

# Exercise session notes - Week 3

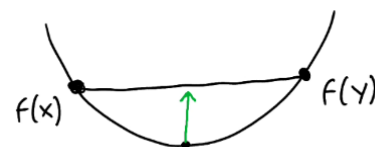
## Convex Functions

**Definitions.** A function  $f : X \rightarrow \mathbb{R}$  is convex if  $X$  is convex and one of the following (equivalent) conditions hold:

- 0th-order characterization: for any  $x, y \in X$  and  $\lambda \in [0, 1]$  we have

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

Meaning: the line between any two points in the graph of  $f$  lies above the function  $f$ .



- 1st-order characterization: for any  $x, y \in X$  we have

$$f(y) \geq f(x) + \nabla f(x)^\top (y - x)$$

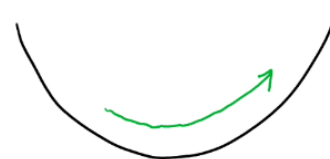
Meaning: the function  $f$  entirely lies above the first order Taylor approximation at each point  $x$ .



- 2nd-order characterization: for any  $x \in X$  we have

$$\begin{aligned} &\nabla^2 f(x) \text{ is Positive Semi Definite} \\ \iff &v^\top \cdot \nabla^2 f(x) \cdot v \geq 0 \quad \forall v \in \mathbb{R}^n \end{aligned}$$

Meaning: the curvature of the function  $f$  is positive (the function  $f$  is "trying to go upwards").



**Examples.** Here are some examples of important convex/concave functions.

Convex Functions.	$\longleftrightarrow$	Concave Functions
Affine $ax + b$ for $a, b \in \mathbb{R}$		Affine $ax + b$ for $a, b \in \mathbb{R}$
Exponentials $e^{ax}$ for $a \in \mathbb{R}$		Logarithms $\log_a(x)$ for $a \geq 1$
Powers $x^a$ in $\mathbb{R}_{>0}$ for $a \leq 0$ or $a \geq 1$		Powers $x^a$ in $\mathbb{R}_{>0}$ for $a \in [0, 1]$
Any norm $\ x\ _p = \left(\sum  x_i ^p\right)^{1/p}$ for $p \in [1, \infty]$		
LogSumExp $\log(e^{x_1} + \dots + e^{x_n})$ . $\hookrightarrow$ This is a smooth approximator of the max function.		

**Properties.** Here are some operations that preserve convexity.

- Sums (conic combinations)  $\sum a_i f_i$  for  $a_i \geq 0$   
 In particular  $f_1 + f_2$  is convex.
- Affine Precompositions. If  $f$  convex then  $f(Ax + b)$  is convex.  
 E.g.  $\|Ax + b\|$  is convex (Norm approximation error)
- If  $f(x, y)$  convex in  $x$  then  $g(x) := \sup_y f(x, y)$  is convex.  
 E.g. Max eigenvalue of symmetric matrix  $\lambda_{\max}(A) = \sup_{\|y\|=1} y^\top A y$
- If  $f$  convex + non-decreasing and  $g$  convex then  $f \circ g$  convex.  
 E.g. If  $g$  convex then  $e^{g(x)}$  convex
- If  $f$  convex + non-increasing and  $g$  concave then  $f \circ g$  convex.  
 E.g. If  $g$  concave+positive then  $1/g(x)$  convex.