

Gradient conjugate method

Consider a quadratic function of the form

$$f(\mathbf{x}) = \frac{1}{2}\mathbf{x}^T A \mathbf{x} - \mathbf{b}^T \mathbf{x} + c, \quad (1)$$

where A is symmetric definite positive matrix, \mathbf{x} and \mathbf{b} are column vectors and c a constant. In the sequel, when there is no confusion, we denote by \mathbb{R}^n the space of all the column vectors of the form $(x_1, \dots, x_n)^T$, $x_i \in \mathbb{R}$ for $1 \leq i \leq n$.

The *Gradient conjugate* method consists to start from an arbitrary \mathbf{x}_0 , and then construct a sequence of directions $(\mathbf{d}_k)_{k \geq 0}$ and points $(\mathbf{x}_k)_{k \geq 0}$ as follows

- $\mathbf{d}_0 = -\nabla f(\mathbf{x}_0)$,
- For $k \geq 0$, $\mathbf{x}_{k+1} = \mathbf{x}_0 + \mathbf{y}_k$ where \mathbf{y}_k is solution of the optimization problem

$$\min_{\mathbf{y} \in W_k} f(\mathbf{x}_0 + \mathbf{y}) \text{ where } W_k = \text{span}\{\mathbf{d}_0, \dots, \mathbf{d}_k\}. \quad (2)$$

- For $k \geq 0$, \mathbf{d}_k is of the form

$$\mathbf{d}_{k+1} = -\nabla f(\mathbf{x}_{k+1}) + \sum_{i=0}^k \mu_i \mathbf{d}_i,$$

where the coefficients μ_0, \dots, μ_k are chosen such that \mathbf{d}_{k+1} are \mathbf{d}_i and A -orthogonal (or *conjugate*) for any $i \leq k$, that is

$$\mathbf{d}_{k+1}^T A \mathbf{d}_i = 0.$$

We set

$$\mathbf{r}_k = -\nabla f(\mathbf{x}_k) \text{ for } k \geq 0.$$

1. Compute the gradient and the hessian matrix of f .
2. Is-it a convex function?
3. Find the minimum of f on \mathbb{R}^n . Is-it easy to compute?
4. Write the optimality conditions for the problem (2).
5. Show that

$$\mathbf{r}_{k+1}^T \mathbf{d}_i = 0 \text{ for any } i \leq k. \quad (3)$$

6. Deduce that $\mathbf{r}_{k+1} \in W_k^\perp$ for any $k \geq 0$.
7. Show that $W_k = \text{span}\{\mathbf{r}_0, \dots, \mathbf{r}_k\}$ for any $k \geq 0$.
8. Deduce also that
 - (a) if $\mathbf{r}_k = 0$ for some $k \geq 0$, then $\mathbf{r}_j = 0$ for any $j \geq k + 1$,
 - (b) there exists a unique integer $m \leq n$ such that $\mathbf{x}_m = \mathbf{x}$ ($\mathbf{r}_m = 0$) and $\mathbf{r}_{m-1} \neq 0$ or $m = 0$,
 - (c) If $\mathbf{r}_k \neq \mathbf{0}$ for some $k \geq 0$, then $\dim W_k = k + 1$.
9. Show that for $k < m$

$$\mathbf{y}_k = \sum_{i=0}^k \frac{\mathbf{r}_0^T \mathbf{d}_i}{\mathbf{d}_i^T A \mathbf{d}_i} \mathbf{d}_i.$$

(write $\mathbf{y} = \sum_{i=0}^k \eta_i \mathbf{d}_i$ and find η_i for each i).

10. Deduce that

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \lambda_k \mathbf{d}_k, \quad \lambda_k = \frac{\mathbf{r}_0^T \mathbf{d}_k}{\mathbf{d}_k^T A \mathbf{d}_k} = \frac{\mathbf{r}_k^T \mathbf{d}_k}{\mathbf{d}_k^T A \mathbf{d}_k}.$$

11. Show that $W_k = \text{span}\{\mathbf{r}_0, A\mathbf{r}_0, \dots, A^k \mathbf{r}_0\}$ for each $k \leq m$.
12. Show that

$$\mathbf{r}_{k+1}^T A \mathbf{d}_i = 0 \text{ for each } 0 \leq i < k.$$

13. Deduce that

$$\mathbf{d}_{k+1} = \mathbf{r}_{k+1} + \beta_k \mathbf{d}_k,$$

with

$$\beta_k = -\frac{\mathbf{r}_{k+1}^T A \mathbf{d}_k}{\mathbf{d}_k^T A \mathbf{d}_k}$$