{1+x^2})(1) - x\left(\frac{x}{\sqrt{1+x^2}}\right)}{(1+x^2)} = \frac{(1+x^2-x^2)}{(1+x^2)^{3/2}}$$

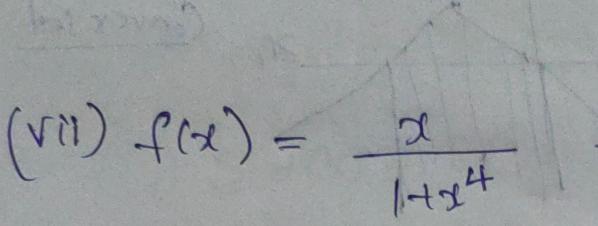
$$= \frac{1}{(1+x^2)^{3/2}} \geq 0 \rightarrow \text{strictly convex}$$

\rightarrow Convex Set

$$(i) f(x) = 7x - 15$$

$$f'(x) = 7$$

$f''(x) = 0 \rightarrow$ Both convex & concave set



$$(ii) f(x) = \frac{x}{1+x^4} \rightarrow \text{neither convex nor concave set}$$

$$f'(x) = \frac{(1+x^4) - x(4x^3)}{(1+x^4)^2} = \frac{1-3x^4}{(1+x^4)^2}$$

$$f''(x) = \frac{(1+x^4)^2(-12x^3) - (1-3x^4)2(1+x^4)(4x^3)}{(1+x^4)^4}$$

~~$$\frac{-12}{(1+x^4)^3}$$~~

$$= \frac{(x^8+2x^4+1)(-12x^3) - 8x^3(1-3x^4)(1+x^4)}{(1+x^4)^4}$$

$$= \frac{4x^3}{(1+x^4)^4} \left[-3x^8 - 6x^4 - 3 - 8(1+x^4 - 3x^4 - 3x^5) \right]$$

$$= \frac{4x^3}{(1+x^4)^4} \left[21x^8 + 16x^4 - 8x^4 - 11 \right]$$

$$= \frac{4x^3}{(1+x^4)^4} \left[21x^8 + 10x^4 - 11 \right] \rightarrow \begin{matrix} \text{can take both} \\ \text{+ve \& -ve} \\ \text{values} \end{matrix}$$

\rightarrow neither convex nor concave set.

Positive Semidefinite matrix

$$\rightarrow d^T F d \geq 0 \quad (\text{convex set})$$

$$F = \nabla^2 f$$

• Positive definite matrix: $d^T F d > 0$ (strictly convex set)

Ex 8.20: Determine $f(x_1, x_2) = 2x_1^2 - 3x_1 x_2 + 5x_2^2 - 2x_1 + 6x_2$

is convex, concave, both or neither for $x \in \mathbb{R}^2$.

Sol: $d^T F d$?

$$F = \nabla^2 f ; \quad \nabla f = \begin{bmatrix} 4x_1 - 3x_2 & 2 \\ 10x_2 - 3x_1 & 6 \end{bmatrix} \quad \nabla^2 f = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} \end{bmatrix}$$

$$F = \begin{bmatrix} 4 & -3 \\ -3 & 10 \end{bmatrix} \quad \text{let } d = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$$

$$\begin{bmatrix} y_1 & y_2 \end{bmatrix} \begin{bmatrix} 4 & -3 \\ -3 & 10 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}_{2 \times 1} = \begin{bmatrix} y_1 & y_2 \end{bmatrix} \begin{bmatrix} 4y_1 - 3y_2 \\ -3y_1 + 10y_2 \end{bmatrix}_{2 \times 1}$$

$$= 4y_1^2 - 3y_1 y_2 - 3y_1 y_2 + 10y_2^2$$

$$= 4y_1^2 - 6y_1 y_2 + 10y_2^2$$

• Calculating eigen values of F \rightarrow

$$F = \begin{bmatrix} 4 & -3 \\ -3 & 10 \end{bmatrix}$$

$$|F - \lambda I| = \begin{vmatrix} 4-\lambda & -3 \\ -3 & 10-\lambda \end{vmatrix}$$

$$= (4-\lambda)(10-\lambda) - (-3)(-3)$$

$$= \lambda^2 - 14\lambda + 40 - 9$$

$$= \lambda^2 - 14\lambda + 31$$

$$\lambda = \frac{14 \pm \sqrt{14^2 - 4(31)}}{2}$$

$$\Rightarrow \lambda = \frac{14 \pm 8.48}{2}$$

$$\lambda = \frac{14 \pm \sqrt{72}}{2} \rightarrow \text{the values}$$

- Eigen values are +ve \Rightarrow Strictly convex set
(positive definite)

Optimality conditions for convex optimization problems

LPP : Simplex, Big M, 2-phase, Dual LPP

Unconstrained Non-LPP : Line Search \leftarrow ③

↓
all the constraints
considered as inactive

Least P.L. opt.
Least Square opt.

Least Squares opt.

Constrained Optimization problems: (Non-LPP) Richard W.H.

- Active constraints vs Inactive constraints
- Initial guess ~~always~~ should be in feasible region.
- When a constraint is active, often it can be used to remove one of the parameters from the error function.

Example 1.1: Minimize

$$f(x) = x_1^2 + 2x_2^2 + 3x_3^2 + 4x_4^2$$

Constraints: (a) $x_1 \geq 0.4$ (b) $x_2 + x_3 \geq 0.5$

(c) $x_3 + x_4 \geq 0.6$

- 8 cases
- This procedure varies the parameters, which are related by the active constraints, until a minimum is reached.
- The active constraints could be used to simplify error function, which could then be minimized by an unconstrained optimization program.

Cases: (1) none might be active (2) a (3) b (or)

(4) c might be active (5) a&b (6) a&c

(7) b&c (8) a,b&c might be active.

- But as no. of possibilities increase, it's large that it is impractical to analyse all of them.

Transformations :

- ~~Defining~~ Converting Constrained problem to Unconstrained problem

Ex: $x_1 \geq 5 \Rightarrow x_1 = 5 + z_1^2$; z_1 can take any value
 (replace)

Restrictions

 $y_1 \leq 1 \Rightarrow y_1 = 1 - z_2^2$

$$-3 \leq x \leq 5 \Rightarrow x = (-3) + (5 - (-3)) \sin z$$

$$x_{iL} \leq x \leq x_{iu} \Rightarrow x = x_{iL} + (x_{iu} - x_{iL}) \sin^2 z$$

Penalty functions :

Restrictions

$$y_1 \leq 1 \Rightarrow y_1 = 1 - z_2^2$$

$$-3 \leq x \leq 5 \Rightarrow x = (-3) + (5 - (-3)) \sin z$$

$$x_{iL} \leq x \leq x_{iU} \Rightarrow x = x_{iL} + (x_{iU} - x_{iL}) \sin^2 z$$

Penalty functions ;

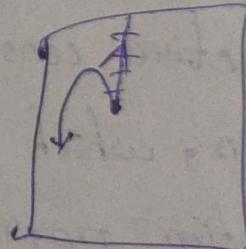
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For constraints like: $x_1 + x_2 \leq 5$, $x_1 - 2x_2 \geq 10$

$$E^*(x) = E(x) + \text{penalty function}$$

$$5 - x_1 - x_2 \geq 0, \quad x_1 - 2x_2 - 10 \geq 0$$

★ Penalty function $= \sum_{i=1}^{\infty} \frac{1}{C_i(x)}$



$$= \sum_{i=1}^{\infty} \frac{1}{C_i(x)}$$

- As x approaches a boundary of the feasible region the penalty function will become very large - which is exactly what is desired.

Problem: Given Area of sheet A_0 (rectangular one), objective is to make cylinder with maximize volume.

$$\text{Volume of cylinder} = \pi r^2 h$$

$$\text{Surface area of cylinder} = 2\pi r^2 + 2\pi rh$$

$$\text{Maximize: } V(r, h) = \pi r^2 h$$

$$A_{\text{sheet}} = 2\pi r^2 + 2\pi rh \\ = 2\pi r(r+h)$$

$$\Rightarrow h = \frac{A_0 - 2\pi r^2}{2\pi r}$$

$$\Rightarrow V(r, h) = \pi r^2 h = \pi r^2 \left(\frac{A_0 - 2\pi r^2}{2\pi r} \right)$$

$$(r = \frac{A_0 r}{2} - \pi r^3) V = (r, r)$$

$$\Rightarrow V(r) = \frac{A_0 r}{2} - \pi r^3$$

$$\text{Based on FOC: } \frac{dV}{dr} = 0$$

$$\Rightarrow \frac{A_0}{2} - 3\pi r^2 = 0$$

$$\Rightarrow r^2 = \frac{A_0}{6\pi}$$

$$\Rightarrow r = \sqrt{\frac{A_0}{6\pi}}$$

$$r = \sqrt{\frac{A_0}{6\pi}} \Rightarrow h = \frac{A_0 - 2\pi r^2}{2\pi r}$$

$$\Rightarrow h = \frac{1}{2\pi} \sqrt{\frac{6\pi}{A_0}} \left[A_0 - 2\pi \left(\frac{A_0}{6\pi} \right) \right]$$

$$= \sqrt{\frac{3}{2\pi A_0}} \left[A_0 - \frac{A_0}{3} \right]$$

$$= \frac{2A_0}{3} \sqrt{\frac{3}{2\pi A_0}}$$

$$\Rightarrow h = \sqrt{\frac{2A_0}{3\pi}}$$

$$\therefore r = \sqrt{\frac{A_0}{6\pi}}, h = \sqrt{\frac{2A_0}{3\pi}}$$

Book

Lagrange's Multiplier Method : Stephen Boyd - Convex opt.

(Used when presence of equality constraints) Lagrange's multipliers - opt.

$$\text{Ex. } J(r, h, d) = V(r, h) + d(A(r, h) - A_0)$$

Cambridge Ch.

→ Here, 'J' units in meters; as dimensions should be matched (always)

$$\rightarrow \frac{\partial J}{\partial r} = 0, \quad \frac{\partial J}{\partial h} = 0, \quad \frac{\partial J}{\partial d} = 0$$

$$J(r, h, d) = \pi r^2 h + d [2\pi r^2 + 2\pi rh - A_0]$$

$$\frac{\partial J}{\partial r} = 2\pi rh + d [4\pi r + 2\pi h] \rightarrow ①$$

$$\frac{dJ}{dh} = \pi r^2 + 2\pi rh \rightarrow ②$$

$$\frac{dJ}{dr} = 2\pi rh + 2\pi r^2 - A_0 \rightarrow ③$$

$$① \Rightarrow 2\pi rh + 4\pi r^2 + 2\pi h^2 = 0 \\ \Rightarrow rh + 2r^2 + h^2 = 0$$

$$② \Rightarrow \pi r^2 + 2\pi rh = 0 \\ \Rightarrow r^2 + 2rh = 0$$

$$③ \Rightarrow 2\pi r^2 + 2\pi rh - A_0 = 0$$

$$\Rightarrow 2\pi r(r+h) = A_0$$

$$\Rightarrow h = \frac{A_0 - 2\pi r^2}{2\pi r}$$

$$\text{Diagram showing a cylinder with radius } r \text{ and height } h. \text{ The surface area } A_0 \text{ is shown as the sum of the lateral surface area } 2\pi rh \text{ and the area of the two circular bases } 2\pi r^2.$$

$$\Rightarrow h = -\frac{r}{2}$$

$$\Rightarrow r \left(\frac{A_0 - 2\pi r^2}{2\pi r} \right) + 2r \left(-\frac{r}{2} \right) + \left(\frac{A_0 - 2\pi r^2}{2\pi r} \right) \left(-\frac{r}{2} \right) = 0$$

$$\Rightarrow \frac{A_0 - 2\pi r^2}{2\pi} - r^2 - \frac{(A_0 - 2\pi r^2)}{4\pi} = 0$$

$$\Rightarrow 2A_0 - 4\pi r^2 - 4\pi r^2 - A_0 + 2\pi r^2 = 0$$

$$\Rightarrow A_0 - 6\pi r^2 = 0$$

$$\Rightarrow r^2 = \frac{A_0}{6\pi}$$

$$\Rightarrow r = \pm \sqrt{\frac{A_0}{6\pi}}$$

$$\boxed{\therefore r = \sqrt{\frac{A_0}{6\pi}}} \\ h = \sqrt{\frac{2A_0}{3\pi}}$$

Example: Minimize: $f_0(x)$

S.T : $f_i(x) \leq 0 ; i=1, \dots, m$

$h_i(x) = 0 ; i=1, \dots, p$

L:

$$L(x, \lambda, \nu) = f_0(x) + \sum_{i=1}^m \lambda_i f_i(x) + \sum_{i=1}^p \nu_i h_i(x)$$

→ Vectors λ & ν are called dual variables or Lagrange multipliers

06/04/2023

LPP

max/min $f(x)$

Constraints $h_i(x) = 0 ; i=1, 2, \dots, l$

$$g_j(x) \leq b_j ; j=1, 2, \dots, m$$

NLPP

Unconstrained

$$\int f(x)$$

Constrained → (i) Equality
(ii) Inequality

$$L(x, \lambda) = \text{Obj} + \lambda (\text{Equality constraint})$$

Lagrange's Multiplier Method

FONC: $\nabla L = 0$

$$L = f + \lambda h$$

$$\nabla f + \lambda \nabla h = 0$$

$\lambda = \frac{\nabla f}{\nabla h}$ ⇒ "rate of change" objective function w.r.t constraints

$\lambda \rightarrow$ sensitivity parameter
 Shadow price → gives the indication of profit
 w.r.t constraints / raw materials

λ is unrestricted in sign when there are equality constraints.

$$L(x, \lambda_1, \lambda_2) = \text{obj} + d_1 (\underset{\text{constraint 1}}{\text{equality}}) + d_2 (\underset{\text{constraint 2}}{\text{equality}})$$

Stationary values / points - which first derivative goes to zero are point at

By Hessian matrix, it is decided whether function goes to max. or min at that stationary point

$$x^T \nabla^2 f x > 0 \rightarrow \text{Positive definite}$$

(Eigenvalues)

$$x^T \nabla^2 f x \geq 0 \rightarrow \text{+ve semidefinite}$$

$$x^T \nabla^2 f x < 0 \rightarrow \text{Negative definite}$$

$$x^T \nabla^2 f x \leq 0 \rightarrow \text{-ve semidefinite}$$

Principal Diagonal elements

• Principal Minors

$$D_1 = |a_{11}| (\leq a_{11} \Rightarrow \text{matrix } x \text{ should have principle diagonal elements less than } a_{11})$$

$$D_2 = \begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix} (\leq a_{22} \Rightarrow a_{11}, a_{22} \checkmark)$$

$$D_3 = \begin{vmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{vmatrix} (\leq a_{33} \Rightarrow a_{11}, a_{22}, a_{33} \checkmark)$$

(DN)

$D_1 > 0, D_2 > 0, D_3 > 0 \Rightarrow D_N > 0 \Rightarrow$ +ve definite

Ex: $\begin{bmatrix} 4 & -3 \\ -3 & 10 \end{bmatrix} \quad D_1 = 4 > 0$
 $D_2 = 40 - 9 = 31 > 0$

Positive definite

$D_1 > 0, D_2 \geq 0, D_3 \geq 0, \dots, D_N \geq 0 \Rightarrow$ +ve

$D_1 < 0, D_2 \geq 0, D_3 \leq 0, \dots, D_N < 0 \Rightarrow$ -ve
 (Concave) (alternative signs) definite

$D_1 < 0, D_2 \geq 0, D_3 \leq 0, \dots, D_N \leq 0 \Rightarrow$ -ve
semidefinite

KKT conditions: (FONC)

Optimize: $f(x)$ S.T: $h_i(x), g_j(x) \leq b_j$

→ Used when there are both equality & inequality constraints present.

$g_j(x) \leq b_j \rightarrow$ slack variable

New inequality constraint: $g_j(x) + s_j^2 = b_j$

$$g_j(x) + s_j^2 - b_j = 0$$

$$g_j'(x) = 0$$

$$L(x, \lambda, u) = f(x) - \sum_i \lambda_i h_i(x) - \sum_j u_j g_j^1(x)$$

$$\boxed{\frac{\partial L}{\partial x} = 0}$$

$$\Rightarrow \frac{\partial f}{\partial x} + \sum_i \lambda_i \frac{\partial h_i}{\partial x} + \sum_j u_j \frac{\partial g_j^1}{\partial x} [g_j^1(x) + s_j^2 - b_j] = 0$$

$$\Rightarrow \frac{\partial f}{\partial x} + \sum_i \lambda_i \frac{\partial h_i}{\partial x} + \sum_j u_j \frac{\partial g_j^1}{\partial x} = 0$$

$$\boxed{\Delta f + \sum_i \lambda_i \Delta h_i + \sum_j u_j \nabla g_j^1 = 0} \rightarrow \text{1st KKT condition}$$

→ let us first consider there are no equality constraints

$$\frac{\partial L}{\partial u_i} = 0 \Rightarrow g_j^1(x) + s_j^2 - b_j = 0$$

$$\Rightarrow s_j^2 = b_j - g_j^1(x)$$

$$\frac{\partial L}{\partial s_j^2} = 0 \Rightarrow \sum j s_j^2 u_j = 0$$

$$\Rightarrow s_j^2 u_j = 0$$

$$\Rightarrow [b_j - g_j^1(x)] u_j = 0$$

$$\boxed{u_j g_j^1 = 0}$$

→ complementary slackness conditions
→ 2nd KKT condition

Lagrange's constraint
Multipliers

11/04/2023

NCP

$$\text{Ex: Max: } Z = 3.6x_1 - 0.4x_1^2 + 1.6x_2 - 0.2x_2^2$$

$$\text{s.t.: } 2x_1 + x_2 \leq 10$$

$$x_1, x_2 \geq 0$$

KKT conditions:

$$\frac{\partial L}{\partial x} = 0, \lambda g_i = 0, \lambda \geq 0 \text{ (max)} \\ \leq 0 \text{ (min)}$$

$$h_i(x) = 0; g_j(x) \geq 0 \\ \downarrow 0$$

$$\text{Sof: } L = f(x) - \lambda g(x)$$

$$= (3.6x_1 - 0.4x_1^2 + 1.6x_2 - 0.2x_2^2) \\ - \lambda(2x_1 + x_2 - 10)$$

$$\text{Necessary conditions: } \frac{\partial L}{\partial x} = 0, \lambda g = 0, g \leq 0, \lambda \geq 0, x \geq 0$$

$$\frac{\partial L}{\partial x_1} = 0 \Rightarrow 3.6 - 0.8x_1 - 2\lambda = 0 \rightarrow ①$$

$$\frac{\partial L}{\partial x_2} = 0 \Rightarrow 1.6 - 0.4x_2 - \lambda = 0 \rightarrow ②$$

$$\lambda(2x_1 + x_2 - 10) = 0 \rightarrow ③$$

$$\lambda \geq 0 \rightarrow ④$$

$$2x_1 + x_2 \leq 10 \rightarrow ⑤$$

$$x_1, x_2 \geq 0 \rightarrow ⑥$$

Case I : for $\lambda = 0$, $x_1 = 4.5, x_2 = 4$ - not a feasible solution,
 $2(4.5) + 4 \leq 10$ (False)

Case II : $\lambda \neq 0$: $x_1 = \frac{3.6 - 2\lambda}{0.8}$; $x_2 = \frac{1.6 - \lambda}{0.4}$

$$2\left(\frac{3.6 - 2\lambda}{0.8}\right) + \frac{1.6 - \lambda}{0.4} = 10$$

$$\Rightarrow \lambda = 0.4$$

Hence, $x_1 = 3.5, x_2 = 3$ - optimal solution.

$$\therefore (x_1, x_2; \lambda) = (3.5, 3, 0.4)$$

$$\therefore Z = 10.7$$

Ex: Min: $Z = -\log x_1 - \log x_2$

NLP

s.t.: $x_1 + x_2 \leq 2$; $x_1, x_2 \geq 0$

Sf: $L(x, \lambda) = -\log x_1 - \log x_2 - \lambda(x_1 + x_2 - 2)$

$$\frac{\partial L}{\partial x_1} = 0 \Rightarrow -\frac{1}{x_1} - \lambda = 0 \rightarrow ①$$

$$\frac{\partial L}{\partial x_2} = 0 \Rightarrow -\frac{1}{x_2} - \lambda = 0 \rightarrow ②$$

$$\lambda(x_1 + x_2 - 2) = 0 \rightarrow ③$$

$$x_1 + x_2 \leq 2 \rightarrow ④$$

$$\lambda \leq 0 \rightarrow ⑤$$

$$x_1, x_2 \geq 0 \rightarrow ⑥$$

Case 1: $\lambda = 0 \Rightarrow x_1 = \infty, x_2 = \infty$
→ case is discarded

Case 2: $\lambda \neq 0 \Rightarrow x_1 = -\frac{1}{\lambda} \text{ & } x_2 = -\frac{1}{\lambda}$

$$\left(-\frac{1}{\lambda}\right) + \left(-\frac{1}{\lambda}\right) = 2$$

$$\Rightarrow \lambda = -1$$

Here, $x_1 = 1, x_2 = 1$

$$\therefore (x_1, x_2, \lambda) = (1, 1, -1)$$

$$\therefore Z = 0$$

$$\text{Ex: Max: } Z = 8x_1 + 10x_2 - x_1^2 - x_2^2$$

s.t: $3x_1 + 2x_2 \leq 6$

$$x_1, x_2 \geq 0$$

Part 2

Ex 6
Ques
Constr

Ques
Ans

for NLP:

$$L = f(x) - \sum_i g_i(x)$$

① Max $f(x)$ & S.t: $g_i(x) \leq 0$ Lagrangian function

Necessary conditions: $\frac{\partial L}{\partial x} = 0, \lambda_i g_i = 0, g_i(x) \leq 0, \lambda_i \geq 0$

② Min $f(x)$ & s.t: $g_i(x) \leq 0$

Necessary conditions: $\frac{\partial L}{\partial x} = 0, \lambda_i g_i = 0, g_i(x) \leq 0, \lambda_i \leq 0$

Ex: Max: $Z = 12x_1 + 21x_2 + 2x_1x_2 - 2x_1^2 - 2x_2^2$

S.t: $x_1 + x_2 \leq 10, x_2 \leq 8, x_1, x_2 \geq 0$

Advanced Optimization Techniques

Genetic Algorithm (GA):

- A GA is a search technique used in computing to find true or approximate solutions to optimization and search problems.
- GAs are categorized as global search heuristics.

Ex: A population of n random strings.

Suppose that $k=10$ & $n=6$, fitness expo. of 1's

Toss a fair coin 60 times & get following initial population.

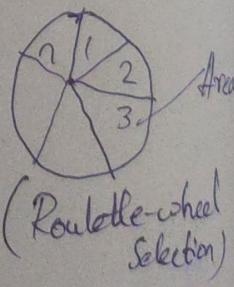
$$S_1 = 111010101 \quad f(S_1) = 7, \quad S_2 = 0111000101 \quad f(S_2) = 5$$

$$S_3 = 1110110101 \quad f(S_3) = 7, \quad S_4 = 0100010011 \quad f(S_4) = 4$$

$$S_5 = 1110111101 \quad f(S_5) = 8, \quad S_6 = 0100110000 \quad f(S_6) = 3$$

• $\frac{f(i)}{\sum f(i)}$ = Individual i will have \hat{a} probability to be chosen.

(Ex:	x	$f(x) = x^2$	has more chance
Binary representation	0101 ← 5	25 ←	
1	1	$\frac{f(x_i)}{\sum f(x_i)}$)
10011 ← -3	9		
	-0.1	0.01	



Step 1: Selection

Step 2: Crossover

Step 3: Mutations - intentionally making errors

→ Methods of Representation: Arrays of strings, integers, characters (binary bits)

→ Methods of Selection:

- Roulette-wheel selection
- Elitist Selection
- Fitness-pro
- Scaling Selection
- Rank "
- Cut-off "

→ Methods of Reproduction: (Single-point, Multi-point)

- Crossover
- Mutation

13/04/2023

GAT

① Initialization of the population.

② Calculation of the fitness)

Evaluating the function at given character/trait

③ Selection

④ Pairing

Ex:

P_1

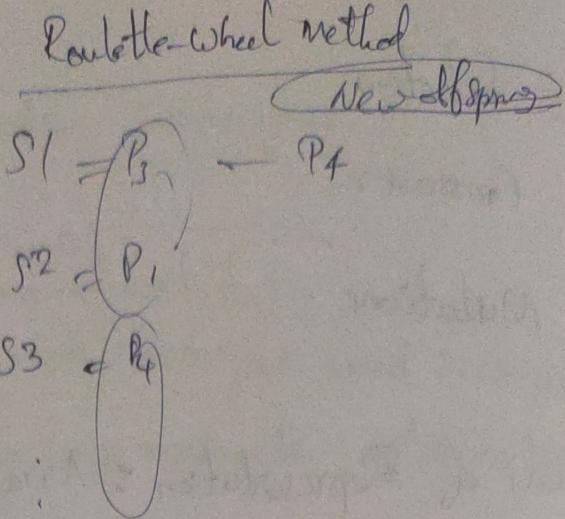
P_2

P_3

P_4

- max. probability

P_{10}



$S_9 = P_4$

$S_{10} = \dots$

Particle Swarm Optimization (PSO)

- Proposed by James Kennedy

- Inspired from nature

- PSO uses a no. of agents (particles) that constitute a swarm moving around in search space looking for the best solution.

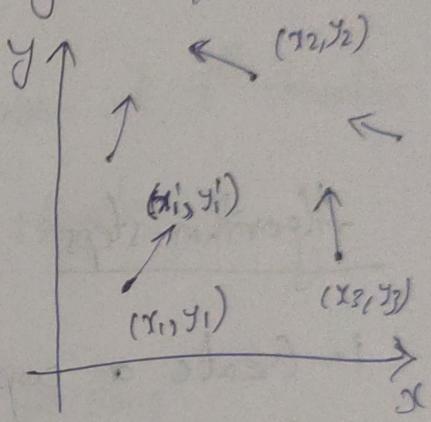
- Each particle in search space adjusts its 'flying' according to its own flying experience as well as flying experience of other particles.

• Each particle has 3 parameters position, velocity and previous best position , particle with best fitness value is called a global best position.

• Particle best : P_{best} - the best position the particle seen so far

• Global best : Best position among all particles.

$$\begin{aligned} (x_1, y_1) & f_1 \leftarrow f_1' \\ (x_2, y_2) & f_2 \leftarrow f_2' \\ (x_3, y_3) & f_3 \leftarrow f_3' \\ f_4 & \leftarrow f_4' \end{aligned}$$



• Particle tries to move towards the particle best.
• Overall, all particles tries to move towards the global best.

• If f_i' -fitness value is more than f_i -fitness value, then f_i' is considered , if it is not a large value compared to previous value then the previous value is only considered.

→ Movement towards a promising area to get global optimum

→

Algorithm-steps

1. Create a population of agents uniformly distributed over X
2. Evaluate ~~all~~ each particle's position according to objective function.
3. If a particle's current position is better than its previous
- 4.
5. Update particle's velocities : $(C_1 C_2)$ (V_1, V_2) \rightarrow some random value
$$V_i^{t+1} = w V_i^t + C_1 U_1^t (p_{best}^t - p_i^t) + C_2 U_2^t (g_{best}^t - p_i^t)$$

Weight Velocities

$t+1$ - i^{th} iteration

pbi^t - i^{th} particle best position at t^{th} iteration

v_i^t - inertia of i^{th} particle at t^{th} iteration

$c_1 v_i^t (pbi^t - p_i^t)$ - personal influence

$c_2 v_i^t (gb^t - p_i^t)$ - Social influence

p_i^t - i^{th} particle present position at t^{th} iteration

gb^t - global best at t^{th} iteration.

6. Move particles to their new positions

$$p_i^{t+1} = p_i^t + v_i^{t+1} \rightarrow \begin{matrix} \text{constant which gives} \\ \text{a value proportional} \\ \text{to velocity} \end{matrix}$$

7. go to step 2 until stopping criteria are satisfied.

Inertia: Makes particle move in same direction & with same velocity.