

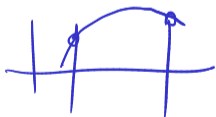
March 25, 2026

## Announcements

- Page grades
- Exam 2
- Retake

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Golden section search



## Goals

n-dim optimization

Steepest descent

Heavy ball etc.

CG

(Nelder-Mead)

Newton

BFGS.

## Steepest descent

$$f: \mathbb{R}^n \rightarrow \mathbb{R}$$

$$\vec{p}_k = -\nabla f(\vec{x}_k) \quad \text{descent direction}$$

$$\vec{x}_{k+1} = \vec{x}_k + \alpha_k \vec{p}_k$$

$$f(\vec{x}) = \frac{1}{2} \vec{x}^T A \vec{x} + \vec{x}^T \vec{b}$$

$$\nabla f = A \vec{x} + \vec{b}$$

CG;

$$x_{k+1} = x_k - \alpha \nabla f(x_k) + \underbrace{\beta(x_k - x_{k-1})}_{\bar{s}_k}$$

Prelema  $f(x) = \frac{1}{2} x^T A x - x^T b$

$$\nabla f(x) = Ax - b = r$$

$$\nabla f \stackrel{!}{=} 0$$

$$\left. \begin{array}{l} r_{k+1}^T \bar{s}_k = 0 \\ r_{k+1}^T \nabla f(x_k) = 0 \end{array} \right\} \dots$$

$$\bar{s}_i^T A \bar{s}_j = 0 \quad (i \neq j)$$



# Quasi-Newton

<sup>2</sup> Hessian

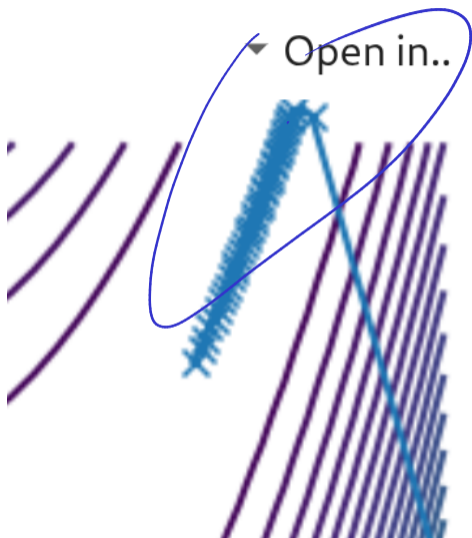


$$\mathbf{x}_{k+1} = \mathbf{x}_k - \alpha_k B_k^{-1} \nabla f(\mathbf{x}_k)$$

- ▶  $\alpha_k$ : a line search/damping parameter.
- ▶  $\mathbf{s}_k = \mathbf{x}_{k+1} - \mathbf{x}_k$
- ▶  $\mathbf{y}_k = \nabla f(\mathbf{x}_{k+1}) - \nabla f(\mathbf{x}_k)$
- ▶ Secant condition:  $B_{k+1} \mathbf{s}_k = \mathbf{y}_k$
- ▶ Ansatz for Hessian update:  $B_{k+1} = B_k + a \mathbf{u} \mathbf{u}^T + b \mathbf{v} \mathbf{v}^T$

$$\mathbf{y}_k^T \mathbf{s}_k > 0$$

$$B_{k+1} = B_k + \frac{\mathbf{y}_k \mathbf{y}_k^T}{\mathbf{y}_k^T \mathbf{s}_k} - \frac{B_k \mathbf{s}_k \mathbf{s}_k^T B_k}{\mathbf{s}_k^T B_k \mathbf{s}_k}$$



$$x^T A x \sim \alpha x^2 + \beta y^2 + \dots$$