

16. Linear Constraint

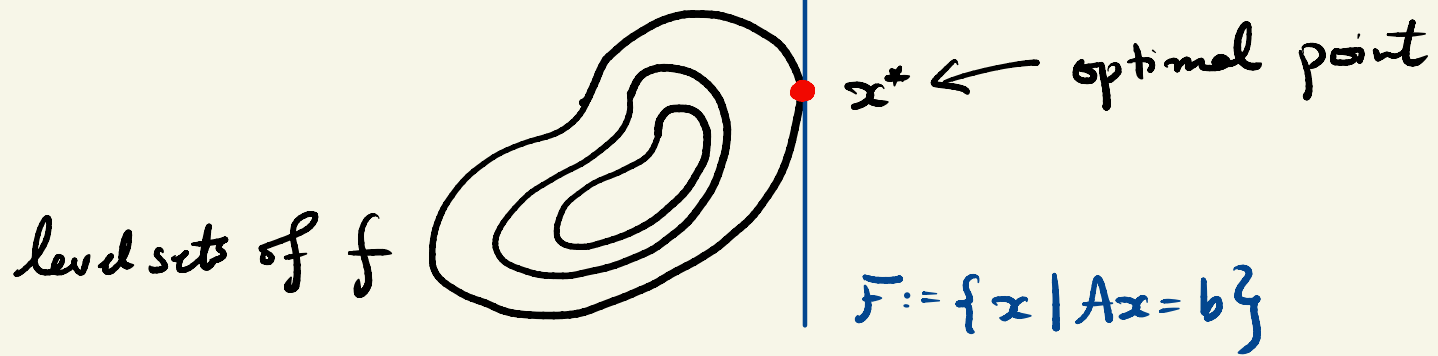
- Reduced gradient
- Optimality conditions

Linear Constrained Optimization

$$\min_{x \in \mathbb{R}^n} f(x) \quad \text{s.t.} \quad Ax = b,$$

where $A \in \mathbb{R}^{m \times n}$, $m \leq n$

• $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is continuously differentiable



F is the feasible set (set of points that satisfy const.)

Variable reduction

Reformulate the linear constrained problem into an unconstrained problem. (Change of variable).

Let

① $\bar{x} \in \mathbb{R}^n$ be any point with $A\bar{x} = b$.
 \bar{x} is a particular solution of $Ax = b$.

② Z be a basis for $\text{Null}(A)$.

$$\text{Null}(A) \oplus \text{R}(A^T) = \mathbb{R}^n$$

If $A \in \mathbb{R}^{m \times n}$ is full row rank, $Z \in ?$

Feasible set:

$$\{x \mid Ax = b\} = \{\bar{x} + Zp \mid p \in \mathbb{R}^{n-m}\}$$

Reduced Unconstrained problem

$$\min_{x \in \mathbb{R}^n} f(x) \text{ s.t. } Ax = b \iff \min_{p \in \mathbb{R}^{n-m}} f(\bar{x} + Zp)$$

- Reduced the linearly constrained problem to an unconstrained problem in $n-m$ variables.
- Use any unconstrained opt. method to get p^* .
- Solution to constrained problem $x^* = \bar{x} + Zp^*$.

2nd order sufficient cond.

A point $x^* \in \mathbb{R}^n$ is a strict local minimizer of $f(x)$ if

$$\textcircled{1} \quad \nabla f(x^*) = 0$$

$$\textcircled{2} \quad \nabla^2 f(x^*) \succ 0$$

Optimality conditions.

Reduced objective function

$$f_z(p) = f(\bar{x} + z_p) = f\left(\bar{x} + \sum_{i=1}^{n-m} z_i p_i\right)$$

The gradient of f_z at p is:

$$\nabla f_z(p) = Z^T \nabla f(\bar{x} + z_p)$$

Stationary:

A point p^* is stationary if

$$\nabla f_z(p^*) = 0 \iff Z^T \nabla f(\bar{x} + z_{p^*}) = 0$$

$$\iff \nabla f(\underbrace{\bar{x} + z_{p^*}}_{:= x^*}) \in \text{Null}(Z^T)$$

First Order Necessary Cond.

Show $\text{Null}(Z^T) = \text{Range}(A^T)$. $A \in \mathbb{R}^{m \times n}$, $Z \in \mathbb{R}^{n \times (n-m)}$

$$N(Z^T) \oplus R(Z) = \mathbb{R}^n \quad \text{and} \quad R(A^T) \oplus N(A) = \mathbb{R}^n$$

• Z is a basis for $\text{Null}(A)$

$$\Rightarrow N(Z^T) = R(A^T)$$

So, $\nabla f_z(x^*) \in N(Z^T) \Leftrightarrow \exists$ a $y \in \mathbb{R}^m$ such that
$$\nabla f(x^*) = A^T y$$

First order necessary cond. A point x^* is a local minimizer of ① only if there exists a point $y \in \mathbb{R}^m$

s.t.

① Optimality: $\nabla f(x^*) = A^T y$

② Feasibility: $Ax^* = b$.

Interpretation

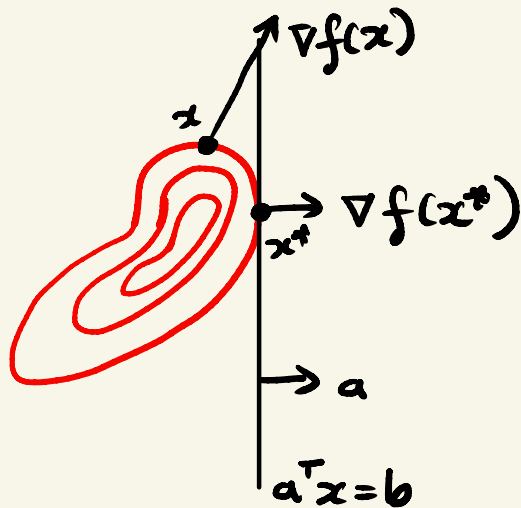
The optimality cond: There exists $y \in \mathbb{R}^m$ s.t.

$$\nabla f(x^*) = A^T y = \sum_{i=1}^m y_i a_i$$

↖ dual variable, Lagrange multiplier

require $\nabla f(x^*)$ aligned with normal vector a .

In general, require $\nabla f(x^*)$ to be in $\mathcal{R}(A^T)$.



Second order necessary cond.

$$f_z(p) = f(\bar{x} + z_p), \quad \nabla f_z(p) = z^T \nabla f(\bar{x} + z_p)$$

The Hessian of f_z at p is:

$$\nabla_z^2 f(p) = z^T \nabla^2 f(\bar{x} + z_p) z \in \mathbb{R}^{m \times m}$$

Second order necessary cond. A point x^* is a minimizer only if

① (Curvature) $z^T \nabla^2 f(x^*) z \geq 0$

② (Feasibility) $Ax^* = b$

Optimality condition.

Second order sufficient condition.

A point $x^* \in \mathbb{R}^n$ is a strict local minimizer of ① if it satisfies.

1. (Feasibility) $Ax^* = b$

2. (Stationary) $\nabla f(x^*) \in \mathcal{N}(A^T)$

$$\Leftrightarrow \nabla f(x^*) = A^T y \text{ for some } y \in \mathbb{R}^m$$

3. (Positivity) $z^T \nabla^2 f(x^*) z > 0$

$$\Leftrightarrow p^T \nabla^2 f(x^*) p > 0 \text{ for all } p \in \mathcal{R}(z) \setminus \{0\}$$

$$\Leftrightarrow p^T \nabla^2 f(x^*) p > 0 \text{ for all } p \in \text{Null}(A) \setminus \{0\}.$$

Example

Consider $\min_{x \in \mathbb{R}^n} \|x\|_2$ s.t. $Ax = b$.

WLOG: assume $f(x) = \frac{1}{2} \|x\|_2^2$ as objective function.

$$\text{so } \nabla f(x) = x$$

First order optimality:

$$\textcircled{1} \quad \nabla f(x) \in \mathcal{R}(A^T) \Rightarrow x = A^T y \text{ for some } y.$$

$$\textcircled{2} \quad Ax = b.$$

$$\Leftrightarrow \begin{bmatrix} -I & A^T \\ A & 0 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ b \end{bmatrix}$$

Example contd.

So, if $Ax=b$ is $e^T x = 1$, we get

$$\begin{bmatrix} -I & e \\ e^T & 0 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \Rightarrow \begin{cases} -x + e \cdot y = 0 \\ e^T x = 1 \end{cases}$$

$$\Rightarrow -e^T x + e^T e y = 0$$

$$\Rightarrow e^T e y = 1$$

$$\Rightarrow y = \frac{1}{e^T e}$$

$$\Rightarrow x^* = \left\| \frac{e}{e^T e} \right\|$$