

Optimization Techniques

Lecture 3

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*Unconstrained Optimization,
Local and Global Minimizer,
Feasible Direction,
FONC and SOSC for a local minimizer*

Unconstrained Optimization,

$$\begin{array}{ll} \text{minimize} & f(\mathbf{x}) \\ \text{subject to} & \mathbf{x} \in \Omega. \end{array}$$

The function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ that we wish to minimize is a real-valued function, and is called the *objective function*, or *cost function*. The vector \mathbf{x} is an n -vector of independent variables, that is, $\mathbf{x} = [x_1, x_2, \dots, x_n]^T \in \mathbb{R}^n$. The variables x_1, \dots, x_n are often referred to as *decision variables*. The set Ω is a subset of \mathbb{R}^n , called the *constraint set* or *feasible set*.

The above problem is a general form of a *constrained* optimization problem, because the decision variables are constrained to be in the constraint set Ω . If $\Omega = \mathbb{R}^n$, then we refer to the problem as an *unconstrained* optimization problem.

The constraint " $\mathbf{x} \in \Omega$ " is called a *set constraint*. Often, the constraint set Ω takes the form $\Omega = \{\mathbf{x} : \mathbf{h}(\mathbf{x}) = \mathbf{0}, \mathbf{g}(\mathbf{x}) \leq \mathbf{0}\}$, where \mathbf{h} and \mathbf{g} are given functions. We refer to such constraints as *functional constraints*. The remainder of this chapter deals with general set constraints, including the special case where $\Omega = \mathbb{R}^n$. The case where $\Omega = \mathbb{R}^n$ is called the *unconstrained* case.

minimize	$f(\mathbf{x})$
subject to	$\mathbf{x} \in \Omega.$

minimizer of f over Ω
maximizing f is equivalent to minimizing $-f$

Max versus min: Maximizing a function g is equivalent to minimizing $-g$, so there's no loss of generality in concentrating on minimization. This is the convention in much of optimization theory

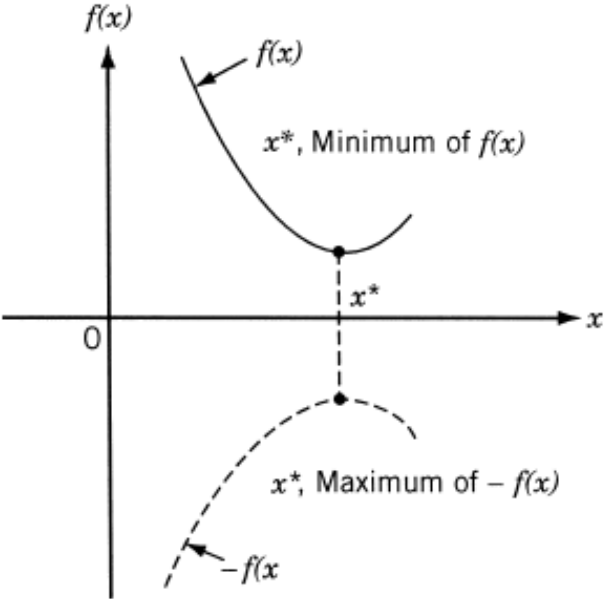


Figure 1.1 Minimum of $f(x)$ is same as maximum of $-f(x)$.

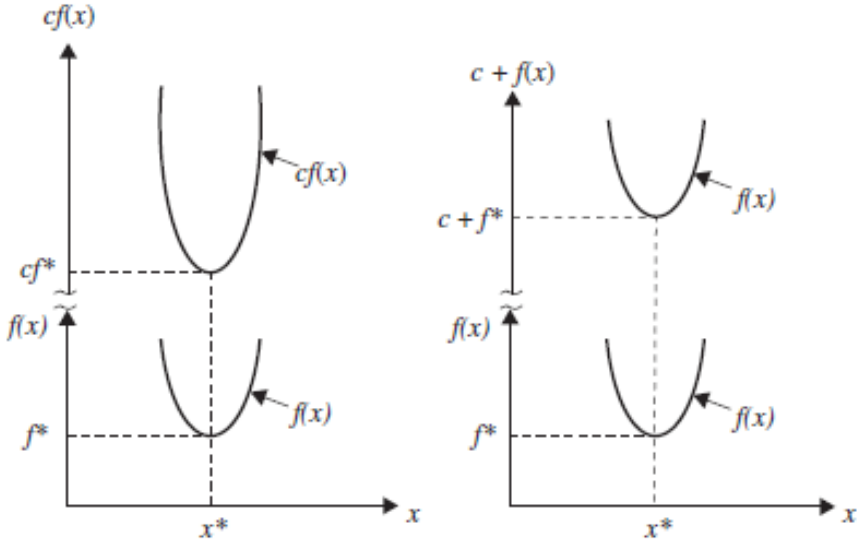


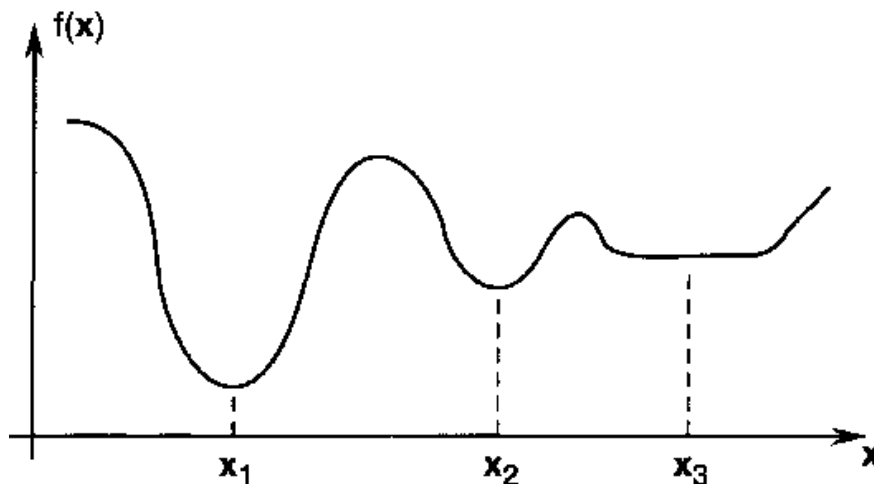
Figure 1.2 Optimum solution of $cf(x)$ or $c + f(x)$ same as that of $f(x)$.

Local and Global Minimizers

Definition 6.1 *Local minimizer.* Suppose that $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is a real-valued function defined on some set $\Omega \subset \mathbb{R}^n$. A point $x^* \in \Omega$ is a *local minimizer* of f over Ω if there exists $\varepsilon > 0$ such that $f(x) \geq f(x^*)$ for all $x \in \Omega \setminus \{x^*\}$ and $\|x - x^*\| < \varepsilon$.

Global minimizer. A point $x^* \in \Omega$ is a *global minimizer* of f over Ω if $f(x) \geq f(x^*)$ for all $x \in \Omega \setminus \{x^*\}$.

If, in the above definitions, we replace “ \geq ” with “ $>$ ”, then we have a *strict local minimizer* and a *strict global minimizer*, respectively.



x_1 : strict global minimizer;

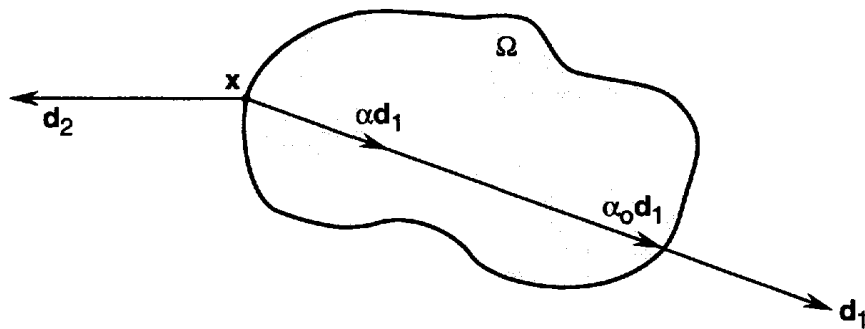
x_2 : strict local minimizer;

x_3 : local (not strict) minimizer

Feasible Direction

Given an optimization problem with constraint set Ω , a minimizer may lie either in the interior or on the boundary of Ω . To study the case where it lies on the boundary, we need the notion of *feasible directions*.

Definition 6.2 Feasible direction. A vector $\mathbf{d} \in \mathbb{R}^n$, $\mathbf{d} \neq \mathbf{0}$, is a *feasible direction* at $\mathbf{x} \in \Omega$ if there exists $\alpha_0 > 0$ such that $\mathbf{x} + \alpha\mathbf{d} \in \Omega$ for all $\alpha \in [0, \alpha_0]$.



\mathbf{d}_1 is a feasible direction,

\mathbf{d}_2 is not a feasible direction

Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a real-valued function and let \mathbf{d} be a feasible direction at $\mathbf{x} \in \Omega$. The *directional derivative of f in the direction \mathbf{d}* , denoted $\partial f / \partial \mathbf{d}$, is the real-valued function defined by

$$\frac{\partial f}{\partial \mathbf{d}}(\mathbf{x}) = \lim_{\alpha \rightarrow 0} \frac{f(\mathbf{x} + \alpha \mathbf{d}) - f(\mathbf{x})}{\alpha}.$$

If $\|\mathbf{d}\| = 1$, then $\partial f / \partial \mathbf{d}$ is the rate of increase of f at \mathbf{x} in the direction \mathbf{d} . To compute the above directional derivative, suppose that \mathbf{x} and \mathbf{d} are given. Then, $f(\mathbf{x} + \alpha \mathbf{d})$ is a function of α , and

$$f(\mathbf{x} + \alpha \mathbf{d}) = F(\alpha)$$

$$\begin{aligned} F'(\alpha) &= \frac{\delta f}{\delta x_1} \frac{dx_1}{d \alpha} + \frac{\delta f}{\delta x_2} \frac{dx_2}{d \alpha} + \dots + \frac{\delta f}{\delta x_n} \frac{dx_n}{d \alpha} \\ &= \nabla f(\mathbf{x})^T \cdot \mathbf{d} \end{aligned}$$

In summary, if \mathbf{d} is a unit vector, that is, $\|\mathbf{d}\| = 1$, then $\langle \nabla f(\mathbf{x}), \mathbf{d} \rangle$ is the rate of increase of f at the point \mathbf{x} in the direction \mathbf{d} .

Theorem *First-Order Necessary Condition (FONC).* Let Ω be a subset of \mathbb{R}^n and $f \in C^1$ a real-valued function on Ω . If \mathbf{x}^* is a local minimizer of f over Ω , and \mathbf{x}^* is an interior point of Ω , then

$$\nabla f(\mathbf{x}^*) = \mathbf{0}.$$

What happens if Ω is an open subset of \mathbb{R}^n ?

FONC: Let Ω be an open set and f is a continuously differentiable function over Ω ($f \in C^1$).

If $\mathbf{x}^* \in \Omega$ is a minimizer of f , then $\nabla f(\mathbf{x}^*) = \mathbf{0}$.

$$\nabla f(x^*) = 0.$$

This is the **first-order necessary condition for optimality**. The condition is "first-order" because it is derived using the first-order expansion. We emphasize that the result is valid when $f \in C^1$ and x^* is an interior point of Ω .

Definition: A point x^* satisfying the FONC condition $\nabla f(x^*) = 0$ is called a **stationary point**.

Definition: A function f has **critical points** at all points x_0 where $f'(x_0) = 0$ or $f(x)$ is not differentiable.

In several variables case, the same definition can be given as:

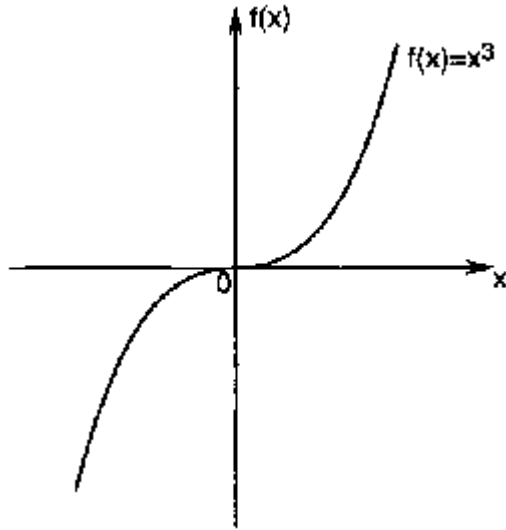
A function with several variables has **critical points** where the gradient is 0 or any of the partial derivatives is not defined.

Second Order Sufficient Condition (SOSC):

Let Ω be an open set and f is a twice continuously differentiable function over Ω ($f \in C^2$). The sufficient condition for a local minimizer ($x^* \in \Omega$) is that the Hessian matrix at x^* is positive semidefinite.

Proof of SOSC:

Example 6.5 Consider a function of one variable $f(x) = x^3$, $f : \mathbb{R} \rightarrow \mathbb{R}$.



The point 0 satisfies the FONC but is not a minimizer

This point is an inflection point.

Definition: An inflection point is a point on a curve at which the concavity changes.

A necessary condition for x to be an inflection point is $f''(x) = 0$. A sufficient condition requires $f''(x + \varepsilon)$ and $f''(x - \varepsilon)$ to have opposite signs in the neighborhood of x .

In multivariable calculus, a point of a function or surface which is a stationary point but not an extremum is called a saddle point.

In summary

FONC: Solve the following equation and obtain all the stationary points.

$$\nabla f(x^*) = 0.$$

SOSC: Form the Hessian at each of the stationary points:

If the Hessian is *positive* definite, then that point is a *strict* local minimum,

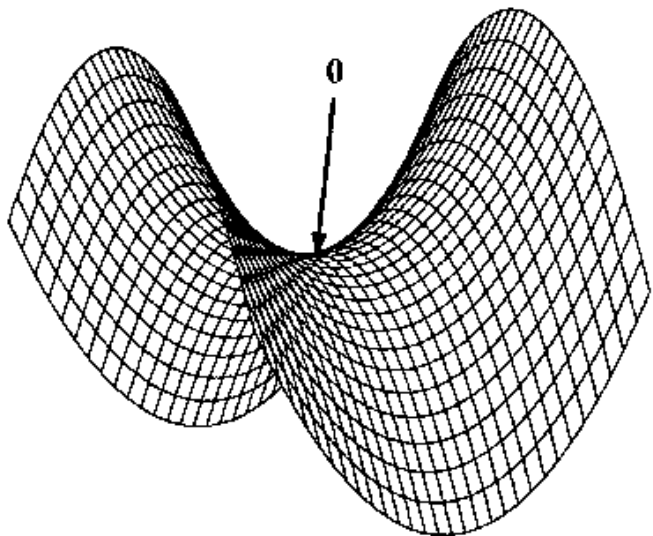
If the Hessian is *positive* semidefinite, then that point is a local minimum,

If the Hessian is *negative* definite, then that point is a *strict* local maximum,

If the Hessian is *negative* semidefinite, then that point is a local maximum.

If the Hessian is indefinite, then that point is a saddle point.

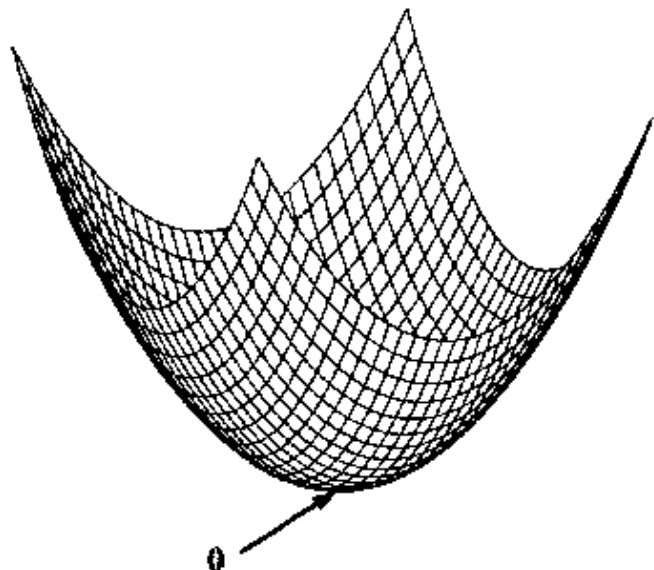
Example 6.6 Consider a function $f : \mathbb{R}^2 \rightarrow \mathbb{R}$, where $f(\mathbf{x}) = x_1^2 - x_2^2$.



The point $\mathbf{0}$ satisfies the FONC but not SOSC;

this point is not a minimizer

Example 6.7 Let $f(\mathbf{x}) = x_1^2 + x_2^2$.



$\mathbf{x} = [0, 0]^T$ is a strict global minimizer.

Example: A small startup company produces speakers and subwoofers for computers that they sell through a website. After extensive research, the company has developed a revenue function,

$$R(x, y) = x(110 - 4.5x) + y(155 - 2y) \text{ thousand dollars}$$

where x is the number of subwoofers produced and sold in thousands and y is the number of speakers produced and sold in thousands. The corresponding cost function is

$$C(x, y) = 3x^2 + 3y^2 + 5xy - 5y + 50 \text{ thousand dollars}$$

Find the production levels that maximize revenue.

Find and classify all the critical points of the following functions:

1) $f(x_1, x_2) = x^3 - x^2y + 2y^2.$

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

$$3) f(x, y) = 7x - 8y + 2xy - x^2 + y^3$$

$$4) f = x_1^3 + x_2^3 + x_3^3 - 3x_1^2x_2 - 3x_2^2x_3 - 3x_3^2x_1 + 6x_1 + 6x_2 + 6x_3$$

$$f(x, y) = x + \frac{1}{2x + y} - \frac{1}{x + y}$$

$$\nabla f = \left(1 - \frac{2}{(2x+y)^2} + \frac{1}{(x+y)^2}, -\frac{1}{(2x+y)^2} + \frac{1}{(x+y)^2} \right) \quad H(f) = \begin{pmatrix} \frac{8}{(2x+y)^3} - \frac{2}{(x+y)^3} & \frac{4}{(2x+y)^3} - \frac{2}{(x+y)^3} \\ \frac{4}{(2x+y)^3} - \frac{2}{(x+y)^3} & \frac{2}{(2x+y)^3} - \frac{2}{(x+y)^3} \end{pmatrix}$$

Need to solve the equations $\nabla f(x, y) = 0$:

$$1 - \frac{2}{(2x + y)^2} + \frac{1}{(x + y)^2} = 0, \quad -\frac{1}{(2x + y)^2} + \frac{1}{(x + y)^2} = 0$$

Subtracting the second equation from the first one we see that $(2x + y)^2 = 1$ and $(x + y)^2 = 1$ which give us 4 critical points

$$1) (0, 1); \quad 2) (0, -1); \quad 3) (2, -3); \quad 4) (-2, 3).$$

$$1) H(f)|_{(0,1)} = \begin{pmatrix} 6 & 2 \\ 2 & 0 \end{pmatrix},$$

$$2) H(f)|_{(0,-1)} = \begin{pmatrix} -6 & -2 \\ -2 & 0 \end{pmatrix}$$

$$3) H(f)|_{(2,-3)} = \begin{pmatrix} 10 & 6 \\ 6 & 4 \end{pmatrix},$$

$$4) H(f)|_{(-2,3)} = \begin{pmatrix} -10 & -6 \\ -6 & -4 \end{pmatrix},$$

Practical Example

A container with an open top is to have 10 m^3 capacity and be made of thin sheet metal. Calculate the dimensions of the box if it is to use the minimum possible amount of metal.

Solution: Let A be the total area of metal used to make the box, and let x and y be the length and width and z the height. Then

$$A = 2xz + 2yz + xy$$

Also

$$xyz = 10$$

because the volume is 10 m^3 . This implies that $z = \frac{10}{xy}$. Putting this into the formula for A gives A as a function of x and y only:

$$\begin{aligned} A &= 2x \left(\frac{10}{xy} \right) + 2y \left(\frac{10}{xy} \right) + xy \\ &= \frac{20}{y} + \frac{20}{x} + xy \end{aligned}$$

We shall apply our techniques to this function. Now

$$\frac{\partial A}{\partial x} = -\frac{20}{x^2} + y, \quad \frac{\partial A}{\partial y} = -\frac{20}{y^2} + x$$

and for a stationary point we need $\partial A/\partial x = \partial A/\partial y = 0$. this gives

$$y = \frac{20}{x^2} \quad \text{and} \quad x = \frac{20}{y^2}.$$

Therefore

$$y = \frac{20}{(20/y^2)^2} = \frac{y^4}{20}$$

Since the zero root $y = 0$ is obviously not consistent with having a volume of 10 m^3 we reject $y = 0$ and conclude that $y^3 = 20$ so that $y = 20^{1/3} = 2.714$ metres. From $x = 20/y^2$ we conclude $x = 2.714$ metres also. To find z , use $z = \frac{10}{xy}$ so that $z = 1.357 \text{ m}$.

We have to show that these values do indeed give a **minimum**. Now

$$\frac{\partial^2 A}{\partial x \partial y} = 1, \quad \frac{\partial^2 A}{\partial x^2} = \frac{40}{x^3}, \quad \frac{\partial^2 A}{\partial y^2} = \frac{40}{y^3}$$

So, when $(x, y) = (2.714, 2.714)$,

$$A_{xx}A_{yy} - A_{xy}^2 = (2)(2) - 1^2 = 3 > 0$$

so it is either a max or a min. But $A_{xx} > 0$ and $A_{yy} > 0$ so it is a minimum. Our conclusion is that the box should have length 2.714 m, width 2.714 m and height 1.357 m. The actual area of metal used will then (from the formula for A) be 22.1 m^2 .