# **Optimization Theory**

Lecture 03

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## Outline

Second-Order Characterization

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### Theorem (Smoothness and Convexity)

Let  $f(\cdot)$  be a twice differentiable function defined on  $\mathbb{R}^d$ 

- **1** It is L-smooth if and only if  $-L\mathbf{I} \leq \nabla^2 f(\mathbf{x}) \leq L\mathbf{I}$  for all  $\mathbf{x} \in \mathbb{R}^d$ .
- ② It is convex if and only if  $\nabla^2 f(\mathbf{x}) \succeq \mathbf{0}$  for all  $\mathbf{x} \in \mathbb{R}^d$ .
- **3** It is  $\mu$ -strongly-convex if and only if  $\nabla^2 f(\mathbf{x}) \succeq \mu \mathbf{I}$  for all  $\mathbf{x} \in \mathbb{R}^d$ .

We also say  $f(\cdot)$  is  $\ell$ -weakly convex if

$$\nabla^2 f(\mathbf{x}) \succeq -\ell \mathbf{I}$$
.

for some  $\ell > 0$ .

#### Second-Order Characterization

#### Some examples:

For unconstrained quadratic problem

$$\min_{\mathbf{x} \in \mathbb{R}^d} f(\mathbf{x}) \triangleq \frac{1}{2} \mathbf{x}^\top \mathbf{A} \mathbf{x} - \mathbf{b}^\top \mathbf{x},$$

where  $\mathbf{A} \in \mathbb{R}^{d \times d}$ . We have

$$\nabla^2 f(\mathbf{x}) = \mathbf{A}.$$

2 For regularized generalized linear model

$$\min_{\mathbf{x} \in \mathbb{R}^d} f(\mathbf{x}) \triangleq \frac{1}{n} \sum_{i=1}^n \phi_i(\mathbf{a}^\top \mathbf{x}) + \frac{\lambda}{2} \|\mathbf{x}\|_2^2.$$

where  $\phi_i : \mathbb{R}^d \to \mathbb{R}$  is twice differentiable. We have

$$\nabla f(\mathbf{x}) = \frac{1}{n} \sum_{i=1}^{n} \phi_i'(\mathbf{a}_i^{\mathsf{T}} \mathbf{x}) \mathbf{a} + \lambda \mathbf{x} \quad \text{and} \quad \nabla^2 f(\mathbf{x}) = \frac{1}{n} \sum_{i=1}^{n} \phi_i''(\mathbf{a}_i^{\mathsf{T}} \mathbf{x}) \mathbf{a}_i \mathbf{a}_i^{\mathsf{T}} + \lambda \mathbf{I}.$$