



Local and Global Optimization

Understanding Optima in Complex Landscapes

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INDUSTRIAL ENGINEERING

Delve into the dynamics of optimization landscapes, differentiating between local optima and the overarching global optimum, and the techniques to approach each.

Calculus Methods: Using mathematical tools to solve problems involving change and motion.

- ▶ Determining the fastest moment a car was going during a trip.

Calculus of Variations: A field of mathematical analysis that deals with maximizing or minimizing functionals.

- ▶ Finding the shortest path a beam of light can take to reflect off a surface.

Nonlinear Programming: Optimizing functions that are not straight lines.

- ▶ Maximizing profit when the production cost changes as you produce more.

Geometric Programming: Optimization technique based on polynomial equations.

- ▶ Designing a soda can with the least material but a specific volume.

Quadratic Programming: Optimizing quadratic functions, which are polynomials of degree 2.

- ▶ Minimizing the cost of production given certain constraints.

Linear Programming: A method to achieve the best outcome in a mathematical model whose requirements are represented by linear relationships.

- ▶ Finding the best combination of products to manufacture to maximize profit.

Dynamic Programming: Breaking down a problem into simpler parts and solving each part only once.

- ▶ Figuring out the most efficient way to store data to minimize retrieval time.

Integer Programming: Optimization where some of the variables are restricted to integer values.

- ▶ Deciding the number of buses a school should deploy, as you can't have a fraction of a bus.

Stochastic Programming: Making decisions in the face of uncertainty.

- ▶ Planning for the future stock of a store when future demand is uncertain.

Separable Programming: A nonlinear program where the objective and constraint functions are separable.

- ▶ Maximizing crop yield by optimizing the amount of water and fertilizer used when the effects of each are independent.

Multi-objective Programming: Making decisions while considering multiple goals simultaneously.

- ▶ Designing a product that's both low-cost and high-quality.

Network Methods, CPM and PERT: Tools for project planning and control.

- ▶ Organizing tasks when building a house to ensure it's done efficiently and on time.

Game Theory: Studying mathematical models of strategic interactions among rational decision-makers.

- ▶ Two businesses deciding on the price of a product, considering what the other might charge.

Stochastic Processing Techniques: Techniques to handle processes that involve uncertainty.

- ▶ Predicting stock prices based on past fluctuations.

Statistical Decision Theory: Making decisions using data analysis.

- ▶ Choosing to launch a product based on customer survey data.

Markov Processes: Processes where the next state depends only on the current state.

- ▶ Predicting tomorrow's weather based on today's.

Queuing Theory: Studying the behavior of waiting lines.

- ▶ Optimizing supermarket cashiers to reduce wait times.

Renewal Theory: Statistics of the time to events in processes.

- ▶ Predicting machine failure based on past breakdowns.

Simulation Methods: Imitating a real-world process using a model.

- ▶ Predicting drug spread using a computer model.

Reliability Theory: Predicting and enhancing system durability.

- ▶ Determining average lifespan of a car part.

Regression Analysis: Examining relationships between variables.

- ▶ Determining sales relation to advertising.

Cluster Analysis & Pattern Recognition: Grouping based on similarities.

- ▶ Grouping customers by buying habits.

Design of Experiments: Planning experiments to get valid data.

- ▶ Testing if new fertilizer improves growth.

Discriminant Analysis/Factor Analysis: Breaking down data into core influences.

- ▶ Understanding factors influencing grades.

Genetic Algorithms: Optimization using natural selection principles.

- ▶ Finding best airplane wing design by "evolving" designs.

Simulated Annealing: Probabilistic optimization mimicking the annealing process.

- ▶ Optimizing delivery routes.

Ant Colony Optimization: Optimization using ant behavior.

- ▶ Optimizing city traffic flow.

Particle Swarm Optimization: Optimization based on flock behavior.

- ▶ Adjusting wind turbine design for efficiency.

Neural Networks: Algorithms designed to recognize patterns.

- ▶ Recognizing faces in photos.

Fuzzy Optimization: Optimization using fuzzy logic rather than binary.

- ▶ Adjusting car heat based on "warm" or "cold".

Equations Involved: Based on the nature of equations.

- ▶ Linear vs. Nonlinear equations.

Design Variables Values: Based on permissible values.

- ▶ Discrete variables in selecting warehouse locations.

Deterministic Nature: Based on variables' determinacy.

- ▶ Predictable machine outputs vs. unpredictable stock prices.

Existence of Constraints: Whether constraints are present.

- ▶ Maximizing revenue with a limited budget.

Design Variables Nature: Nature of the variables involved.

- ▶ Binary choices in a network design.

Physical Structure: Based on the problem's inherent structure.

- ▶ Structural engineering optimizations.

Separability of Functions: If functions can be separated.

- ▶ Independent departmental budgets in a company.

Number of Objectives: Based on the number of goals.

- ▶ Balancing cost, quality, and time in project management.

Objective Function: Maximize or Minimize

The choice between maximizing and minimizing a function can often be translated by considering the function's opposite or a scaled version of the function.

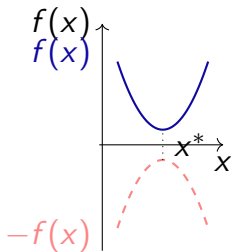


Figure: $\min_x f(x) \iff \max_x -f(x)$

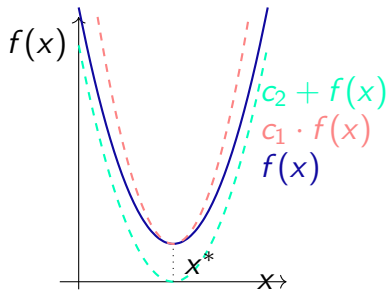
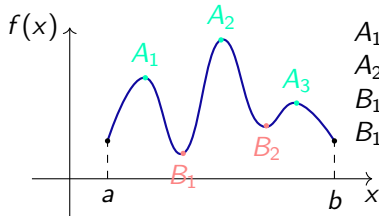


Figure: Scaled $c_1 \cdot f(x)$ and translated $c_2 + f(x)$ both retain the original shape.

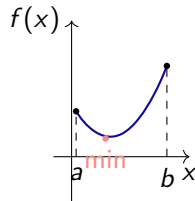
Single variable optimization with no constraints

Determine the value of $x = x^*$ within the interval $[a, b]$ that minimizes the function $f(x)$.

Necessary Condition If a function $f(x)$ is defined in the interval $a \leq x \leq b$ and has a relative minimum at $x = x^*$, where $a < x^* < b$, and if the derivative $\frac{df(x)}{dx} = f'(x)$ exists as a finite number at $x = x^*$, then $f'(x^*) = 0$.



A_1, A_2, A_3 are local maxima
 A_2 is the global maximum
 B_1, B_2 are local minima
 B_1 is the global minimum



local minimum
is also global
minimum

Considerations

- ▶ The proof holds even if x^* is a local maximum.
- ▶ The derivative's existence at x^* is not guaranteed for every minimum or maximum.
- ▶ Extrema at the endpoints of the function's definition interval are not covered.
- ▶ A zero derivative doesn't guarantee the presence of an extremum; it could be an inflection (or saddle) point.

Sufficient Condition for Extrema

Let's assume the first $n - 1$ derivatives at point x^* are zero, but the n th derivative is not zero.

- ▶ If the n th derivative at x^* is positive and n is even, then $f(x^*)$ is a minimum.
- ▶ If the n th derivative at x^* is negative and n is even, then $f(x^*)$ is a maximum.
- ▶ If n is odd, $f(x^*)$ is neither a maximum nor a minimum.

Think of the even n as giving the function "another chance" to decide if it's curving up or down. Odd n means the function hasn't settled into a curve direction.

Multivariable Optimization: Necessity vs. Sufficiency

In single-variable optimization, a zero derivative suggests potential extrema. Similarly, in the multivariable case, all first partial derivatives should be zero at a stationary point, constituting the **necessary condition**. To further discern if it's genuinely a maximum or minimum (and not a saddle point), we turn to the Hessian matrix for the **sufficient condition**.

Simply put, for a point to be a high or low point in multiple dimensions, the function shouldn't be rising or falling in any of those directions.

Necessary Condition For a function $f(\mathbf{x})$ to have an extreme point at $\mathbf{x} = \mathbf{x}^*$:

$$\frac{\partial f}{\partial x_1}(\mathbf{x}^*) = \frac{\partial f}{\partial x_2}(\mathbf{x}^*) = \dots = \frac{\partial f}{\partial x_n}(\mathbf{x}^*) = 0$$

Sufficient Condition To determine the nature of a stationary point \mathbf{x}^* of the function $f(\mathbf{x})$:

- ▶ If the Hessian matrix at \mathbf{x}^* is positive definite, \mathbf{x}^* is a local minimum.
- ▶ If it's negative definite, \mathbf{x}^* is a local maximum.

This helps us be certain about the nature of the stationary point.

Refresher: The Hessian Matrix

The Hessian matrix H of a function $f(\mathbf{x})$ is the matrix of its second-order partial derivatives. It provides insight into the curvature of the function:

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

A matrix A is considered:

- ▶ **Positive definite** if all its eigenvalues are positive. This suggests the function is curving upwards, indicating a minimum. That means all values of λ that satisfy the determinantal equation $|A - \lambda I| = 0$ should be positive.
- ▶ **Negative definite** if all its eigenvalues are negative. This suggests the function is curving downwards, indicating a maximum.

Determining Definiteness Using Determinants

To assess the definiteness of a matrix A of order n , evaluate the determinants of all the leading principal minors.

Example: For a $n \times n$ matrix A :

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix}$$

The determinants of the leading principal minors are:

$$A_1 = |a_{11}|, \quad A_2 = \begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix}, \quad \dots \quad A_n = \begin{vmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{vmatrix}$$

The matrix A will be:

- ▶ **Positive definite** if all A_1, A_2, \dots, A_n are positive.
- ▶ **Negative definite** if the sign of A_j alternates starting with negative, i.e., the sign of A_j is $(-1)^{j+1}$ for $j = 1, 2, \dots, n$.

Laplace expansion is a technique to compute matrix determinants using cofactors. For more, see [Wikipedia: Laplace Expansion](#).

Multivariable Optimization with Equality Constraints

Goal: Minimize a function $f(\vec{x})$ where $\vec{x} = [x_1, x_2, \dots, x_n]$.

Constraints: Equations given by $g_j(\vec{x}) = 0$, dictating the rules our solution must follow.

Note If the number of constraints (m) is greater than the elements in our solution list (n), the problem is **overdefined**. Typically $m > n$ means no solution exists.

Example

Find the dimensions of a box of largest volume that can be inscribed in a sphere of unit radius.

Setup

- ▶ Let the origin of the Cartesian coordinate system x_1, x_2, x_3 be at the center of the sphere.
- ▶ Let the sides of the box be $2x_1, 2x_2$, and $2x_3$.
- ▶ The volume of the box is:

$$f(x_1, x_2, x_3) = 8x_1x_2x_3$$

- ▶ Since the corners of the box lie on the sphere:

$$x_1^2 + x_2^2 + x_3^2 = 1$$

Constraints and Reformulation

- ▶ This problem has three design variables and one equality constraint.
- ▶ Use the equality constraint to eliminate one variable:

$$x_3 = \sqrt{1 - x_1^2 - x_2^2}$$

- ▶ The objective becomes:

$$f(x_1, x_2, x_3) = 8x_1x_2\sqrt{1 - x_1^2 - x_2^2}$$

Necessary Conditions for the maximum of f provide a system of equations.

$$\frac{\partial f}{\partial x_1} = 8x_2 \left[\sqrt{1 - x_1^2 - x_2^2} - \frac{x_1^2}{\sqrt{1 - x_1^2 - x_2^2}} \right] = 0$$
$$\frac{\partial f}{\partial x_2} = 8x_1 \left[\sqrt{1 - x_1^2 - x_2^2} - \frac{x_2^2}{\sqrt{1 - x_1^2 - x_2^2}} \right] = 0$$

After simplification, the equations become:

$$1 - 2x_1^2 - x_2^2 = 0,$$

$$1 - x_1^2 - 2x_2^2 = 0.$$

Solving this system of equations yields the solution $x_1^* = x_2^* = \frac{1}{\sqrt{3}}$ and hence

$x_3^* = \frac{1}{\sqrt{3}}$. Therefore, the volume of the box is $f(\vec{x}^*) = \frac{8}{3\sqrt{3}}$.

To verify that this is a maximum, we need to check the sufficient conditions to $f(x_1, x_2)$. The second-order partial derivatives of f at \vec{x}^* are given by

$$\frac{\partial^2 f}{\partial x_1^2}(\vec{x}^*) = -\frac{32}{\sqrt{3}}, \quad \frac{\partial^2 f}{\partial x_2^2}(\vec{x}^*) = -\frac{32}{\sqrt{3}}, \quad \frac{\partial^2 f}{\partial x_1 \partial x_2}(\vec{x}^*) = -\frac{16}{\sqrt{3}},$$

and since $\frac{\partial^2 f}{\partial x_1^2} < 0$ and $\frac{\partial^2 f}{\partial x_1^2} \frac{\partial^2 f}{\partial x_2^2} - \left(\frac{\partial^2 f}{\partial x_1 \partial x_2} \right)^2 > 0$ then the Hessian matrix of f at \vec{x}^* is negative definite and hence \vec{x}^* is a maximum point of f .