

MATH 4211/6211 – Optimization

Conjugate Gradient Method

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Conjugate Gradient Method

Motivation: Design an improved gradient method without storing or inverting Hessian.

Definition. Let $Q \succ 0$. The directions $d^{(0)}, d^{(1)}, \dots, d^{(k)}$ are called (mutually) **Q -conjugate** if $d^{(i)\top} Q d^{(j)} = 0$ for all $i \neq j$.

Remark: We can define Q -inner product by $\langle x, y \rangle_Q := x^\top Q y$. Then x and y are Q -conjugate if they are orthogonal, i.e., $\langle x, y \rangle_Q = 0$, in the sense of Q -inner product. Also note that $\langle x, x \rangle_Q = \|x\|_Q^2$.

Lemma. Let $Q \succ 0$ be an n -by- n positive definite matrix. If $d^{(0)}, \dots, d^{(k)}$ ($k \leq n - 1$) are Q -conjugate, then they are linearly independent.

Proof. Suppose $\alpha_0 d^{(0)} + \alpha_1 d^{(1)} + \dots + \alpha_k d^{(k)} = \mathbf{0}$. For each i , multiplying $d^{(i)\top} Q$ yields $\alpha_i d^{(i)\top} Q d^{(i)} = 0$ due to the mutual Q -conjugacy. Hence $\alpha_i = 0$.

Example. Find a set of Q -conjugate directions $\mathbf{d}^{(0)}, \mathbf{d}^{(1)}, \mathbf{d}^{(2)} \in \mathbb{R}^3$ where

$$Q = \begin{bmatrix} 3 & 0 & 1 \\ 0 & 4 & 2 \\ 1 & 2 & 3 \end{bmatrix}$$

Solution. We first check that $Q \succ 0$ by its leading principal minors:

$$3 > 0, \quad \begin{vmatrix} 3 & 0 \\ 0 & 4 \end{vmatrix} = 12 > 0, \quad \begin{vmatrix} 3 & 0 & 1 \\ 0 & 4 & 2 \\ 1 & 2 & 3 \end{vmatrix} = 22 > 0$$

We can set $\mathbf{d}^{(0)}$ to any nonzero vector. For instance, we can set with $\mathbf{d}^{(0)} = [1, 0, 0]^\top$.

Then we need to find $\mathbf{d}^{(1)} = [d_1^{(1)}, d_2^{(1)}, d_3^{(1)}]^\top$ such that

$$\mathbf{d}^{(1)\top} \mathbf{Q} \mathbf{d}^{(0)} = 3d_1^{(1)} + d_3^{(1)} = 0$$

For example, we can set $d_1^{(1)} = 1$, $d_2^{(1)} = 0$, and $d_3^{(1)} = -3$, and hence $\mathbf{d}^{(1)} = [1, 0, -3]^\top$.

Finally we need $\mathbf{d}^{(2)} = [d_1^{(2)}, d_2^{(2)}, d_3^{(2)}]^\top$ such that

$$\mathbf{d}^{(2)\top} \mathbf{Q} \mathbf{d}^{(0)} = 3d_1^{(2)} + d_3^{(2)} = 0$$

$$\mathbf{d}^{(2)\top} \mathbf{Q} \mathbf{d}^{(1)} = -6d_2^{(2)} - 8d_3^{(2)} = 0$$

from which we solve for $\mathbf{d}^{(2)}$ to get $\mathbf{d}^{(2)} = [1, 4, -3]^\top$.

In the end, we obtain $\mathbf{d}^{(0)} = [1, 0, 0]^\top$, $\mathbf{d}^{(1)} = [1, 0, -3]^\top$, $\mathbf{d}^{(2)} = [1, 4, -3]^\top$.

The idea of **Gram-Schmidt process** can be used to produce Q -conjugate directions:

First select an arbitrary set of linearly independent directions $\mathbf{v}^{(0)}, \dots, \mathbf{v}^{(n-1)}$.
Set $\mathbf{d}^{(0)} = \mathbf{v}^{(0)} / \|\mathbf{v}^{(0)}\|_Q$.

Suppose we have got $\mathbf{d}^{(0)}, \dots, \mathbf{d}^{(k-1)}$, then compute $\mathbf{d}^{(k)}$ by

$$\mathbf{d}^{(k)} = \mathbf{v}^{(k)} - \sum_{i=0}^{k-1} (\mathbf{v}^{(k)\top} Q \mathbf{d}^{(i)}) \mathbf{d}^{(i)}$$

and then normalize $\mathbf{d}^{(k)} \leftarrow \mathbf{d}^{(k)} / \|\mathbf{d}^{(k)}\|_Q$.

It is easy to verify that $\mathbf{d}^{(k)\top} Q \mathbf{d}^{(i)} = 0$ for $i = 0, \dots, k - 1$.

Now we consider using conjugate directions $\mathbf{d}^{(0)}, \dots, \mathbf{d}^{(n-1)}$ (assume given) to solve

$$\text{minimize}_{\mathbf{x} \in \mathbb{R}^n} f(\mathbf{x}), \quad \text{where} \quad f(\mathbf{x}) = \frac{1}{2} \mathbf{x}^\top \mathbf{Q} \mathbf{x} - \mathbf{b}^\top \mathbf{x}$$

Basic conjugate direction algorithm: For $k = 0, 1, \dots, n - 1$, do

$$\begin{aligned} \mathbf{g}^{(k)} &= \nabla f(\mathbf{x}^{(k)}) = \mathbf{Q} \mathbf{x}^{(k)} - \mathbf{b} \\ \alpha_k &= -\frac{\mathbf{g}^{(k)\top} \mathbf{d}^{(k)}}{\mathbf{d}^{(k)\top} \mathbf{Q} \mathbf{d}^{(k)}} \\ \mathbf{x}^{(k+1)} &= \mathbf{x}^{(k)} + \alpha_k \mathbf{d}^{(k)} \end{aligned}$$

Note that above $\alpha_k = \arg \min_{\alpha > 0} f(\mathbf{x}^{(k)} + \alpha \mathbf{d}^{(k)})$ is the steepest step size.

Theorem. The basic conjugate direction algorithm converges in n steps.

Proof. First keep in mind that

$$\begin{aligned}\mathbf{x}^{(n)} &= \mathbf{x}^{(n-1)} + \alpha_{n-1} \mathbf{d}^{(n-1)} \\ &= \dots \\ &= \mathbf{x}^{(0)} + \alpha_0 \mathbf{d}^{(0)} + \dots + \alpha_{n-1} \mathbf{d}^{(n-1)}\end{aligned}$$

Now suppose $\mathbf{x}^* - \mathbf{x}^{(0)} = \beta_0 \mathbf{d}^{(0)} + \dots + \beta_{n-1} \mathbf{d}^{(n-1)}$ (this is possible since $\mathbf{d}^{(0)}, \dots, \mathbf{d}^{(n-1)}$ is a basis of \mathbb{R}^n .)

Now we will check that $\beta_k = \alpha_k$ for all $k = 0, \dots, n-1$: multiplying $\mathbf{x}^* - \mathbf{x}^{(0)}$ by $\mathbf{d}^{(k)\top} \mathbf{Q}$, we obtain $\mathbf{d}^{(k)\top} \mathbf{Q}(\mathbf{x}^* - \mathbf{x}^{(0)}) = \beta_k \mathbf{d}^{(k)\top} \mathbf{Q} \mathbf{d}^{(k)}$.

We can solve for β_k :

$$\begin{aligned}\beta_k &= \frac{\mathbf{d}^{(k)\top} \mathbf{Q}(\mathbf{x}^* - \mathbf{x}^{(0)})}{\mathbf{d}^{(k)\top} \mathbf{Q} \mathbf{d}^{(k)}} \\ &= \frac{\mathbf{d}^{(k)\top} \mathbf{Q}[(\mathbf{x}^* - \mathbf{x}^{(k)}) + (\mathbf{x}^{(k)} - \mathbf{x}^{(0)})]}{\mathbf{d}^{(k)\top} \mathbf{Q} \mathbf{d}^{(k)}} \\ &= -\frac{\mathbf{d}^{(k)\top} \mathbf{g}^{(k)}}{\mathbf{d}^{(k)\top} \mathbf{Q} \mathbf{d}^{(k)}} = \alpha_k\end{aligned}$$

where the 3rd equality above is due to $\mathbf{Q}(\mathbf{x}^* - \mathbf{x}^{(k)}) = -(\mathbf{Q}\mathbf{x}^{(k)} - \mathbf{b}) = -\mathbf{g}^{(k)}$ and that $\mathbf{x}^{(k)} - \mathbf{x}^{(0)} = \sum_{j=0}^{k-1} \alpha_j \mathbf{d}^{(j)}$ which is a linear combination of $\{\mathbf{d}^{(j)} : 0 \leq j \leq k-1\}$ that are all \mathbf{Q} -conjugate with $\mathbf{d}^{(k)}$.

Therefore $\mathbf{x}^{(n)} - \mathbf{x}^{(0)} = \mathbf{x}^* - \mathbf{x}^{(0)}$, hence $\mathbf{x}^{(n)} = \mathbf{x}^*$.

Lemma. For any $k = 0, 1, \dots, n - 1$, there are

$$\mathbf{g}^{(k+1)\top} \mathbf{d}^{(j)} = 0, \quad \forall j \leq k.$$

Proof. Multiplying both sides of $\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} + \alpha_k \mathbf{d}^{(k)}$ by \mathbf{Q} :

$$\mathbf{Q}\mathbf{x}^{(k+1)} = \mathbf{Q}\mathbf{x}^{(k)} + \alpha_k \mathbf{Q}\mathbf{d}^{(k)}$$

which yields $\mathbf{g}^{(k+1)} = \mathbf{g}^{(k)} + \alpha_k \mathbf{Q}\mathbf{d}^{(k)}$ since $\mathbf{g}^{(k)} = \mathbf{Q}\mathbf{x}^{(k)} - \mathbf{b}$ for all k .

We will use this and induction to prove the claim.

Proof (cont). It is easy to show $\mathbf{g}^{(1)\top} \mathbf{d}^{(0)} = 0$.

Suppose the claim holds for k , i.e.,

$$\mathbf{g}^{(k)\top} \mathbf{d}^{(i)} = 0, \quad \text{for } i = 0, 1, \dots, k - 1.$$

Then $\mathbf{g}^{(k+1)\top} \mathbf{d}^{(i)} = \mathbf{g}^{(k)\top} \mathbf{d}^{(i)} + \alpha_k \mathbf{d}^{(k)\top} \mathbf{Q} \mathbf{d}^{(i)}$.

If $i \leq k - 1$, then $\mathbf{g}^{(k+1)\top} \mathbf{d}^{(i)} = 0$ due to induction hypothesis and \mathbf{Q} -conjugacy. If $i = k$, then $\mathbf{g}^{(k+1)\top} \mathbf{d}^{(k)} = \mathbf{g}^{(k)\top} \mathbf{d}^{(k)} + \alpha_k \mathbf{d}^{(k)\top} \mathbf{Q} \mathbf{d}^{(k)} = 0$ due to the definition of α_k . Therefore the claim also holds for $k + 1$.

Conjugate direction method can also be interpreted as an “expanding subspace” method:

Denote $D^{(k)} := \text{span}\{\mathbf{d}^{(0)}, \mathbf{d}^{(1)}, \dots, \mathbf{d}^{(k-1)}\}$. Then $\mathbf{x}^{(k)} - \mathbf{x}^{(0)} \in D^{(k)}$, and $\mathbf{x}^{(k)}$ is selected such that

$$\mathbf{x}^{(k)} = \arg \min_{\mathbf{x} \in \mathbf{x}^{(0)} + D^{(k)}} f(\mathbf{x})$$

Therefore $D^{(0)} \subset D^{(1)} \subset \dots \subset D^{(n)} = \mathbb{R}^n$, and $\mathbf{x}^{(n)}$ is the minimizer of $f(\mathbf{x})$ over $D^{(n)} = \mathbb{R}^n$.

Now we have one more practical issue to solve: how to get Q -conjugate directions?

Conjugate gradient method generates a new conjugate direction in every iteration.

More specifically, suppose we have got $\mathbf{x}^{(k)}$ and $\mathbf{d}^{(k)}$, then compute

$$\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} + \alpha_k \mathbf{d}^{(k)}$$

where $\alpha_k = -\frac{\mathbf{g}^{(k)\top} \mathbf{d}^{(k)}}{\mathbf{d}^{(k)\top} \mathbf{Q} \mathbf{d}^{(k)}}$.

The new conjugate direction is given by

$$\mathbf{d}^{(k+1)} = -\mathbf{g}^{(k+1)} + \beta_k \mathbf{d}^{(k)}$$

where $\beta_k = \frac{\mathbf{g}^{(k+1)\top} \mathbf{Q} \mathbf{d}^{(k)}}{\mathbf{d}^{(k)\top} \mathbf{Q} \mathbf{d}^{(k)}}$.

Conjugate gradient method for quadratic function $f(\mathbf{x}) = \frac{1}{2}\mathbf{x}^\top \mathbf{Q}\mathbf{x} - \mathbf{b}^\top \mathbf{x}$.

First give initial $\mathbf{x}^{(0)}$, compute $\mathbf{g}^{(0)} = \nabla f(\mathbf{x}^{(0)})$ and set $\mathbf{d}^{(0)} = -\mathbf{g}^{(0)}$.

For $k = 0, 1, 2, \dots, n - 1$, iterate

$$\begin{aligned}\alpha_k &= -\frac{\mathbf{g}^{(k)\top} \mathbf{d}^{(k)}}{\mathbf{d}^{(k)\top} \mathbf{Q} \mathbf{d}^{(k)}} \\ \mathbf{x}^{(k+1)} &= \mathbf{x}^{(k)} + \alpha_k \mathbf{d}^{(k)} \\ \mathbf{g}^{(k+1)} &= \nabla f(\mathbf{x}^{(k+1)}) = \mathbf{Q} \mathbf{x}^{(k+1)} - \mathbf{b} \\ \beta_k &= \frac{\mathbf{g}^{(k+1)\top} \mathbf{Q} \mathbf{d}^{(k)}}{\mathbf{d}^{(k)\top} \mathbf{Q} \mathbf{d}^{(k)}} \\ \mathbf{d}^{(k+1)} &= -\mathbf{g}^{(k+1)} + \beta_k \mathbf{d}^{(k)}\end{aligned}$$

Most expensive computation is $Qd^{(k)}$, which requires n^2 multiplications and $n(n-1) = O(n^2)$ summations. This is done 1 time in every iteration.

We also need storing $Qx^{(k)}$ which is updated for every k by $Qx^{(k+1)} = Qx^{(k)} + \alpha_k Qd^{(k)}$.

Also, $g^{(k+1)} = g^{(k)} + \alpha_k Qd^{(k)}$ can be updated by vector summation.

But all these computations are of order $O(n)$.

Now we show CG converges in n steps for quadratic $f(\mathbf{x})$. To this end, we only need the following result.

Proposition. The directions $\mathbf{d}^{(0)}, \mathbf{d}^{(1)}, \dots, \mathbf{d}^{(n-1)}$ generated by CG algorithm are Q -conjugate.

Proof. We prove this by induction.

First, $\mathbf{d}^{(1)\top} Q \mathbf{d}^{(0)} = (-\mathbf{g}^{(1)} + \beta_0 \mathbf{d}^{(0)})^\top Q \mathbf{d}^{(0)} = 0$ due to definition of β_0 .

Now assume $\mathbf{d}^{(0)}, \dots, \mathbf{d}^{(k)}$ are Q -conjugate. We need to show $\mathbf{d}^{(k+1)}$ is Q -conjugate with all of them.

Proof (cont).

We need the following facts:

- $\mathbf{d}^{(k)} = -\mathbf{g}^{(k)} + \beta_{k-1}\mathbf{d}^{(k-1)}$, $\forall k$, by definition of $\mathbf{d}^{(k)}$ in CG.
- $\mathbf{g}^{(k+1)} = \mathbf{g}^{(k)} + \alpha_k \mathbf{Q} \mathbf{d}^{(k)}$, $\forall k$, by $\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} + \alpha_k \mathbf{d}^{(k)}$ in CG.
- $\mathbf{g}^{(k+1)\top} \mathbf{d}^{(j)} = 0$, $\forall j \leq k$, by previous lemma.
- $\mathbf{g}^{(k+1)\top} \mathbf{g}^{(j)} = 0$, $\forall j \leq k$, since $\mathbf{g}^{(k+1)\top} \mathbf{g}^{(j)} = \mathbf{g}^{(k+1)\top} (\mathbf{d}^{(j)} - \beta_{j-1} \mathbf{d}^{(j)}) = 0$.

Proof (cont).

Now we come back to $LHS := \mathbf{d}^{(k+1)\top} \mathbf{Q} \mathbf{d}^{(j)} = (-\mathbf{g}^{(k+1)} + \beta_k \mathbf{d}^{(k)})^\top \mathbf{Q} \mathbf{d}^{(j)}$.

If $j < k$, then $LHS = -\mathbf{g}^{(k+1)\top} \mathbf{Q} \mathbf{d}^{(j)} = -\mathbf{g}^{(k+1)\top} \frac{\mathbf{g}^{(j+1)} - \mathbf{g}^{(j)}}{\alpha_j} = 0$.

If $j = k$, then $LHS = \mathbf{d}^{(k+1)\top} \mathbf{Q} \mathbf{d}^{(k)} = (-\mathbf{g}^{(k+1)} + \beta_k \mathbf{d}^{(k)})^\top \mathbf{Q} \mathbf{d}^{(k)} = 0$
due to definition of β_k .

Therefore $\mathbf{d}^{(k+1)\top} \mathbf{Q} \mathbf{d}^{(j)}$ for all $j \leq k$.

We now consider **Conjugate Gradient** method for **non-quadratic** problems.

If we have $x^{(k)}$ and $d^{(k)}$, we can get step size α_k using line search such as

$$\alpha_k = \arg \min_{\alpha \geq 0} f(x^{(k)} + \alpha d^{(k)})$$

So we only need to find β_k for $d^{(k+1)} = g^{(k+1)} + \beta_k d^{(k)}$, so $d^{(0)}, \dots, d^{(n)}$ are Q -conjugate. In quadratic case

$$\beta_k = \frac{g^{(k+1)\top} Q d^{(k)}}{d^{(k)\top} Q d^{(k)}}$$

However, for non-quadratic f , the Hessian $\nabla^2 f(x)$ is not constant Q .

There are several modifications to get β_k by eliminating the need of $Qd^{(k)}$.

- **Hestenes-Stiefel** formula:

$$\beta_k = \frac{\mathbf{g}^{(k+1)\top} (\mathbf{g}^{(k+1)} - \mathbf{g}^{(k)})}{\mathbf{d}^{(k)\top} (\mathbf{g}^{(k+1)} - \mathbf{g}^{(k)})}$$

- **Polak-Ribière** formula:

$$\beta_k = \frac{\mathbf{g}^{(k+1)\top} (\mathbf{g}^{(k+1)} - \mathbf{g}^{(k)})}{\|\mathbf{g}^{(k)}\|^2}$$

- **Fletcher-Reeves** formula:

$$\beta_k = \frac{\|\mathbf{g}^{(k+1)}\|^2}{\|\mathbf{g}^{(k)}\|^2}$$

Remark.

- All three modifications are identical if f is quadratic;
- Need reinitialization $d^{(k)} = -g^{(k)}$ for $k = n, 2n, \dots$;
- Line search accuracy affects overall performance.

Some experience.

- Use Hestenes-Stiefel if line search is inaccurate.
- Use Polak-Ribière if $g^{(k)}$ are bounded away from 0.
- Fletcher-Reeves has better global convergence property.