

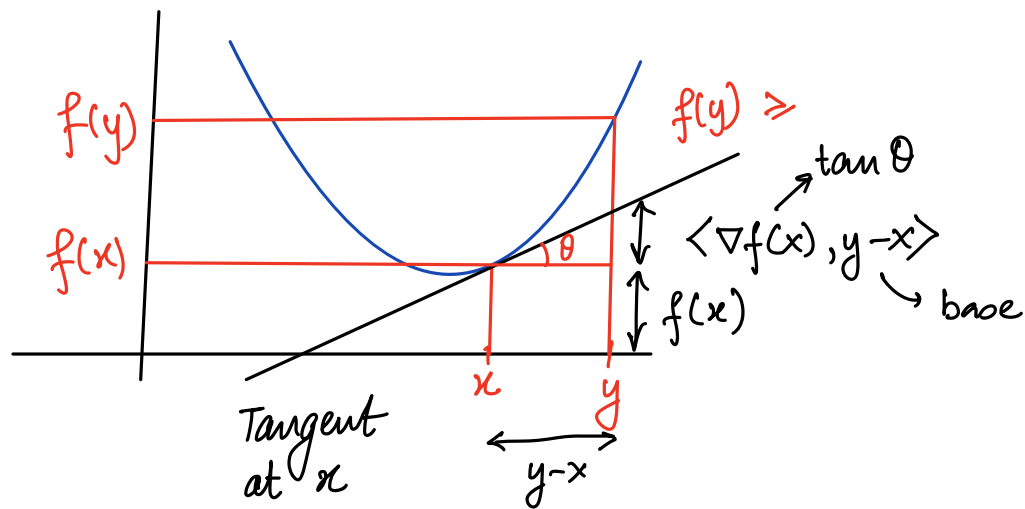
## First and Second Order Conditions

First order condition (gradient-based)

$$f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle$$

note  $[\nabla f(x)]_i = \frac{\partial f}{\partial x_i} \quad x \in \mathbb{R}^n$

Eg  $n=1 \quad \nabla f(x) = \frac{df}{dx} \quad (\text{slope})$



Note : bound holds  $\forall y \in \text{dom} f$  (global behavior)  
but depends only on  $\nabla f(x)$  (local property)

Eg Suppose  $\exists x_0$  s.t.  $\nabla f(x_0) = 0$

1st order:  $f(y) - f(x_0) \underset{=0}{\geq} \langle \nabla f(x_0), y - x_0 \rangle$

$$\Rightarrow f(y) \geq f(x_0) \quad \forall y \in \text{dom } f$$

$$\Rightarrow x_0 = \arg \min_x f(x)$$

$$\text{or } f(x_0) = \min_x f(x)$$

### Second order condition

Hessian: 
$$[\nabla^2 f]_{ij} = \frac{\partial^2 f}{\partial x_i \partial x_j} \quad \begin{matrix} i=1, \dots, n \\ j=1, \dots, n \end{matrix}$$

Eg:  $f(x) = a^T x + b$   $\nabla^2 f = 0$

2nd order condition :  $\nabla^2 f(x) \succeq 0 \quad \forall x \in \text{dom} f$   
P.S.D.