

Non-Linear Programming

Basics of Mathematical Programming and unconstrained optimization

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Basics of mathematical programming

Goal of optimization

A (single objective) optimization is concerned with computing

$$\max_{\mathbf{x} \in S} f(\mathbf{x}).$$

The solution (values of \mathbf{x} which accomplish this) are called maxima¹ (minima) or maximizers (minimizers). The function value at the maxima is called the *maximum value*.

- Generally computing the maxima is not computationally easy. Even by exploiting some characteristics.
- Often we settle for local maxima. Solutions that perform well in a certain vicinity and not everywhere. They are easier to compute/

¹This is the global optima or global optimal solution

Local maxima

Local maxima

$\mathbf{x}^* \in S \subseteq \mathbb{R}^n$ is a local optima for the problem $\max_{\mathbf{x} \in S} f(\mathbf{x})$ if
 $f(\mathbf{x}^*) \geq f(\mathbf{x}) \forall \mathbf{x} : \|\mathbf{x}^* - \mathbf{x}\| < \varepsilon$ for some $\varepsilon > 0$.

- There are computationally efficient methods to find the local maxima.
- For special optimization problem classes like Concave Maximization Problems (CMP) local and global optima are the same.
- All global maxima are also local maxima.
- Local maxima enjoy special properties.

Mathematical basics: Jacobian

Let $\mathbf{f}(\mathbf{x}) = \begin{bmatrix} f_1(\mathbf{x}) \\ f_2(\mathbf{x}) \\ \vdots \\ f_m(\mathbf{x}) \end{bmatrix}$. The function is a vector function with m components $\mathbf{f}: \mathbb{R}^n \mapsto \mathbb{R}^m$. The derivative matrix or Jacobian for \mathbf{f} is given by

$$D\mathbf{f}(\mathbf{x}) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \dots & \frac{\partial f_1}{\partial x_m} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_n}{\partial x_1} & \dots & \frac{\partial f_n}{\partial x_m} \end{bmatrix}.$$

For a univariate function, the transpose of the derivative matrix is called the gradient vector.

Mathematical basics: Gradient (contd.)

For the transpose of the derivative matrix is called the gradient vector $\nabla f(\mathbf{x})$. Suppose the function is a scalar function instead of a vector function.

$$\nabla f(\mathbf{x}) = \begin{pmatrix} \frac{\partial f}{\partial x_1}(x) \\ \vdots \\ \frac{\partial f}{\partial x_m}(x) \end{pmatrix}.$$

Mathematical basics: Hessian matrix (contd.)

Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be twice continuously differentiable. The Hessian matrix (H or $\nabla^2 f(x)$) of f at $x \in \mathbb{R}^n$ is defined as

$$\nabla^2 f(x) = \begin{pmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & \cdots & \frac{\partial^2 f}{\partial x_2 \partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_1} & \frac{\partial^2 f}{\partial x_n^2} & \cdots & \frac{\partial^2 f}{\partial x_n \partial x_n} \end{pmatrix}.$$

Multivariate Taylor Series

Given $f: \mathbb{R}^n \mapsto \mathbb{R}$ and its derivatives at a point \mathbf{x} , we can approximate the function value at another point $\mathbf{x} + \mathbf{h}$ as a polynomial below.

$$f(\mathbf{x} + \mathbf{h}) = f(\mathbf{x}) + \mathbf{h}^T \nabla f(\mathbf{x}) + \frac{1}{2} \mathbf{h}^T \mathbf{H} \mathbf{h} + o(||\mathbf{h}||^2)$$

- This approximation works so long as the function is smooth.
- The last few terms are jointly represented as $o(||\mathbf{h}||^2)$. They go to zero faster than $||\mathbf{h}||^2$.
 - You could ignore these terms if $||\mathbf{h}||^2 \approx 0$
 - However ignoring some these terms means that the polynomial series becomes an approximation which works well in the vicinity of \mathbf{x} .

Vectors, Matrices, and Negative Semi-definiteness

A vector is a member of the real vector space, i.e., $\mathbf{v} \in \mathbb{R}^n$. A matrix $\mathbf{A} \in \mathbb{R}^{n \times m}$ is a row vector of several column vector elements. i.e.,

$$\mathbf{A} = [\mathbf{v}_1 \ \mathbf{v}_2 \ \dots \ \mathbf{v}_m]$$

Negative (Positive) semi-definite matrix

A matrix $\mathbf{A} \in \mathbb{R}^{n \times n}$ is negative (positive) semi-definite if
 $\mathbf{v}^T \mathbf{A} \mathbf{v} \leq (\geq) 0 \forall \mathbf{v} \in \mathbb{R}^n$.

- In case the inequality is strict, we use the term negative (positive) definite and avoid the usage of term phrase semi.
- In this course, we are more concerned with negative semi-definiteness and negative definiteness, since these are associated with properties enjoyed by maximizers (as we shall see subsequently).

Alternate definition for negative definiteness

A matrix \mathbf{A} is negative definite if and only if all its Eigen values are negative. In case of semi-definite the Eigen values should be of \leq type.

Sylvester's criterion for Negative definiteness

Sylvester's criterion

A symmetric square matrix is a negative definite if its leading principal minors $\Delta_1, \Delta_2, \dots, \Delta_n$ are such that $(-1)^i \Delta_i > 0$. That is the leading principal minors have alternating signs with the first principal minor being negative.

- $A \succ 0$ if $\Delta_i > 0 \forall i = 1, 2, \dots, n$.
- $A \prec 0$ If $(-1)^i \Delta_i > 0 \forall i = 1, 2, \dots, n$.
- Indefinite if the first minor that breaks the pattern is of opposite sign.
- Inconclusive if the first minor which breaks the pattern is 0. In this case, apply the definition to check for definiteness (semi-definiteness).

Directional derivative

Let $f: \mathbb{R}^n \mapsto \mathbb{R}$ and $\mathbf{d} \in \mathbb{R}^n$ be an arbitrary direction of unit magnitude $\|\mathbf{d}\| = 1$.

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

Directional derivative quantifies the level of change in a function if a unit distance is moved in a particular direction.

Directional derivative: A simpler equation

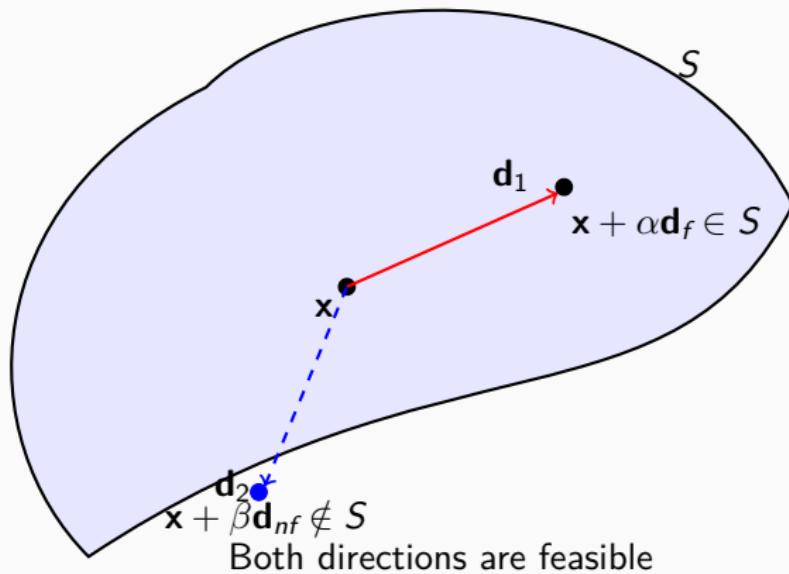
$$\begin{aligned}\frac{\partial f}{\partial \mathbf{d}} &= \lim_{\alpha \rightarrow 0} \left(\frac{f(\mathbf{x} + \alpha \mathbf{d}) - f(\mathbf{x})}{\alpha} \right) \\ &= \left(\frac{\nabla f(\mathbf{x} + \alpha \mathbf{d})^T \mathbf{d}}{1} \right)_{\alpha=0} \\ \therefore \frac{\partial f}{\partial \mathbf{d}} &= \mathbf{d}^T \nabla f(\mathbf{x})\end{aligned}$$

Feasible directions and FONC for Maxima

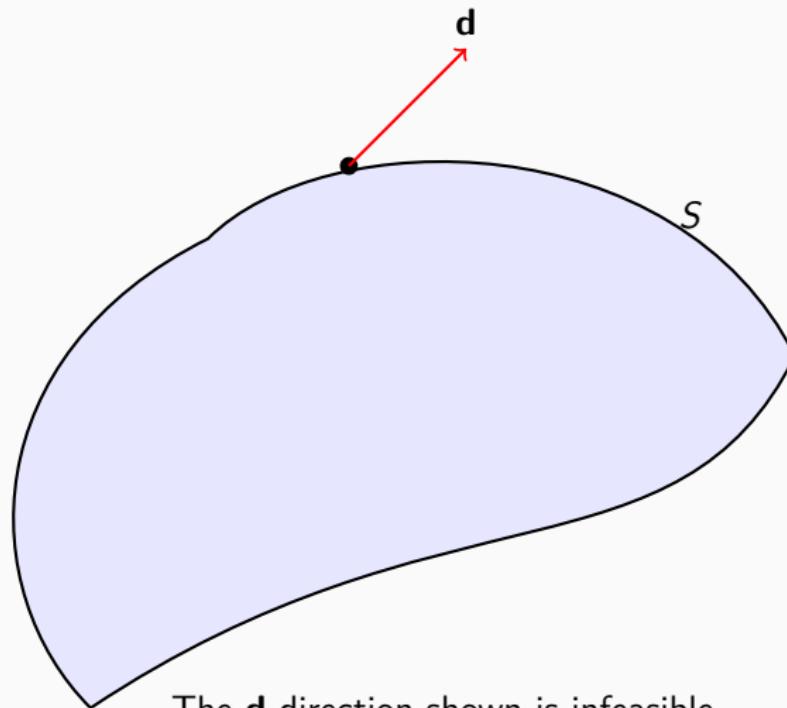
Feasible directions

Consider the maximization problem $\max_{\mathbf{x} \in S} f(\mathbf{x})$. Then a feasible direction $\mathbf{d} : \|\mathbf{d}\| = 1$ is unit vector such that $\exists \alpha > 0 : \mathbf{x} + \alpha \mathbf{d} \in S$.

Let \mathcal{D} denote set of feasible directions.



Feasible direction (contd.)



The \mathbf{d} direction shown is infeasible

FONC and SONC for set constrained maximizers

FONC for local maximizer

Lemma

If \mathbf{x}^* is a local maximizer, then $\mathbf{d}^T \nabla f(\mathbf{x}^*) \leq 0$ for all feasible directions.

Let \mathbf{d} be some feasible direction at the local maximizer \mathbf{x}^* .

$$f(\mathbf{x} + \alpha \mathbf{d}) = f(\mathbf{x}) + \alpha \mathbf{d}^T \nabla f(\mathbf{x}) + o(||\alpha \mathbf{d}||)$$

At $\alpha \rightarrow 0$, we have $f(\mathbf{x} + \alpha \mathbf{d}) - f(\mathbf{x}) = \alpha \mathbf{d}^T \nabla f(\mathbf{x})$. Since \mathbf{x}^* is a local maximizer, this difference must not be positive. Thus, $\mathbf{d}^T \nabla f(\mathbf{x}^*) \leq 0$ \square

SONC for local maximizer

Lemma

If \mathbf{x}^* is a local maximizer, and for some $\mathbf{d} \in \mathcal{D}$, $\mathbf{d}^T \nabla f(\mathbf{x}) = 0$, then $\mathbf{d}^T \mathbf{Hd} \leq 0$ for all feasible directions.

Proof by contradiction. Assume this claim is false. i.e., let \mathbf{d} be a feasible direction such that $\mathbf{d}^T \nabla f(\mathbf{x}) = 0$ and \mathbf{x}^* is a local maximizer. However, assume that $\mathbf{d}^T \mathbf{Hd} > 0$.

From Multivariate Taylor series up to two terms we have,

$$f(\mathbf{x}^* + \alpha \mathbf{d}) = f(\mathbf{x}^*) + \alpha \mathbf{d}^T \nabla f(\mathbf{x}^*) + \frac{\alpha^2}{2} \mathbf{d}^T \mathbf{Hd} + o(||\alpha \mathbf{d}||^2)$$

$$\alpha \rightarrow 0, \mathbf{d}^T \nabla f(\mathbf{x}^*) = 0 \implies f(\mathbf{x}^* + \alpha \mathbf{d}) - f(\mathbf{x}^*) = \frac{\alpha^2}{2} \mathbf{d}^T \mathbf{Hd} > 0$$

This implies that \mathbf{x}^* cannot be optimal. Therefore, optimality of \mathbf{x}^* implies that for $\mathbf{d} : \mathbf{d}^T \nabla f(\mathbf{x}^*) = 0$, $\mathbf{d}^T \mathbf{Hd} \leq 0$ must hold. □

FONC and SOSC for interior point/set constrained maximizers

FONC for unconstrained maximizers and interior points

Lemma (FONC for interior /unconstrained optima)

For an interior point maximizer \mathbf{x}^* , $\nabla f(\mathbf{x}^*) = \mathbf{0}$

$\forall \mathbf{d} \in \mathbb{R}^n$, $-\mathbf{d}$ is also feasible.

$$\mathbf{d}^T \nabla f(\mathbf{x}^*) = -\mathbf{d}^T \nabla f(\mathbf{x}^*) = 0$$

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

□

SOSC for interior point/ unconstrained optimizer

Lemma (SOSC for interior point / unconstrained optima)

If \mathbf{x}^* is an interior point and

- $\nabla f(\mathbf{x}^*) = \mathbf{0}$
- H is negative definite

Then, \mathbf{x}^* is a strict local maximizer of f .

Given that $\nabla f(\mathbf{x}^*) = \mathbf{0}$, we perform a Taylor series expansion around \mathbf{x}^* along any direction $\mathbf{d} \in \mathbb{R}^n$ by moving $\alpha \rightarrow 0$ units.

$$f(\mathbf{x}^* + \alpha\mathbf{d}) - f(\mathbf{x}^*) = \frac{\alpha^2}{2}\mathbf{d}^T H \mathbf{d} + o(||\alpha\mathbf{d}||^2) < 0 \quad \forall \mathbf{d} \in \mathbb{R}^n$$

Therefore \mathbf{x}^* is a local optimizer.

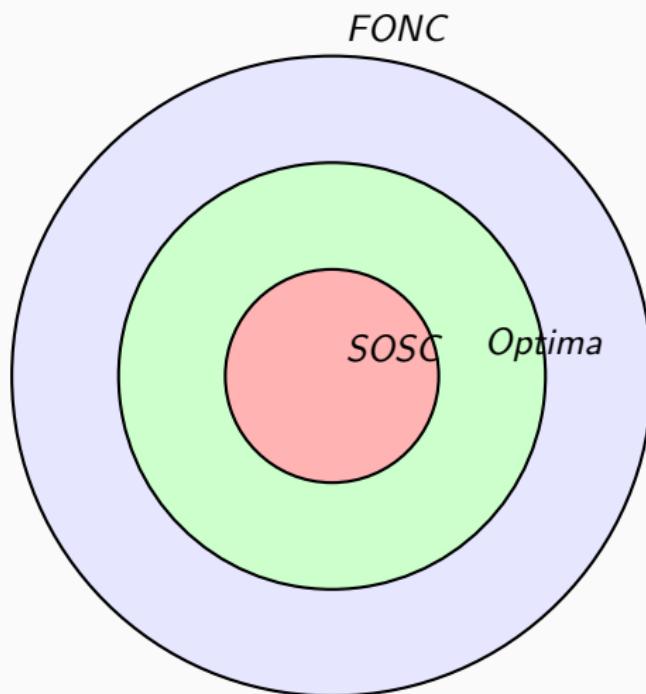


Figure 1: Necessary and sufficient conditions

Summary

- All set constrained maximizers² need to satisfy non-positivity of directional derivative in all feasible directions. This is the general FONC.
 - For interior point maxima or unconstrained maxima, this condition simplifies to $\nabla f(\mathbf{x}^*) = \mathbf{0}$.
- In addition to FONC, every maximizer must satisfy the SONC.
 - The SONC for set constrained maximizers says that if there is a zero directional derivative in any direction \mathbf{d} , then the $\mathbf{d}^T \mathbf{H} \mathbf{d} \leq 0$ long that direction when evaluated at that point.
 - The SONC for interior local maximizers says that the Hessian matrix should be negative semi definite at that maximizer point.
- There is a SOSC for interior point maximizers which says that the point should be a stationary point (gradient=0) and Hessian matrix should be negative definite.
- The FONC, SONC, and SOSC for interior point maximizers are applicable for unconstrained optimization problems.

²We mean local maximizers throughout

Example problems

1. Find the value of $x \in \mathbb{R}$ that minimizes the function

$$f(x) = x^2 - 6x + 13.$$

2. Find the value of $x \in \mathbb{R}$ that maximizes the function

$$f(x) = xe^{-x}.$$

3. Find the values of $(x, y) \in \mathbb{R}^2$ that minimize the function

$$f(x, y) = 3x^2 + 2y^2 - 4x - 8y + 10.$$

4. Find the values of $(x, y) \in \mathbb{R}^2$ that minimize the function

$$f(x, y) = x^2 + xy + y^2 - 6x - 4y.$$

5. Find all critical points and classify them for the function

$$f(x, y) = x^3 - 3xy^2.$$

6. Find the values of $(x, y) \in \mathbb{R}^2$ that maximize the function

$$f(x, y) = xye^{-(x^2+y^2)}.$$

7. Find the values of $(x, y) \in \mathbb{R}^2$ that maximize the function

$$f(x, y) = \ln(1+x^2) + \ln(1+y^2) - (x^2 + y^2).$$

8. Find the values of $(x_1, x_2, x_3) \in \mathbb{R}^3$ that minimize the function

$$f(x_1, x_2, x_3) = x_1^2 + 2x_2^2 + 3x_3^2 - 4x_1 - 8x_2 + 6x_3.$$

9. Find the values of $(x, y) \in \mathbb{R}^2$ that minimize the function

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

10. Find the value of $q \in \mathbb{R}$ that maximizes the profit function

$$\pi(q) = 50q - 2q^2 - 10\ln(1+q).$$