

Monotonicity of gradient of strongly convex smooth function

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Content

$\phi(\mathbf{x}) = f(\mathbf{x}) - \frac{m}{2} \|\mathbf{x}\|_2^2$ is $(L - m)$ -smooth

$$\langle \nabla f(\mathbf{x}) - \nabla f(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \geq \frac{mL}{m + L} \|\mathbf{x} - \mathbf{y}\|_2^2 + \frac{1}{m + L} \|\nabla f(\mathbf{x}) - \nabla f(\mathbf{y})\|_2^2.$$

Recall of convex, smooth and strongly convex function (details [here](#))

▶ Given $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$ with $\text{dom}f = \mathbb{R}^n$ is a convex set

▶ f is **convex** if $\forall \mathbf{x}, \mathbf{y} \in \text{dom}f$

▶ $f(\lambda \mathbf{x} + (1 - \lambda)\mathbf{y}) \leq \lambda f(\mathbf{x}) + (1 - \lambda)f(\mathbf{y})$

▶ $\langle \mathbf{x} - \mathbf{y}, \nabla f(\mathbf{x}) - \nabla f(\mathbf{y}) \rangle \geq 0$

▶ $f(\mathbf{y}) \geq f(\mathbf{x}) + \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle$

Jensen
grad is monotone
linear global under-estimator

▶ f is **L -smooth** ($L > 0$) if $\forall \mathbf{x}, \mathbf{y} \in \text{dom}f$

▶ $\|\nabla f(\mathbf{x}) - \nabla f(\mathbf{y})\| \leq L\|\mathbf{x} - \mathbf{y}\|$

▶ $f(\mathbf{y}) \leq f(\mathbf{x}) + \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle + \frac{L}{2}\|\mathbf{x} - \mathbf{y}\|_2^2$

∇f is L -Lipschitz
global quadratic over-estimator

▶ f is **m -strongly convex** ($m > 0$) if $\forall \mathbf{x}, \mathbf{y} \in \text{dom}f$

▶ $f(\lambda \mathbf{x} + (1 - \lambda)\mathbf{y}) \leq \lambda f(\mathbf{x}) + (1 - \lambda)f(\mathbf{y}) - \frac{m}{2}\lambda(1 - \lambda)\|\mathbf{x} - \mathbf{y}\|_2^2$

▶ $\langle \mathbf{x} - \mathbf{y}, \nabla f(\mathbf{x}) - \nabla f(\mathbf{y}) \rangle \geq m\|\mathbf{x} - \mathbf{y}\|_2^2$

▶ $f(\mathbf{y}) \geq f(\mathbf{x}) + \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle + \frac{m}{2}\|\mathbf{x} - \mathbf{y}\|_2^2$

▶ $f(\mathbf{x}) - \frac{m}{2}\|\mathbf{x}\|_2^2$ is convex

Jensen with a quadratic term
grad is strongly monotone
quadratic global under-estimator

▶ This PDF: prove if f is m -strongly convex and L -smooth, then

$$\langle \nabla f(\mathbf{x}) - \nabla f(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \geq \frac{mL}{m + L}\|\mathbf{x} - \mathbf{y}\|_2^2 + \frac{1}{m + L}\|\nabla f(\mathbf{x}) - \nabla f(\mathbf{y})\|_2^2.$$

Lemma: $\phi(\mathbf{x}) = f(\mathbf{x}) - \frac{m}{2}\|\mathbf{x}\|_2^2$ is $(L - m)$ -smooth

► Goal: show $\phi(\mathbf{y}) - \phi(\mathbf{x}) - \nabla\phi(\mathbf{x})^\top(\mathbf{y} - \mathbf{x}) - \frac{L - m}{2}\|\mathbf{y} - \mathbf{x}\|_2^2 \leq 0$

► By $\phi(\mathbf{x}) = f(\mathbf{x}) - \frac{m}{2}\|\mathbf{x}\|_2^2$:

$$\begin{aligned} & \phi(\mathbf{y}) - \phi(\mathbf{x}) - \nabla\phi(\mathbf{x})^\top(\mathbf{y} - \mathbf{x}) - \frac{L - m}{2}\|\mathbf{y} - \mathbf{x}\|_2^2 \\ \stackrel{\phi=f-\frac{m}{2}\|\cdot\|_2^2}{=} & f(\mathbf{y}) - \frac{m}{2}\|\mathbf{y}\|_2^2 - f(\mathbf{x}) + \frac{m}{2}\|\mathbf{x}\|_2^2 - \nabla\phi(\mathbf{x})^\top(\mathbf{y} - \mathbf{x}) - \frac{L - m}{2}\|\mathbf{y} - \mathbf{x}\|_2^2 \\ = & f(\mathbf{y}) - f(\mathbf{x}) + \frac{m}{2}(\|\mathbf{x}\|_2^2 - \|\mathbf{y}\|_2^2) - \nabla\phi(\mathbf{x})^\top(\mathbf{y} - \mathbf{x}) - \frac{L - m}{2}\|\mathbf{y} - \mathbf{x}\|_2^2 \\ \stackrel{(1)}{\leq} & \nabla f(\mathbf{x})^\top(\mathbf{y} - \mathbf{x}) + \frac{m}{2}(\|\mathbf{x}\|_2^2 - \|\mathbf{y}\|_2^2) - \nabla\phi(\mathbf{x})^\top(\mathbf{y} - \mathbf{x}) + \frac{m}{2}\|\mathbf{y} - \mathbf{x}\|_2^2 \end{aligned}$$

(1): f is L -smooth so $f(\mathbf{y}) - f(\mathbf{x}) \leq \nabla f(\mathbf{x})^\top(\mathbf{y} - \mathbf{x}) + \frac{L}{2}\|\mathbf{y} - \mathbf{x}\|_2^2$ and $\frac{L}{2}\|\mathbf{y} - \mathbf{x}\|_2^2$ cancels with $\frac{L - m}{2}\|\mathbf{y} - \mathbf{x}\|_2^2$.

► Our goal is now showing

$$\nabla f(\mathbf{x})^\top(\mathbf{y} - \mathbf{x}) + \frac{m}{2}(\|\mathbf{x}\|_2^2 - \|\mathbf{y}\|_2^2) - \nabla\phi(\mathbf{x})^\top(\mathbf{y} - \mathbf{x}) + \frac{m}{2}\|\mathbf{y} - \mathbf{x}\|_2^2 \leq 0$$

To show $\phi(\mathbf{x})$ is $(L - m)$ -smooth ... 2

► Goal: show $\nabla f(\mathbf{x})^\top(\mathbf{y} - \mathbf{x}) + \frac{m}{2}(\|\mathbf{x}\|_2^2 - \|\mathbf{y}\|_2^2) - \nabla\phi(\mathbf{x})^\top(\mathbf{y} - \mathbf{x}) + \frac{m}{2}\|\mathbf{y} - \mathbf{x}\|_2^2 \leq 0$

► By $\phi(\mathbf{x}) = f(\mathbf{x}) - \frac{m}{2}\|\mathbf{x}\|_2^2 \implies \nabla\phi(\mathbf{x}) = \nabla f(\mathbf{x}) - m\mathbf{x}$

$$\begin{aligned} & \nabla f(\mathbf{x})^\top(\mathbf{y} - \mathbf{x}) + \frac{m}{2}(\|\mathbf{x}\|_2^2 - \|\mathbf{y}\|_2^2) - (\nabla f(\mathbf{x}) - m\mathbf{x})^\top(\mathbf{y} - \mathbf{x}) + \frac{m}{2}\|\mathbf{y} - \mathbf{x}\|_2^2 \\ &= \underbrace{\frac{m}{2}(\|\mathbf{x}\|_2^2 - \|\mathbf{y}\|_2^2) + m\mathbf{x}^\top(\mathbf{y} - \mathbf{x}) + \frac{m}{2}\|\mathbf{y} - \mathbf{x}\|_2^2}_{=0} \end{aligned}$$

So $\phi(\mathbf{y}) - \phi(\mathbf{x}) - \nabla\phi(\mathbf{x})^\top(\mathbf{y} - \mathbf{x}) - \frac{L - m}{2}\|\mathbf{y} - \mathbf{x}\|_2^2 \leq 0$

□

We need: L -smooth function has co-coercive gradient

- ▶ If f is L -smooth, then

$$\langle \nabla f(\mathbf{y}) - \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle \geq \frac{1}{\beta} \|\nabla f(\mathbf{y}) - \nabla f(\mathbf{x})\|_2^2$$

Details p.10 [here](#)

- ▶ ϕ is $(L - m)$ -smooth, so

$$\langle \nabla \phi(\mathbf{y}) - \nabla \phi(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle \geq \frac{1}{L - m} \|\nabla \phi(\mathbf{y}) - \nabla \phi(\mathbf{x})\|_2^2 \quad (\#)$$

What's next: use $(\#)$ to prove

$$\langle \nabla f(\mathbf{x}) - \nabla f(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \geq \frac{mL}{m + L} \|\mathbf{x} - \mathbf{y}\|_2^2 + \frac{1}{m + L} \|\nabla f(\mathbf{x}) - \nabla f(\mathbf{y})\|_2^2.$$

Monotonicity of gradient of m -strongly convex L -smooth function

$$\langle \nabla\phi(\mathbf{y}) - \nabla\phi(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle \geq \frac{1}{L-m} \|\nabla\phi(\mathbf{y}) - \nabla\phi(\mathbf{x})\|_2^2 \quad (\#)$$

► $\nabla\phi(\mathbf{x}) = \nabla f(\mathbf{x}) - m\mathbf{x}$

$$\langle \nabla f(\mathbf{y}) - \nabla f(\mathbf{x}) - m(\mathbf{y} - \mathbf{x}), \mathbf{y} - \mathbf{x} \rangle \geq \frac{1}{L-m} \|\nabla f(\mathbf{y}) - \nabla f(\mathbf{x}) - m(\mathbf{y} - \mathbf{x})\|_2^2$$

► Left hand side = $\langle \nabla f(\mathbf{y}) - \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle - m\|\mathbf{y} - \mathbf{x}\|_2^2$

► Right hand side =
$$\frac{\|\nabla f(\mathbf{x}) - \nabla f(\mathbf{y})\|_2^2 - 2m\langle \nabla f(\mathbf{y}) - \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle + m^2\|\mathbf{x} - \mathbf{y}\|_2^2}{L-m}$$

► Grouping the similar terms yields

$$\left(1 + \frac{2m}{L-m}\right) \langle \nabla f(\mathbf{y}) - \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle \geq \frac{\|\nabla f(\mathbf{x}) - \nabla f(\mathbf{y})\|_2^2}{L-m} + \left(\frac{m^2}{L-m} + m\right) \|\mathbf{x} - \mathbf{y}\|_2^2$$

Divide the whole equation by $\left(1 + \frac{2m}{L-m}\right)$ gives

$$\langle \nabla f(\mathbf{x}) - \nabla f(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \geq \frac{mL}{m+L} \|\mathbf{x} - \mathbf{y}\|_2^2 + \frac{1}{m+L} \|\nabla f(\mathbf{x}) - \nabla f(\mathbf{y})\|_2^2 \quad \square$$