

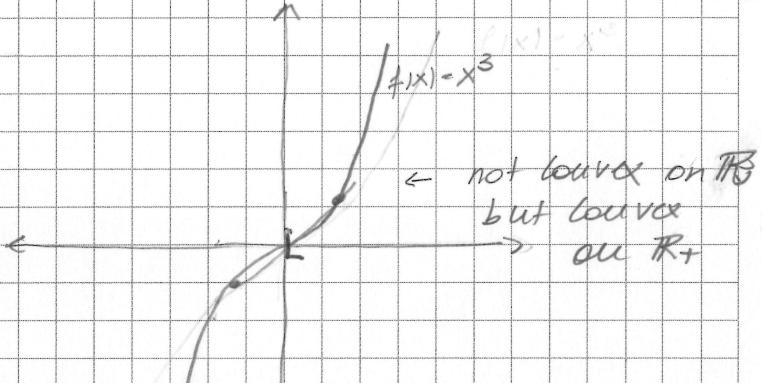
Convex functions

Week 2 Lec 2 (1)

Def. $S \subseteq \mathbb{R}^n$; a function $f: S \rightarrow \mathbb{R}$ is called convex if S is convex and $\forall \vec{v}, \vec{w} \in S$ and $\forall \lambda \in [0, 1]$

$\lambda \leftarrow$ strictly convex

$$f(\lambda \vec{v} + (1-\lambda) \vec{w}) \leq \lambda f(\vec{v}) + (1-\lambda) f(\vec{w})$$



\Leftarrow Line segment between any two distinct points lies above the graph between the two points

Convex optimisation problem: set of constraints S and objective function F is convex

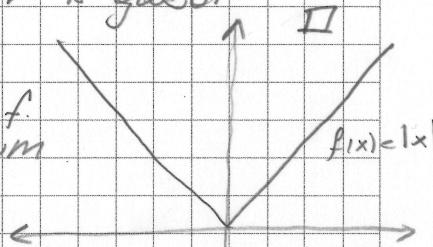
Thm: Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be a convex function. Then any local minimiser of f is a global minimiser.

Proof: Let \vec{v}^* be a local minimiser & assume it's not global.

$$\exists \vec{v} \in \mathbb{R}^n \text{ s.t. } f(\vec{v}) < f(\vec{v}^*) \quad \text{Since } f \text{ convex we can add for}$$

$\therefore \vec{v} \in \mathbb{R}^n \text{ s.t. } f(\vec{v}) < f(\vec{v}^*)$
 \therefore Since f is convex we have that for any $\lambda \in [0, 1]$ and $\vec{v} = \lambda \vec{v} + (1-\lambda) \vec{v}^*$
 holds for all line seg. $\Rightarrow f(\vec{v}) \leq \lambda f(\vec{v}) + (1-\lambda) f(\vec{v}^*) < \lambda f(\vec{v}^*) + (1-\lambda) f(\vec{v}^*) = f(\vec{v}^*)$
 connecting to and \vec{v}^*

\therefore Every open neighborhood N of \vec{v}^* contains a bit of this line segment
 \Rightarrow Every open neighborhood N of \vec{v}^* contains $\vec{v} + \vec{v}^*$ s.t. $f(\vec{v}) < f(\vec{v}^*)$
 \Rightarrow By assumption that \vec{v}^* is a local min $\Rightarrow \vec{v}^*$ is global!

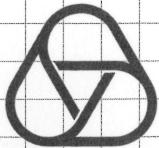


This makes no assumption about differentiability of f .
 E.g. $f(x) = |x|$ is convex and $x=0$ is global minimum

Examples of convex functions:

$$\text{if } f(\vec{x}) = \langle \vec{a}, \vec{x} \rangle + b \quad \vec{a}, \vec{x} \in \mathbb{R}^n, b \in \mathbb{R}$$

$$\begin{aligned} f(\lambda \vec{x} + (1-\lambda) \vec{y}) &= \langle \vec{a}, \lambda \vec{x} + (1-\lambda) \vec{y} \rangle + b \\ &= \lambda \langle \vec{a}, \vec{x} \rangle + (1-\lambda) \langle \vec{a}, \vec{y} \rangle + b \\ &= \lambda \langle \vec{a}, \vec{x} \rangle + 2b + (1-\lambda) \langle \vec{a}, \vec{y} \rangle + (1-\lambda)b \\ &= \lambda f(\vec{x}) + (1-\lambda) f(\vec{y}) \end{aligned}$$



ii) $f(x) = |x| \quad \text{for } x \in \mathbb{R}$

$$\begin{aligned} f(2x + (1-\lambda)y) &= \sqrt{|2x + (1-\lambda)y|^2} \\ &\leq \sqrt{2|x|^2 + (1-\lambda)^2|y|^2} \\ &\stackrel{\Delta}{=} \sqrt{2\|x\|^2 + (1-\lambda)\|y\|^2} \end{aligned}$$

Δ -inequality

iii) l_p -norms

$$\|\vec{x}\| = (\|x_1\|^p + \dots + \|x_n\|^p)^{1/p} \quad \leftarrow l_p \text{ norm}$$

$$\|2\vec{x} + (1-\lambda)\vec{y}\| \stackrel{\Delta}{=} \sqrt{2\|\vec{x}\|^2 + (1-\lambda)^2\|\vec{y}\|^2}$$

iv) Operator norm

$$\|\tilde{A}\|_2 = \max_{\vec{G}: \|\vec{G}\|=1} \frac{\|\tilde{A}\vec{G}\|_2}{\|\vec{G}\|}$$

You can show that $\|\tilde{A}\|_2 = \sigma_1(A) \leftarrow \text{largest singular value}$
see algebra 2

Characterise convexity using differentiability

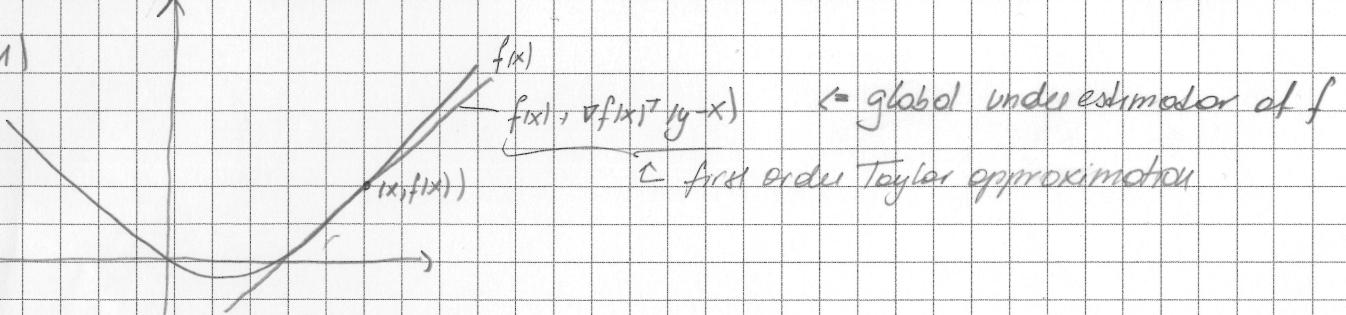
Thm 1) Let $f \in C^1(\mathbb{R}^n)$. Then f is convex if and only if $\forall \vec{v}, \vec{w} \in \mathbb{R}^d$

$$f(\vec{v}) \geq f(\vec{w}) + \nabla f(\vec{v})^\top (\vec{v} - \vec{w})$$

2) Let $f \in C^2(\mathbb{R}^n)$. Then f is convex if and only if $\nabla^2 f(\vec{v})$ is positive semi-definite $\forall \vec{v} \in \mathbb{R}^n$

If $\nabla^2 f(\vec{v})$ is positive definite $\forall \vec{v} \in \mathbb{R}^n \Rightarrow f$ is strictly convex

Ad. 1)



Ad. 2.) $f(x) = \frac{1}{2}x^2 \quad \text{dom } f = \{x \in \mathbb{R} : x \neq 0\}$

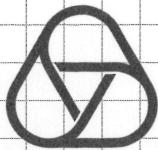
$f''(x) > 0$ for all $x \in \text{dom } f$ but f is not convex

Examples of convex fct.

v) $f(x) = e^x \quad f'' = e^x > 0 \Rightarrow \text{convex}$

vi) $f(x) = -\log x \quad f'(x) = -\frac{1}{x} \quad f''(x) = \frac{1}{x^2} > 0 \quad \text{for } x > 0$

$$\geq e^x + g e^x - x e^x$$



Proof of 1) for $n=1$

We show that $f: \mathbb{R} \rightarrow \mathbb{R}$ is convex $\Leftrightarrow f(y) \geq f(x) + f'(x)(y-x)$

" \Rightarrow " Assume f is convex therefore

$$f(x+t(y-x)) \leq (1-t)f(x) + t f(y) \quad | : t \quad \text{for } t \in [0,1]$$

$$\frac{f(x+t(y-x))-f(x)}{t} \leq -f'(x) + f'(y)$$

or $f(y) \geq f(x) + \frac{f(x+t(y-x))-f(x)}{t}$ \Leftarrow take limit as $t \rightarrow 0$

" \Leftarrow " Assume that $f(y) \geq f(x) + f'(x)(y-x)$ holds

Choose $x \neq y$ and $z \in [0,1]$; $z = \lambda x + (1-\lambda)y$

$$f(x) \geq f(z) + f'(z)(x-z) \quad | : \lambda \\ f(y) \geq f(z) + f'(z)(y-z) \quad | : (1-\lambda)$$

$$\underline{\underline{f(x) + (1-\lambda)f(y) \geq f(z) + (1-\lambda)f(z) + \lambda f'(z)(x-z) + (1-\lambda)f'(z)(y-z)}}$$

$$2f(x) + (1-\lambda)f(y) \geq 2f(z) + (1-\lambda)f(z) + \lambda f'(z)(x-z) + (1-\lambda)f'(z)(y-z)$$

$$2f(x) + (1-\lambda)f(y) \geq f(z) + 2f'(z)x - 2f'(z)z + f'(z)y - f'(z)z \\ - \lambda f'(z)y + \lambda f'(z)z \quad | \quad = \lambda x + (1-\lambda)y$$

$$\Rightarrow 2f(x) + (1-\lambda)f(y) \geq f(z) \Rightarrow f \text{ is convex}$$