

1 Cheat Sheet

1.1 Lipschitz Continuous

Definition 1. $f \in C_L^{k,p}(Q)$ is k times continuously differentiable on Q if for all $x, y \in Q$,

$$\|\nabla^p f(y) - \nabla^p f(x)\| \leq L \|y - x\| \quad (1)$$

$f \in C_L^{1,1}(\mathbb{R}^n)$ is continuously differentiable on \mathbb{R}^n if for all $x, y \in \mathbb{R}^n$

$$\|\nabla f(y) - \nabla f(x)\| \leq L \|y - x\| \quad (2)$$

Definition 2. $f \in C_L^{2,1}(\mathbb{R}^n) \subset C_L^{1,1}(\mathbb{R}^n)$ if for all $x \in \mathbb{R}^n$, either condition is satisfied

$$\|\nabla^2 f(x)\| \leq L \quad (3)$$

$$-L\mathbf{I} \preceq \nabla^2 f(x) \preceq L\mathbf{I} \quad (4)$$

Property for $f \in C_L^{1,1}(\mathbb{R}^n)$,

$$|f(y) - f(x) - \langle \nabla f(x), y - x \rangle| \leq \frac{L}{2} \|y - x\|^2 \quad (5)$$

$$f(x - \alpha \nabla f(x)) \leq f(x) - \alpha \left(1 - \frac{\alpha}{2} L\right) \|\nabla f(x)\|^2 \quad (6)$$

$$f\left(x - \frac{1}{L} \nabla f(x)\right) \leq f(x) - \frac{1}{2L} \|\nabla f(x)\|^2 \quad (7)$$

Note (5) implies that quadratic functions $\phi_-(\cdot), \phi_+(\cdot)$ are global lower/upper bound of $f(\cdot)$ respectively, i.e. $\phi_-(y) \leq f(y) \leq \phi_+(y)$ for any $x \in \mathbb{R}^n$, where

$$\begin{aligned} \phi_-(y) &= f(x) + \langle \nabla f(x), y - x \rangle - \frac{L}{2} \|y - x\|^2 \\ \phi_+(y) &= f(x) + \langle \nabla f(x), y - x \rangle + \frac{L}{2} \|y - x\|^2 \end{aligned}$$

Note (7) is important in proving convergence of descent methods, where we see progress made in reducing function value of iterates by stepping in $-\frac{1}{L} \nabla f(x)$ is at least some constant times the gradient norm.

Property for $f \in C_M^{2,2}(\mathbb{R}^n)$,

$$\|\nabla f(y) - \nabla f(x) - \nabla^2 f(x)(y - x)\| \leq \frac{M}{2} \|y - x\|^2 \quad (8)$$

$$\nabla^2 f(x) - C \preceq \nabla^2 f(y) \preceq \nabla^2 f(x) + C \quad \text{where } c = M \|y - x\| \mathbf{I} \quad (9)$$

1.2 Convex

Definition 3. The following are equivalent

1. A continuously differentiable function f is convex on convex set Q ($f \in \mathcal{F}^1(Q)$)
2. For all $x, y \in Q$

$$f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle \quad (10)$$

3. For all $x, y \in Q$ and $\lambda \in [0, 1]$,

$$f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y) \quad (11)$$

4. For all $x, y \in Q$,

$$\langle \nabla f(x) - \nabla f(y), x - y \rangle > 0 \quad (12)$$

Definition 4. A twice differentiable function f belongs to $\mathcal{F}^2(Q)$ if for any $x \in Q$,

$$\nabla^2 f(x) \succeq 0 \quad (13)$$

1.3 Smooth & Convex

Definition 5. $f \in \mathcal{F}_L^{1,1}(Q, \|\cdot\|)$ if f is convex with Lipschitz continuous gradient, i.e. for all $x, y \in Q$,

$$\|\nabla f(x) - \nabla f(y)\|_* \leq L \|x - y\| \quad (14)$$

Property of $f \in \mathcal{F}^{1,1}(\mathbb{R}^n, \|\cdot\|)$. Let $x, y \in \mathbb{R}^n$ and $\lambda \in [0, 1]$

$$0 \leq f(y) - f(x) - \langle \nabla f(x), y - x \rangle \leq \frac{L}{2} \|x - y\|^2 \quad (15)$$

$$f(x) + \langle \nabla f(x), y - x \rangle + \frac{1}{2L} \|\nabla f(x) - \nabla f(y)\|_*^2 \leq f(y) \quad (16)$$

$$\frac{1}{L} \|\nabla f(x) - \nabla f(y)\|_*^2 \leq \langle \nabla f(x) - \nabla f(y), x - y \rangle \quad (17)$$

$$0 \leq \langle \nabla f(x) - \nabla f(y), x - y \rangle \leq L \|x - y\|^2 \quad (18)$$

Note (15) implies a tighter (linear) lower bound to $f(\cdot)$ if we assume convexity. In fact, the lower bound can be improved further to a upward quadratic by (16).

1.4 Strongly Convex

Definition 6. A continuously differentiable function f is strongly convex on \mathbb{R}^n ($f \in \mathcal{S}_\mu^1(Q, \|\cdot\|)$) if there exists a convexity parameter $\mu > 0$ such that for all $x, y \in Q$,

$$f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle + \frac{\mu}{2} \|y - x\|^2 \quad (19)$$

Property for $f \in \mathcal{S}_\mu^1(\mathbb{R}^n)$. Let $x, y \in Q$ and $\lambda \in [0, 1]$,

$$f(x) \geq f(x^*) + \frac{\mu}{2} \|x - x^*\|^2 \quad \text{where} \quad \nabla f(x^*) = 0 \quad (20)$$

$$\langle \nabla f(x) - \nabla f(y), x - y \rangle \geq \mu \|x - y\|^2 \quad (21)$$

$$\lambda f(x) + (1 - \lambda)f(y) \geq f(\lambda x + (1 - \lambda)y) + \lambda(1 - \lambda)\frac{\mu}{2} \|x - y\|^2 \quad (22)$$

1.5 Smooth & Strongly Convex

Definition 7. A continuously differentiable function f that is strongly convex with L -lipschitz continuous gradients ($f \in \mathcal{S}_{L,\mu}^{1,1}(\mathbb{R}^n)$). Note $\kappa = L/\mu \geq 1$ is the condition number of f .

Property for $f \in \mathcal{S}_{\mu,L}^{1,1}(\mathbb{R}^n)$. For any $x, y \in \mathbb{R}^n$

$$\langle \nabla f(x) - \nabla f(y), x - y \rangle \geq \frac{\mu L}{\mu + L} \|x - y\|^2 + \frac{1}{\mu + L} \|\nabla f(x) - \nabla f(y)\|^2 \quad (23)$$