# A Brief Review of The Hessian

#### The Hessian is a Matrix of a Function's Second Derivatives

#### **Definition: Hessian of a function**

If  $f:\mathbb{R}^n\to\mathbb{R}$  is twice differentiable at  $\bar{x}\in\mathbb{R}^n$ , then the Hessian of f at  $\bar{x}$  is the matrix

$$\nabla^{2} f(\bar{x}) \equiv H = \begin{bmatrix} \frac{\partial^{2} f}{\partial x_{1}^{2}} & \frac{\partial^{2} f}{\partial x_{2} \partial x_{1}} & \cdots & \frac{\partial^{2} f}{\partial x_{n} \partial x_{1}} \\ \frac{\partial^{2} f}{\partial x_{1} \partial x_{2}} & \frac{\partial^{2} f}{\partial x_{2}^{2}} & \cdots & \frac{\partial^{2} f}{\partial x_{n} \partial x_{2}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^{2} f}{\partial x_{1} \partial x_{n}} & \frac{\partial^{2} f}{\partial x_{2} \partial x_{n}} & \cdots & \frac{\partial^{2} f}{\partial x_{n}^{2}} \end{bmatrix},$$

where each of the partial derivatives is evaluated at  $\bar{x}$ .

# We Will Rely on the Symmetry of the Hessian

## Theorem: Symmetry of the Hessian

Consider  $f: \mathbb{R}^n \to \mathbb{R}$ . If the second-partial derivatives  $\partial^2 f/\partial x_i \partial x_j$  are continuous at  $\bar{x}$ , for all i, j, then

$$\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial^2 f}{\partial x_j \partial x_i}$$

and, therefore,

$$H^T = H$$
.

## We Will Also Need to Know About Positive Definite Matrices

### **Definition: Positive Definite**

A matrix  $H \in \mathbb{R}^{n \times n}$  is said to be positive definite if  $p^T H p > 0$  for all  $p \neq 0$ .