



INDIAN INSTITUTE OF SCIENCE

Water Resources Systems: **Modeling Techniques and Analysis**

Lecture - 4

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Summary of the previous lecture

- Optimization and simulation
- Optimization: Methods of Calculus
 - Function of a single variable
 - Local maximum, Local minimum
 - Saddle point
 - Global maximum, Global minimum
 - Convex, Concave functions

Optimization: Methods of Calculus

$f(x)$: function of a single variable

The necessary condition:

At a local optimum (maximum or minimum),

$$f'(x) = 0$$

$x = x_0$ Stationary point

Sufficiency condition

$$f''(x) \Big|_{x_0} < 0 \quad \dots \quad \text{maximum}$$

$$f''(x) \Big|_{x_0} > 0 \quad \dots \quad \text{minimum}$$

Optimization: Methods of Calculus

$$\text{If } \frac{d^2 f}{dx^2} = 0$$

Find the first higher order non-zero derivative; let this be n^{th} order derivative,

$$\left. \begin{aligned} \frac{df}{dx} = \frac{d^2 f}{dx^2} = \frac{d^3 f}{dx^3} = \dots = \frac{d^{n-1} f}{dx^{n-1}} = 0 \\ \frac{d^n f}{dx^n} \neq 0 \end{aligned} \right\} \begin{array}{l} \text{at the stationary point,} \\ x = x_0 \end{array}$$

Optimization: Methods of Calculus

- If n is even and

- if $\left. \frac{d^n f}{dx^n} \right|_{x_0} > 0$, x_0 is a local minimum

- if $\left. \frac{d^n f}{dx^n} \right|_{x_0} < 0$, x_0 is a local maximum

- If n is odd, x_0 is a saddle point (neither a minimum nor a maximum)

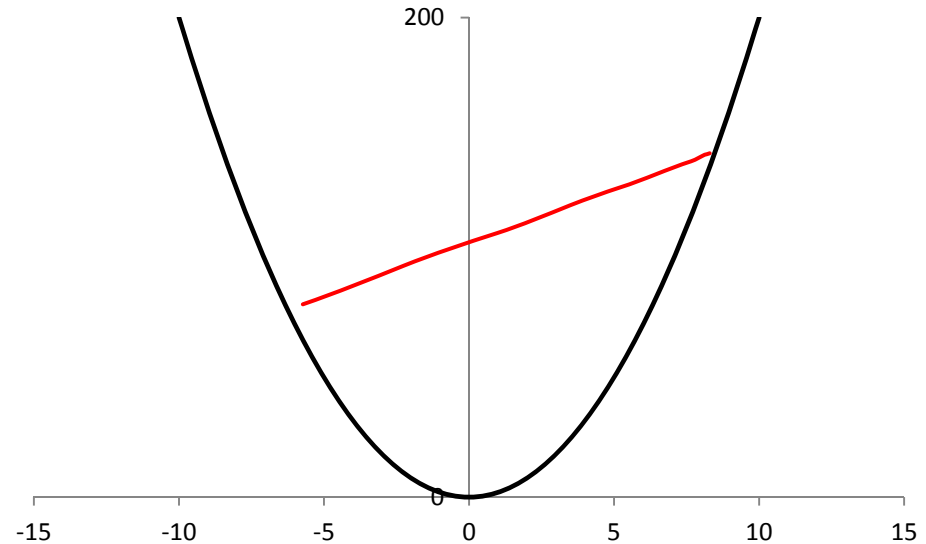
Example – 1

Convex function:

$$f(x) = 2x^2$$

$$\frac{df}{dx} = 4x$$

$$\frac{d^2 f}{dx^2} = 4 > 0$$



For a convex function,

$$f[\alpha x_1 + (1-\alpha)x_2] < \alpha f(x_1) + (1-\alpha)f(x_2)$$

Example – 1 (Contd.)

$$x_1 = 0; x_2 = 2 \quad \alpha = 0.5$$

$$\begin{aligned} \text{LHS} &= f[\alpha x_1 + (1-\alpha)x_2] & \text{RHS} &= \alpha f(x_1) + (1-\alpha)f(x_2) \\ &= f[0 + 0.5 \times 2] & &= 0.5 \times f(0) + 0.5 \times f(2) \\ &= f[1] & &= 0.5 \times 0 + 0.5 \times 2 \times 4 \\ &= 2 & &= 4 \end{aligned}$$

$$\text{LHS} < \text{RHS}$$

$$\text{i.e., } f[\alpha x_1 + (1-\alpha)x_2] < \alpha f(x_1) + (1-\alpha)f(x_2)$$

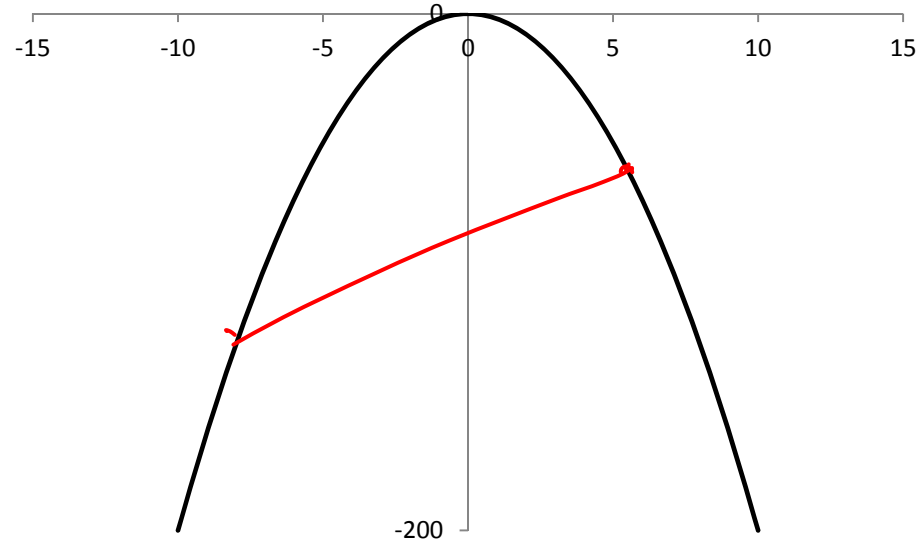
Example – 1 (Contd.)

Concave function:

$$f(x) = -2x^2$$

$$\frac{df}{dx} = -4x$$

$$\frac{d^2 f}{dx^2} = -4 < 0$$



For a concave function,

$$f[\alpha x_1 + (1 - \alpha)x_2] > \alpha f(x_1) + (1 - \alpha)f(x_2)$$

Example – 2

Check for optimal values of

$$f(x) = 3x^3 - 6x^2 + 4x - 7$$

$$f'(x) = 9x^2 - 12x + 4$$

$$f'(x) = 0$$

$$9x^2 - 12x + 4 = 0$$

$$x_0 = \frac{12 \pm \sqrt{144 - 4 \times 9 \times 4}}{2 \times 9} = \frac{2}{3}$$

Only one solution exists

Example – 2 (Contd.)

$$f'(x) = 9x^2 - 12x + 4$$

$$f''(x) = 18x - 12$$

$$f''(x)|_{x_0} = 18 \times \frac{2}{3} - 12 = 0$$

Looking for next higher derivatives

$$f'''(x) = 18 \neq 0$$

As $n (= 3)$ is odd, the function $f(x)$ is neither a minimum nor a maximum at $x_0 = 2/3$

Example – 3

Check for optimal values of

$$f(x) = 12x^5 - 15x^4 - 40x^3 + 81$$

$$f'(x) = 60x^4 - 60x^3 - 120x^2$$

$$f'(x) = 0$$

$$60x^4 - 60x^3 - 120x^2 = 0$$

$$60x^2(x+1)(x-2) = 0$$

$$x = 0, \quad x = -1 \quad \text{and} \quad x = 2$$

Example – 3 (Contd.)

$$f'(x) = 60x^4 - 60x^3 - 120x^2$$

$$f''(x) = 240x^3 - 180x^2 - 240x$$

$$f''(x)|_{x=0} = 0$$

$$f'''(x) = 720x^2 - 360x - 240$$

$$f'''(x)|_{x=0} = 240 \neq 0$$

Neither a minimum nor a maximum exists at $x = 0$

Example – 3 (Contd.)

$$f''(x) = 240x^3 - 180x^2 - 240x$$

$$f''(x)\Big|_{x=-1} = -180 \quad \text{-ve value}$$

Therefore maximum occurs at $x = -1$

$$\begin{aligned} f(x) &= 12x^5 - 15x^4 - 40x^3 + 81 \\ &= 94 \end{aligned}$$

Example – 3 (Contd.)

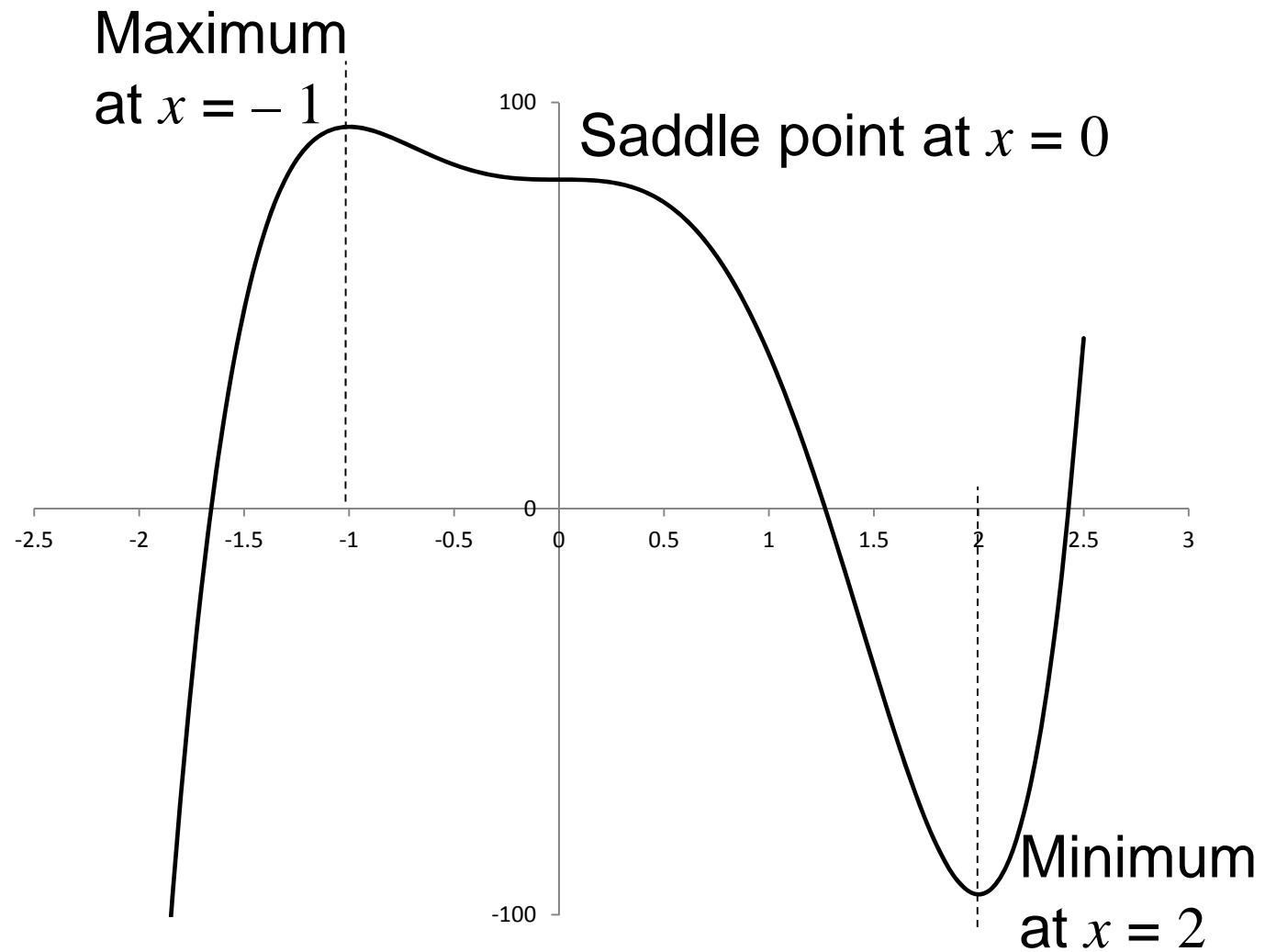
$$f''(x) = 240x^3 - 180x^2 - 240x$$

$$f''(x)\Big|_{x=2} = 720 \quad \text{+ve value}$$

Therefore minimum occurs at $x = 2$

$$\begin{aligned} f(x) &= 12x^5 - 15x^4 - 40x^3 + 81 \\ &= -95 \end{aligned}$$

Example – 3 (Contd.)



Optimization: Methods of Calculus

Function of multiple variables:

- $f(X)$ is a function of n variables represented by vector $X = (x_1, x_2, x_3, \dots, x_n)$
- Necessary condition for stationary point $X = X_0$ is, each first partial derivative of $f(X)$ should be zero.

$$\frac{\partial f}{\partial x_1} = \frac{\partial f}{\partial x_2} = \dots = \frac{\partial f}{\partial x_n} = 0$$

Optimization: Methods of Calculus

- $H[f(X)]$ is Hessian matrix of function $f(X)$
- Hessian matrix is defined as

$$H[f(X)] = \begin{matrix} & x_1 & x_2 & \dots & x_n \\ \begin{matrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ x_n \end{matrix} & \begin{bmatrix} \frac{\partial^2 f(X)}{\partial x_1^2} & \frac{\partial^2 f(X)}{\partial x_1 \partial x_2} & \dots & \frac{\partial^2 f(X)}{\partial x_1 \partial x_n} \\ \frac{\partial^2 f(X)}{\partial x_2 \partial x_1} & \frac{\partial^2 f(X)}{\partial x_2^2} & \dots & \frac{\partial^2 f(X)}{\partial x_2 \partial x_n} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \frac{\partial^2 f(X)}{\partial x_n \partial x_1} & \frac{\partial^2 f(X)}{\partial x_n \partial x_2} & \dots & \frac{\partial^2 f(X)}{\partial x_n^2} \end{bmatrix} \end{matrix}$$

Optimization: Methods of Calculus

- Sufficiency condition:
 - H positive definite at $X = X_0 \dots$ ~~Maximum~~ Minimum
 - H negative definite at $X = X_0 \dots$ ~~Minimum~~ Maximum
- A square matrix is positive definite if all the eigen values are positive.
- A square matrix is negative definite if all the eigen values are negative.

Optimization: Methods of Calculus

- The eigen values (λ) of Hessian matrix are given by roots of characteristic equation

$$|\lambda I - H| = 0$$

I is identity matrix.

Optimization: Methods of Calculus

- If all the eigen values of Hessian matrix are positive, then the function is strictly convex.
- If all the eigen values of Hessian matrix are negative, then the function is strictly concave.
- If some eigen values are positive and some are negative or if some are zero, then the function is neither strictly convex nor strictly concave.

Optimization: Methods of Calculus

Whether the function is minimum or maximum at $X = X_0$ depends on nature of eigen values of its Hessian matrix evaluated at X_0 .

1. If all eigen values are positive at X_0 , X_0 is a local minimum. If all eigen values are positive for all possible values of X , then X_0 is a global minimum.
2. If all eigen values are negative at X_0 , X_0 is a local maximum. If all eigen values are negative for all possible values of X , then X_0 is a global maximum.
3. If some eigen values are positive and some are negative or some are zero, then X_0 is neither a local minimum nor a local maximum.

Example – 4

Examine the function for convexity/concavity and determine the values at extreme points

$$f(X) = x_1^2 + x_2^2 - 4x_1 - 2x_2 + 5$$

The stationary point is obtained by solving

$$\frac{\partial f}{\partial x_1} = 2x_1 - 4 = 0 \quad \text{and} \quad \frac{\partial f}{\partial x_2} = 2x_2 - 2 = 0$$

$$x_1 = 2, x_2 = 1$$

$$X = (2, 1)$$

Example – 4 (Contd.)

- Hessian matrix is

$$H[f(X)] = \begin{bmatrix} \frac{\partial^2 f(X)}{\partial x_1^2} & \frac{\partial^2 f(X)}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f(X)}{\partial x_2 \partial x_1} & \frac{\partial^2 f(X)}{\partial x_2^2} \end{bmatrix} \quad (2,1)$$

Hessian matrix evaluated at stationary point (2,1)

Example – 4 (Contd.)

$$f(X) = x_1^2 + x_2^2 - 4x_1 - 2x_2 + 5$$

$$\frac{\partial f}{\partial x_1} = 2x_1 - 4 \qquad \frac{\partial^2 f}{\partial x_1 \partial x_2} = 0$$

$$\frac{\partial^2 f}{\partial x_1^2} = 2$$

$$\frac{\partial f}{\partial x_2} = 2x_2 - 2 \qquad \frac{\partial^2 f}{\partial x_2 \partial x_1} = 0$$

$$\frac{\partial^2 f}{\partial x_2^2} = 2$$

Example – 4 (Contd.)

Hessian matrix is

$$H[f(X)] = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}$$

Eigen values of Hessian matrix:

$$|\lambda I - H[f(X)]| = 0$$

$$|\lambda I - H| = \begin{vmatrix} \lambda - 2 & 0 \\ 0 & \lambda - 2 \end{vmatrix} = 0$$
$$(\lambda - 2)^2 = 0$$

Eigen values are $\lambda_1 = 2, \lambda_2 = 2$

Example – 4 (Contd.)

- As both the eigen values are positive, the matrix is positive definite

Hence the function has local minimum at $X = (2,1)$

As the Hessian matrix does not depend on x_1 and x_2 and it is positive definite matrix, the function is strictly convex and therefore the local minimum is also the global minimum