

Convergence of Gradient Descent

$$\min_x f(x) \quad \text{Alg: } x^{(k+1)} = x^{(k)} - t \nabla f(x^{(k)})$$

$$x^+ = x - t \nabla f(x)$$

By  $L$ -gradient Lipschitz

$$\begin{aligned} f(x^+) &\leq f(x) + (x^+ - x)^T \nabla f(x) + \frac{L}{2} \|x^+ - x\|_2^2 \\ &= f(x) - t \nabla f(x)^T \nabla f(x) + \frac{L}{2} \|t \nabla f(x)\|_2^2 \\ &= f(x) - t \|\nabla f(x)\|^2 + \frac{t^2 L}{2} \|\nabla f(x)\|^2 \\ &= f(x) - \left(\frac{2t - t^2 L}{2}\right) \|\nabla f(x)\|^2 \end{aligned}$$

$$t \leq \frac{1}{L}$$

$$\leq f(x) - \left(\frac{2t - t}{2}\right) \|\nabla f(x)\|^2$$

$$= f(x) - \frac{t}{2} \|\nabla f(x)\|^2$$

Lem: (Descent Lemma) if  $t \leq \frac{1}{L}$ ,  $f$  obeys  $L$ -smoothness  
then  $\forall x$ ,  $f(x^+) \leq f(x) - \frac{t}{2} \|\nabla f(x)\|^2$

let's apply convexity  $f(x^+) \leq f(x) - \frac{t}{2} \|\nabla f(x)\|^2$

$$f(x^*) \geq f(x) + \nabla f(x)^T (x^* - x)$$

Descent  
lemma  $\rightarrow \geq f(x^+) + \frac{t}{2} \|\nabla f(x)\|^2 + \nabla f(x)^T (x^* - x) + \frac{1}{2t} \|x^* - x\|^2$

$$= f(x^+) + \frac{1}{2t} (\|x^* - x\|^2 + 2t \nabla f(x)^T (x^* - x) + t^2 \|\nabla f(x)\|^2) - \frac{1}{2t} \|x^* - x\|^2$$

$$= f(x^+) + \frac{1}{2t} \|x^* - x + t \nabla f(x)\|^2 - \frac{1}{2t} \|x^* - x\|^2$$

$$= f(x^+) + \frac{1}{2t} \|x^* - x^+\|^2 - \frac{1}{2t} \|x^* - x\|^2$$

Telescope:  $x_0, x_1, \dots, x_k$

$$\left. \begin{aligned} f(x^*) &\geq f(x_1) + \frac{1}{2t} \|x^* - x_1\|^2 - \frac{1}{2t} \|x^* - x_0\|^2 \\ f(x^*) &\geq f(x_2) + \frac{1}{2t} \|x^* - x_2\|^2 - \frac{1}{2t} \|x^* - x_1\|^2 \\ &\vdots \\ f(x^*) &\geq f(x_k) + \frac{1}{2t} \|x^* - x_k\|^2 - \frac{1}{2t} \|x^* - x_{k-1}\|^2 \end{aligned} \right\} \text{add up}$$

$$kf^* \geq \underbrace{\sum_{i=1}^k f(x_i)} + \underbrace{\frac{1}{2t} (\|x^* - x_d\|^2 - \|x^* - x_d\|^2)}$$

$$f(x_k) \leq \underbrace{\frac{1}{k} \sum_{i=1}^k f(x_i)} \leq f^* + \frac{1}{2tk} \|x^* - x_d\|^2$$

$$f(x_1) \geq f(x_2) \geq \dots \geq f(x_k)$$

$$f(x_k) - f^* \leq \frac{1}{2tk} \|x^* - x_d\|^2$$

□

Thm:  $t \leq \frac{1}{L}$ ,  $f$  is  $L$ -smooth, then

$$f(x_k) - f^* \leq \frac{1}{2tk} \|x^* - x_d\|^2$$

Convergence of GD on non-convex but  $L$ -smooth  $f$ :

$$f(x^t) \leq f(x) - \frac{\epsilon}{2} \|\nabla f(x)\|^2$$

for  $k=1, \dots, K$

~~$$f(x_2) \leq f(x_1) - \frac{\epsilon}{2} \|\nabla f(x_1)\|^2$$~~

~~$$f(x_3) \leq f(x_2) - \frac{\epsilon}{2} \|\nabla f(x_2)\|^2$$~~

~~$\vdots$~~

~~$$f(x_k) \leq f(x_{k-1}) - \frac{\epsilon}{2} \|\nabla f(x_{k-1})\|^2$$~~

~~$$f(x_{k+1}) \leq f(x_k) - \frac{\epsilon}{2} \|\nabla f(x_k)\|^2$$~~

Sum

$$f(x_{k+1}) \leq f(x_1) - \frac{\epsilon}{2} \sum_{i=1}^k \|\nabla f(x_i)\|^2$$

$$\min_{i \in \{1, 2, \dots, k\}} \|\nabla f(x_i)\|^2 \leq \frac{1}{k} \sum_{i=1}^k \|\nabla f(x_i)\|^2 \leq \frac{2(f(x_1) - f(x_{k+1}))}{\epsilon k}$$

$$\leq \frac{2}{\epsilon k} (f(x_1) - f^*) \quad \left| \quad f^* \leq f(x_{k+1}) \right.$$

$$\min_{i \in [k]} \|\nabla f(x_i)\| \leq \sqrt{\frac{2(f(x_1) - f^*)}{\epsilon k}}$$

Thm.  $f$  obeys  $m$ -PL condition  $\Rightarrow$  linear convergence

$$f(x^k) \leq f^* + \frac{L}{2} \left(1 - \frac{m}{L}\right)^k \|x - x^*\|^2$$

Proof: By descent lemma

$$f(x^k) \leq f(x^{k-1}) - \frac{t}{2} \|\nabla f(x^{k-1})\|^2$$

Apply  $m$ -PL  $\rightarrow \leq f(x^{k-1}) - mt(f(x^{k-1}) - f^*)$

$$\boxed{\begin{array}{l} \text{PL-condition} \\ \frac{1}{2} \|\nabla f(x)\|^2 \geq m(f(x) - f^*) \end{array}}$$

$$f(x^k) - f^* \leq f(x^{k-1}) - f^* - \underbrace{mt(f(x^{k-1}) - f^*)}$$

$$\leq (1 - mt)(f(x^{k-1}) - f^*)$$

$$f(x^k) - f^* \leq (1 - mt)^k (f(x^1) - f^*)$$

$$t = \frac{1}{L} \quad (1 - \frac{m}{L}) \leq \frac{L}{2} \|x^1 - x^*\|^2 \quad \square$$

$\uparrow$  Lipschitz Gradient

Strong Convexity  $\Rightarrow$  PL Condition

Proof:  $f^* \geq f(x) + \nabla f(x)^T (x^* - x) + \frac{m}{2} \|x^* - x\|^2$

$$= f(x) + \frac{1}{2m} (m^2 \|x^* - x\|^2 + 2m(x^* - x)^T \nabla f(x)$$

$$+ \|\nabla f(x)\|^2 - \|\nabla f(x)\|^2)$$

$$= f(x) + \underbrace{\frac{1}{2m} \|m(x^* - x)^T \nabla f(x)\|^2}_{\geq 0} - \frac{1}{2m} \|\nabla f(x)\|^2$$

$$\frac{1}{2} \|\nabla f(x)\|^2 \geq m(f(x) - f^*)$$

$\square$