# Optimization using Calculus 

## Optimization of <br> Functions of Multiple Variables: Unconstrained Optimization

## Objectives

> To study functions of multiple variables, which are more difficult to analyze owing to the difficulty in graphical representation and tedious calculations involved in mathematical analysis for unconstrained optimization.
> To study the above with the aid of the gradient vector and the Hessian matrix.
> To discuss the implementation of the technique through examples

## Unconstrained optimization

> If a convex function is to be minimized, the stationary point is the global minimum and analysis is relatively straightforward as discussed earlier.
> A similar situation exists for maximizing a concave variable function.
> The necessary and sufficient conditions for the optimization of unconstrained function of several variables are discussed.

## Necessary condition

- In case of multivariable functions a necessary condition for a stationary point of the function $f(\mathbf{X})$ is that each partial derivative is equal to zero. In other words, each element of the gradient vector $\Delta_{x} f$ defined below must be equal to zero. i.e. the gradient vector of $f(\mathbf{X})$, at $\mathbf{X}=\mathbf{X}^{*}$, defined as follows, must be equal to zero:

$$
\Delta_{x} f=\left[\begin{array}{c}
\frac{\partial f}{\partial x_{1}}\left(\mathrm{X}^{*}\right) \\
\frac{\partial f}{\partial x_{2}}\left(\mathrm{X}^{*}\right) \\
\vdots \\
\vdots \\
\frac{\partial f}{\partial d x_{n}}\left(\mathrm{X}^{*}\right)
\end{array}\right]=0
$$

## Sufficient condition

> For a stationary point $\mathbf{X}^{*}$ to be an extreme point, the matrix of second partial derivatives (Hessian matrix) of $f(\mathbf{X})$ evaluated at $\mathbf{X}^{*}$ must be:
> positive definite when $\mathbf{X}^{*}$ is a point of relative minimum, and
> negative definite when $\mathbf{X}^{*}$ is a relative maximum point.
> When all eigen values are negative for all possible values of $\mathbf{X}$, then $\mathbf{X}^{*}$ is a global maximum, and when all eigen values are positive for all possible values of $\mathbf{X}$, then $\mathbf{X}^{*}$ is a global minimum.
> If some of the eigen values of the Hessian at $\mathbf{X}^{*}$ are positive and some negative, or if some are zero, the stationary point, $\mathbf{X}^{*}$, is neither a local maximum nor a local minimum.

## Example

Analyze the function $f(x)=-x_{1}^{2}-x_{2}^{2}-x_{3}^{2}+2 x_{1} x_{2}+2 x_{1} x_{3}+4 x_{1}-5 x_{3}+2$ and classify the stationary points as maxima, minima and points of inflection

## Solution

$$
\Delta_{x} f=\left[\begin{array}{l}
\frac{\partial f}{\partial x_{1}}\left(\mathrm{X}^{*}\right) \\
\frac{\partial f}{\partial x_{2}}\left(\mathrm{X}^{*}\right) \\
\frac{\partial f}{\partial x_{3}}\left(\mathrm{X}^{*}\right)
\end{array}\right]=\left[\begin{array}{c}
-2 x_{1}+2 x_{2}+2 x_{3}+4 \\
-2 x_{2}+2 x_{1} \\
-2 x_{3}+2 x_{1}-5
\end{array}\right]=\left[\begin{array}{l}
0 \\
0 \\
0
\end{array}\right]
$$

## Example ...contd.

Solving these simultaneous equations we get $\mathrm{X}^{*}=[1 / 2,1 / 2,-2]$

$$
\begin{aligned}
& \frac{\partial^{2} f}{\partial x_{1}^{2}}=-2 ; \frac{\partial^{2} f}{\partial x_{2}^{2}}=-2 ; \frac{\partial^{2} f}{\partial x_{3}^{2}}=-2 \\
& \frac{\partial^{2} f}{\partial x_{1} \partial x_{2}}=\frac{\partial^{2} f}{\partial x_{2} \partial x_{1}}=2 \\
& \frac{\partial^{2} f}{\partial x_{2} \partial x_{3}}=\frac{\partial^{2} f}{\partial x_{3} \partial x_{2}}=0 \\
& \frac{\partial^{2} f}{\partial x_{3} \partial x_{1}}=\frac{\partial^{2} f}{\partial x_{1} \partial x_{3}}=2
\end{aligned}
$$

## Example ...contd.

Hessian of $f(\mathbf{X})$ is

$$
\begin{gathered}
\mathbf{H}=\left[\frac{\partial^{2} f}{\partial x_{i} \partial x_{j}}\right] \\
\mathbf{H}=\left[\begin{array}{ccc}
-2 & 2 & 2 \\
2 & -2 & 0 \\
2 & 0 & -2
\end{array}\right] \\
|\lambda \mathbf{I}-\mathbf{H}|=\left|\begin{array}{ccc}
\lambda+2 & -2 & -2 \\
-2 & \lambda+2 & 0 \\
-2 & 0 & \lambda+2
\end{array}\right|=0
\end{gathered}
$$

## Example ...contd.

$$
\begin{gathered}
\text { or }(\lambda+2)(\lambda+2)(\lambda+2)-2(\lambda+2)(2)+2(2)(\lambda+2)=0 \\
(\lambda+2)\left[\lambda^{2}+4 \lambda+4-4+4\right]=0 \\
(\lambda+2)^{3}=0 \\
\text { or } \lambda_{1}=\lambda_{2}=\lambda_{3}=-2
\end{gathered}
$$

Since all eigenvalues are negative the function attains a maximum at the point $\mathbf{X}^{*}=[1 / 2,1 / 2,-2]$

## Thank you

