

17. Reduced Gradient

- Newton's method for linear constraint.

Previous lecture

Sufficient condition for optimality of x^* for

$$\min_{x \in \mathbb{R}^n} f(x) \quad \text{st } Ax = b$$

f -smooth, $A \in \mathbb{R}^{m \times n}$, $m \leq n$

x^* is a strict local minimizer if

- ① Feasibility : $Ax^* = b$
- ② Optimality : $\nabla f(x^*) = Ay$ for some $y \in \mathbb{R}^m$
- ③ Positivity : $p^\top \nabla^2 f(x^*) p > 0$ for all $p \in N(A) \setminus \{0\}$

Equality constrained with quadratic min.

$$\min_{x \in \mathbb{R}^n} \frac{1}{2} x^T P x + g^T x + r \quad \text{s.t. } Ax = b,$$

where $P \succ 0$ and $A \in \mathbb{R}^{m \times n}$.

Optimality conditions:

① Feasibility : $Ax^* = b$

② Optimality : $Px^* + g = A^T y^*$

} KKT system

System of Equation in $n+m$ variables:

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

↑ KKT matrix

Equality constrained with quadratic min (contd.)

- If the KKT system is not solvable, the constrained quadratic opt. problem is unbounded below or infeasible.
- The KKT matrix is non-singular if any of the following holds:
 - ① $N(A) \cap N(P) = \{0\}$.
 - ② For any $x \neq 0$, $Ax = 0 \Rightarrow x^T P x > 0$. (P is PD on $N(A)$)
 - ③ $Z^T P Z \geq 0$, Z is a basis for $N(A)$.

Newton's method for equality constraint

Consider

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

Let \bar{x} be a particular solution and $R(\bar{x}) = N(A)$.

Quadratic approximation at \bar{x} :

$$f(\bar{x} + z_p) \approx f(\bar{x}) + \nabla f(\bar{x})^T (z_p) + \frac{1}{2} p^T \bar{Z}^T \nabla^2 f(\bar{x}) \bar{Z} p$$

We can solve:

$$\min_{p \in \mathbb{R}^{n-m}} \frac{1}{2} p^T \bar{H} p + \bar{g}^T p + \bar{f},$$

$$\bar{H} = \bar{Z}^T \nabla^2 f(\bar{x}) \bar{Z}, \quad \bar{g} = \bar{Z}^T \nabla f(\bar{x}), \quad \bar{f} = f(\bar{x}).$$

Newton direction: $\bar{H} d = -\bar{g}$

Algorithm

Input: \bar{x} feasible point and Z basis for $N(A)$

For $k = 1, 2, 3,$

1. Compute $g := \nabla f(x_k)$
2. Compute $H := \nabla^2 f(x_k)$
3. Solve $Z^T H Z d = -Z^T g$ to get d_k
4. Line search $f(x_k + \alpha Z d_k)$
5. $x_{k+1} = x_k + \alpha_k d_k$
6. Stop if converged.

Example

$$\min_{x \in \mathbb{R}^n} f(x) \text{ subject to } Ax = b \quad \text{--- (1)}$$

- An approach to solving (1) is to solve the system of equations corresponding to optimality condition (KKT system)
- Algorithm approach:
 1. Find particular solution \bar{x} and a basis Z for null space of A (assume A full row rank)
 2. Solve the unconstrained problem
$$\min_{p \in \mathbb{R}^{n-m}} f(\bar{x} + p) \quad \text{s.t. } A(\bar{x} + Zp) = b$$
using a descent method.

Always satisfied.

Basic of Null(A)

① Using QR-decomposition :

$$\vec{A} = [\hat{Q} \quad \bar{Q}] \begin{bmatrix} R \\ 0 \end{bmatrix}$$

$$R(\hat{Q}) \oplus R(\bar{Q}) = \mathbb{R}^n$$

- $R(A^\top) = R(\hat{Q})$
- $N(A) = R(\bar{Q})$

Basis of Null(A)

Permute columns of A so, that

$$A = [B \ N],$$

B - basic matrix, nonsingular (Note that A is full rank)

N - non-basic matrix.

If x is feasible:

$$Ax=b \Leftrightarrow [B \ N] \begin{bmatrix} x_B \\ x_N \end{bmatrix} = b \Leftrightarrow Bx_B + Nx_N = b$$

Consider $Z = \begin{bmatrix} -B^{-1}N \\ I \end{bmatrix}, \quad AZ = 0$.

