

$$f: \mathbb{R}^n \rightarrow \mathbb{R}$$

Unconstrained
Optimization

$$\min f(x)$$

$$\text{s.t. } x \in \mathbb{R}^n$$

Constrained

$$\min f(x)$$

$$\text{s.t.}$$

$$x \in X \subseteq \mathbb{R}^n$$

Some Important Results/Definitions

- Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be continuously differentiable

$$x^* \text{ is pt. of local opt.} \Rightarrow \nabla f(x^*) = \begin{bmatrix} \frac{\partial f(x)}{\partial x_1} \\ \vdots \\ \frac{\partial f(x)}{\partial x_n} \end{bmatrix} = 0$$

- Let f be twice differentiable

$$H(x) = \begin{bmatrix} \frac{\partial^2 f(x)}{\partial x_1^2} & \frac{\partial^2 f(x)}{\partial x_1 \partial x_2} & \dots & \frac{\partial^2 f(x)}{\partial x_1 \partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f(x)}{\partial x_n \partial x_1} & \frac{\partial^2 f(x)}{\partial x_n \partial x_2} & \dots & \frac{\partial^2 f(x)}{\partial x_n^2} \end{bmatrix}$$

$$\text{then } \nabla f(x^*) = 0$$

$$H(x^*) \text{ is P.D.}$$

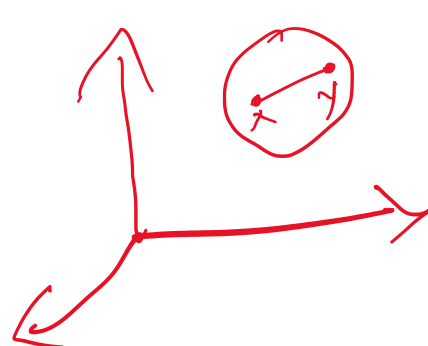
$$\Rightarrow$$

x^* is a
p.t. of
local optimum
(min)

Convex Set:- $X \subseteq \mathbb{R}^n$ is said to be convex if $\forall x, y \in X$

$$\lambda x + (1-\lambda)y \in X$$

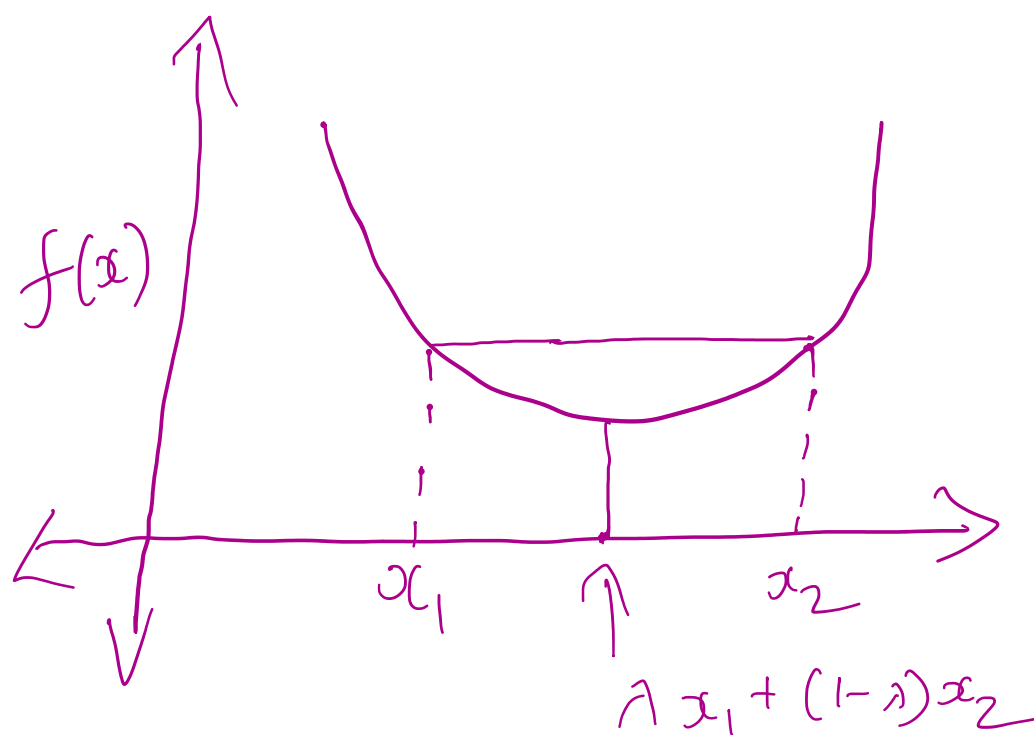
$$\forall 0 \leq \lambda \leq 1$$



Convex fn:- $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is defined over a convex set in following way

$$\forall x_1, x_2$$

$$f(\lambda x_1 + (1-\lambda)x_2) \leq \lambda f(x_1) + (1-\lambda)f(x_2)$$



$f(\cdot)$ is convex

$$\Leftrightarrow H(x) \text{ is P.S.D.}$$

$$\forall x \in X$$

Why Convex fn are important?

- Many useful ML loss fn are Convex

- For Convex
local \Rightarrow Global
Min Min