

Notation :

$$\textcircled{1} \quad x \in \mathbb{R}^n \quad x = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} \Rightarrow x^T = (x_1, \dots, x_n)$$

\textcircled{2}  $f(x)$  is real valued and assume it smooth for now

$$\textcircled{3} \quad \text{Gradient} \quad \nabla f(x) \in \mathbb{R}^n \quad \nabla f = \begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{pmatrix}$$

$$\textcircled{4} \quad \text{Hessian} \quad \nabla^2 f(x) \in \mathbb{R}^{n \times n} \quad [\nabla^2 f]_{ij} = \frac{\partial^2 f}{\partial x_i \partial x_j}$$

$$\textcircled{5} \quad \underline{y^T x} = \langle x, y \rangle = \sum_{i=1}^n x_i y_i$$

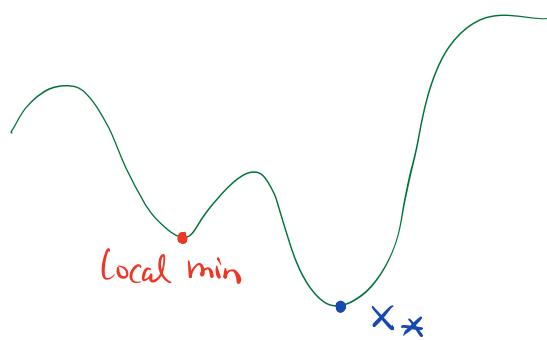
Unconstrained Minimization (Part I):

$$\min_{x \in \mathbb{R}^n} f(x)$$

\textcircled{1} Global minimizer  $x_*$  means

$$f(x_*) \leq f(x), \forall x$$

\textcircled{2} Local minimizer



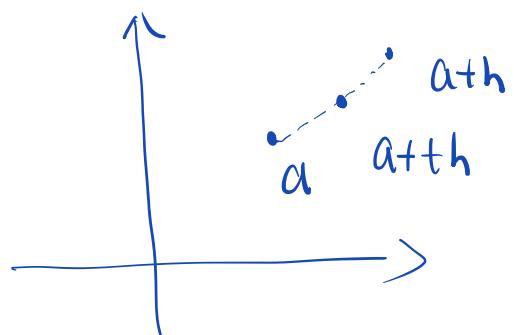
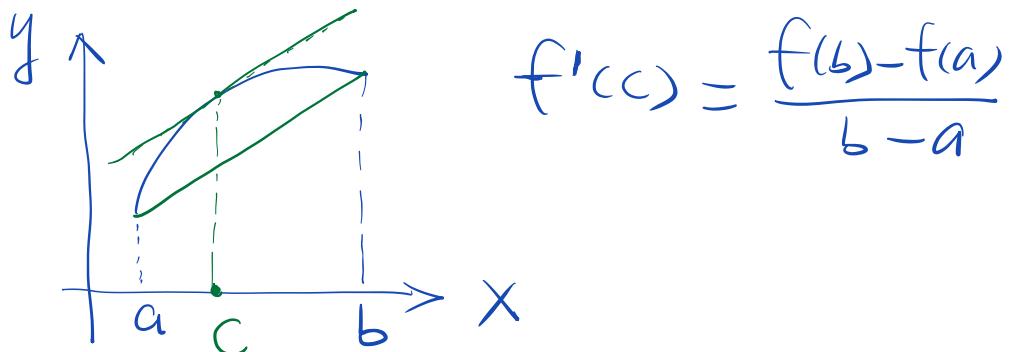
Review of Calculus:

\textcircled{1} Taylor Theorem for single variable:

$$f(x + \Delta x) = f(x) + f'(x) \Delta x + \frac{1}{2} f''(y) \Delta x^2$$

for some  $y \in (x, x + \Delta x)$

② Mean Value Theorem:  $\exists c \in (a, b)$  s.t.



**Theorem B.1** (Multivariate Quadratic Taylor's Theorem). *Suppose that  $S \subset \mathbb{R}^n$  is an open set and that  $f : S \rightarrow \mathbb{R}$  is a function of class  $C^2$  on  $S$ . Then for  $\mathbf{a} \in S$  and  $\mathbf{h} \in \mathbb{R}^n$  such that the line segment connecting  $\mathbf{a}$  and  $\mathbf{a} + \mathbf{h}$  is contained in  $S$ , there exists  $\theta \in (0, 1)$  such that*

$$f(\mathbf{a} + \mathbf{h}) = f(\mathbf{a}) + \nabla f(\mathbf{a}) \cdot \mathbf{h} + \frac{1}{2} \mathbf{h}^T \nabla^2 f(\mathbf{a} + \theta \mathbf{h}) \mathbf{h}.$$

*Proof.* Define  $\underbrace{g(t) = f(\mathbf{a} + t\mathbf{h})}_{\text{s.t.}}$ . By Lemma B.1 on  $g(t)$ , there is  $\theta \in (0, 1)$

$$g(1) = g(0) + g'(0) + \frac{1}{2} g''(\theta).$$

By chain rule, we have  $g'(0) = \nabla f(\mathbf{a}) \cdot \mathbf{h}$  and  $g''(\theta) = \mathbf{h}^T \nabla^2 f(\mathbf{a} + \theta \mathbf{h}) \mathbf{h}$ , which complete the proof.  $\square$

**Lemma B.1** (Second-order Mean Value Theorem). *Suppose that  $I \subset \mathbb{R}$  is an open interval and that  $f(x)$  is a function of class  $C^2$  ( $f''(x)$  exists and is continuous) on  $I$ . For  $a \in I$  and  $h$  such that  $a + h \in I$ , there exists some  $\theta \in (0, 1)$  such that*

$$f(a + h) = f(a) + h f'(a) + \frac{h^2}{2} f''(a + \theta h).$$

*Proof.* Consider  $g_1(x) = f(x) - f(a) - (x - a)f'(a)$  then  $g_1(a) = g'_1(a) = 0$ . Define

$$g(x) = g_1(x) - \left( \frac{x - a}{h} \right)^2 g_1(a + h),$$

then  $g(a) = g'(a) = g(a + h) = 0$ . By Mean Value Theorem , we have

$$g(a) = g(a + h) = 0 \implies g'(a + \alpha h) = 0,$$

for some  $\alpha \in (0, 1)$ . Use Mean Value Theorem again on  $g'(a) = g'(a + \alpha h) = 0$ , we get  $g''(a + \theta h) = 0$  for some  $\theta \in (0, \alpha)$ . Since  $g''(x) = f''(x) - \frac{2}{h^2} g_1(a + h)$ ,  $g''(a + \theta h) = 0$  implies that we get the explicit remainder for the second order Taylor expansion as  $g_1(a + h) = \frac{h^2}{2} f''(a + \theta h)$ .  $\square$

$$\begin{aligned} g'(a) &= 0 \\ g'(a + \alpha h) &= 0 \end{aligned}$$

### Theorem (First Order Necessary Condition)

$x_*$  is a local minimizer  $\Rightarrow \nabla f(x_*) = 0$   
 $f(x)$  is smooth

Proof: Assume  $\nabla f(x_*) \neq 0$ .

Let  $P = -\nabla f(x_*)$ , then  $P^T \nabla f(x_*) = -\|\nabla f(x_*)\|^2 < 0$

$\nabla f(x)$  is continuous  $\Rightarrow P^T \nabla f(x_* + tP) < 0$ ,  $\forall t \in [0, T]$   
 for some  $T$ .  $\hookrightarrow$  for any

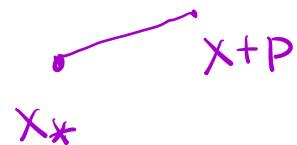
$h(t) = P^T \nabla f(x_* + tP)$  is continuous and  $h(0) < 0$   
 $\forall t \in (0, T]$ , by Taylor's Theorem,

$$f(x_* + tP) = f(x_*) + t P^T \nabla f(x_* + \theta P)$$

for some  $\theta \in (0, t)$

$$\Rightarrow f(x_* + tP) < f(x_*)$$

Contradiction



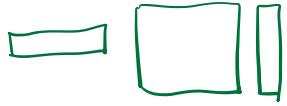
Stationary / Critical Point  $\nabla f(x) = 0$

### Theorem (Second Order Necessary Condition)

$x_*$  is a local minimizer  $\Rightarrow \nabla f(x_*) = 0$ ,  $\nabla^2 f(x_*) \geq 0$   
 $f(x)$  is smooth

$\nabla^2 f(x_*) \geq 0$  means the Hessian Matrix is positive semi-definite,  
 meaning ① all its eigenvalues are non-negative.

$$\textcircled{2} \quad y^T \nabla^2 f(x_*) y \geq 0 \text{ for any } y \in \mathbb{R}^n$$



Proof: We already proved  $\nabla f(x_*) = 0$

Assume  $\nabla^2 f(x_*)$  is NOT PSD.

$$\Rightarrow \exists p \in \mathbb{R}^n \text{ s.t. } p^T \nabla^2 f(x_*) p < 0$$

$\nabla^2 f(x)$  is continuous  $\Rightarrow p^T \nabla^2 f(x_* + tP) p < 0, \forall t \in [0, T]$   
for some  $T$

Taylor's Thm  $\Rightarrow \forall t \in (0, T], \exists \theta \in (0, t) \text{ s.t.}$

$$f(x_* + tP) = f(x_*) + t p^T \underbrace{\nabla f(x_*)}_{\parallel 0} + \frac{1}{2} t^2 \underbrace{p^T \nabla^2 f(x_* + \theta P) p^T}_{< 0} < 0$$

$< f(x_*)$

Contradiction.