

# Optimization Methods

## Lecture 6

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Reading assignment: Ch 9 of Ref[2]

Unconstrained optimization:

$$x^* = \underset{x \in \mathbb{R}^n}{\operatorname{argmin}} f(x)$$

Iterative solution method  $x_{k+1} = x_k + \alpha_k d_k$

Observations:

- Steepest descent algorithm can be very slow with lots of zig-zaging
- Newton method is faster but numerically is expensive due to information equipment associated with the evaluation, storage and inversion of Hessian.

%pause Q: Is it possible to accelerate convergence with low numerical cost?

## Conjugate direction method

- Conjugate direction methods proposed for

$$x^* = \operatorname{argmin}_{x \in \mathbb{R}^n} \frac{1}{2} x^T Q x - b^T x, \quad Q > 0$$

- Conjugate direction methods converge in  $n$  steps
- Can be extended to solve other nonlinear optimization problems

### Defintion:

- Two vectors  $d_1 \in \mathbb{R}^n$  and  $d_2 \in \mathbb{R}^n$  are **orthogonal** if and only if  $d_1^T d_2 = 0$ .
- Given a symmetric matrix  $Q \in \mathbb{R}^{n \times n}$ , two vectors  $d_1$  and  $d_2$  are said to be **Q-orthogonal** or **conjugate with respect to Q** if  $d_1^T Q d_2 = 0$ .
- A finite set of vectors  $\{d_1, d_2, \dots, d_k\}$  is said to be Q-orthogonal or conjugate with respect to Q, if

$$d_i^T Q d_j = 0, \quad \forall i, j, i \neq j.$$

- **Linearly independent vectors:** A set of vectors  $\{d_1, d_2, \dots, d_k\}$  is linearly independent if the relation

$$\alpha_1 d_1 + \alpha_2 d_2 + \dots + \alpha_k d_k = 0$$

implies that  $\alpha_1 = \alpha_2 = \dots = \alpha_k = 0$ .

- **Lemma** If  $\{d_1, d_2, \dots, d_k\}$  is linearly independent set of vectors and  $x \in \text{span}\{d_1, d_2, \dots, d_k\}$ , the relation

$$x = \alpha_1 d_1 + \alpha_2 d_2 + \dots + \alpha_k d_k$$

is unique.

- **Lemma** If  $\{d_1, d_2, \dots, d_n\}$  is a set of  $n$  linearly independent vectors in  $\mathbb{R}^n$ , then every  $x \in \mathbb{R}^n$  can be written as linear combination of  $\{d_1, d_2, \dots, d_n\}$ , i.e.,

$$x = \alpha_1 d_1 + \alpha_2 d_2 + \dots + \alpha_n d_n$$

## Properties of conjugate vectors

**Proposition** If  $Q > 0$ , and the set of non-zero vectors  $\{d_0, \dots, d_k\}$  are  $Q$ -orthogonal then these vectors are linearly independent.

**Proof** Suppose  $\exists \alpha_i, i = 0, 1, \dots, k$  such that

$$\alpha_0 d_0 + \alpha_1 d_1 + \dots + \alpha_k d_k = 0$$

Multiply by  $Q$  and taking the scalar product with  $d_i$ :

$$\alpha_i d_i^T Q d_i = 0$$

Since  $d_i \neq 0$  and  $Q > 0$ , we obtain  $\alpha_i = 0$ . Therefore,  $\{d_0, \dots, d_k\}$  are linearly independent.

## Conjugate gradient algorithm (preliminary version)

Given  $x_0$

**set**  $g_0 \leftarrow Qx_0 - b$ ,  $d_0 \leftarrow -g_0$ ,  $k \leftarrow 0$

**while**  $g_k \neq 0$

$$\alpha_k \leftarrow -\frac{g_k^\top d_k}{d_k^\top Q d_k},$$

$$x_{k+1} \leftarrow x_k + \alpha_k d_k,$$

$$g_{k+1} \leftarrow Q x_{k+1} - b,$$

$$\beta_{k+1} \leftarrow \frac{g_{k+1}^\top Q d_k}{d_k^\top Q d_k},$$

$$d_{k+1} \leftarrow -g_{k+1} + \beta_{k+1} d_k,$$

$$k \leftarrow k + 1;$$

**end(while)**

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$$g_{k+1} \leftarrow g_k + \alpha_k Q d_k,$$

$$\beta_{k+1} \leftarrow \frac{g_{k+1}^\top g_{k+1}}{g_k^\top g_k},$$

$$d_{k+1} \leftarrow -g_{k+1} + \beta_{k+1} d_k,$$

$$k \leftarrow k + 1;$$

**end(while)**

Note:

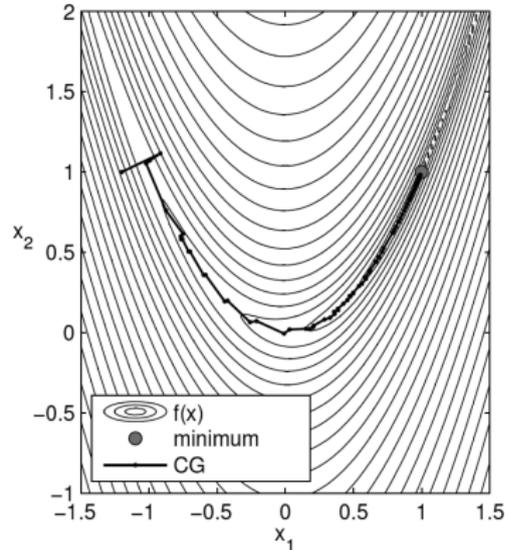
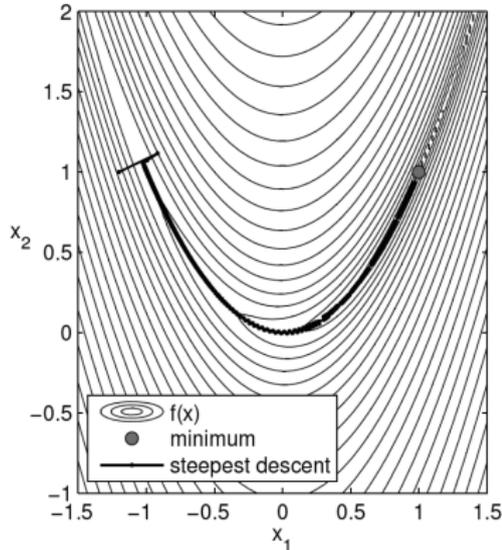
$$g_{k+1} = Qx_{k+1} - b = Q(x_k + \alpha_k d_k) - b = Qx_k - b + Q\alpha_k d_k = g_k + \alpha_k Q d_k.$$

## Numerical example

Minimize Rosenbrock's function,

$$f(x) = 100 \left( x_2 - x_1^2 \right)^2 + (1 - x_1)^2,$$

starting from  $x_0 = (-1.2, 1.0)^T$ .



Solution path of the steepest descent and conjugate gradient methods