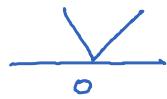


Many convex functions are not differentiable

e.g. $x \mapsto |x|$



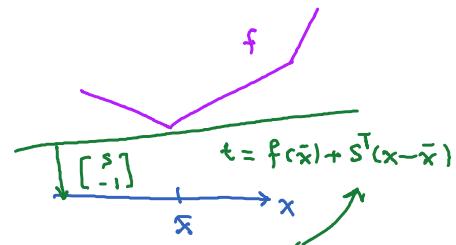
$x \mapsto \max\{x, 0\}$ (ReLU)



Definition: Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be a function. A vector $s \in \mathbb{R}^n$ is

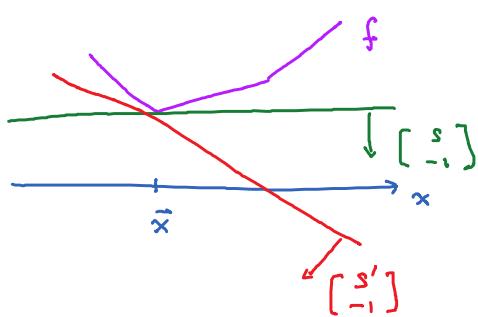
called a subgradient of f at \bar{x} if

$$f(x) \geq f(\bar{x}) + \underbrace{s^T(x - \bar{x})}_{\text{affine in } x} \quad \forall x \in \mathbb{R}^n$$



$$\begin{bmatrix} s \\ -1 \end{bmatrix}^T \begin{bmatrix} x \\ t \end{bmatrix} = s^T x - f(\bar{x})$$

Note: There could be more than one subgradient at \bar{x} :



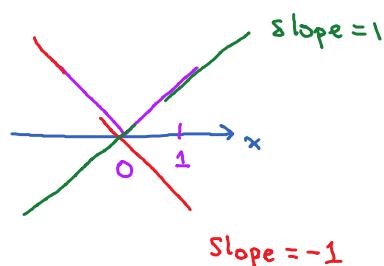
The set of all subgradients of f at \bar{x} is the subdifferential of f at \bar{x} , denoted by

$$\partial f(\bar{x}) = \{s : f(x) \geq f(\bar{x}) + s^T(x - \bar{x}), \forall x\}.$$

Example: $x \mapsto f(x) = |x|$. Take $\bar{x} = 0$. Then,

$$\partial f(0) = \{s : |x| \geq 0 + s x, \forall x\} = [-1, 1]$$

$$|x| \geq s x \quad \begin{cases} x > 0 : s \leq 1 \\ x < 0 : s \geq -1 \end{cases}$$



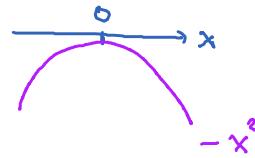
Take $\bar{x} = 1$. Then,

$$\partial f(1) = \{s : |x| \geq 1 + s(x-1), \forall x\} = \{1\},$$

$$\left. \begin{array}{l} \text{Take } x=0 : s \geq 1 \\ \text{Take } x=2 : s \leq 1 \end{array} \right\} \Rightarrow s=1 : |x| \geq x, \forall x \checkmark$$

Example: $x \mapsto f(x) = -x^2$.

$$\partial f(0) = \emptyset \quad (\text{Exercise})$$



Theorem: Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be convex. Then, for any $x \in \mathbb{R}^n$, $\partial f(x)$ is non-empty, convex, compact. Moreover,

$$f \text{ is differentiable at } x \iff \partial f(x) = \{\nabla f(x)\}.$$

Proposition: Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be any function. Consider

$$(P) \quad \inf_{x \in \mathbb{R}^n} f(x).$$

Then, \bar{x} is optimal for (P) $\iff 0 \in \partial f(\bar{x})$

Proof: \bar{x} is optimal for (P)

$$\iff f(x) \geq f(\bar{x}) + \nabla f(\bar{x})^T(x - \bar{x}) \quad \forall x \in \mathbb{R}^n$$

$$\iff 0 \in \partial f(\bar{x})$$

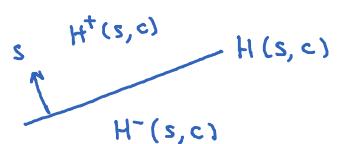
Fundamental objects

- linear functions : $x \mapsto b^T x$

- hyperplanes / halfspaces : $H(s, c) = \{x : s^T x = c\}$

$$H^+(s, c) = \{x : s^T x \geq c\}$$

$$H^-(s, c) = \{x : s^T x \leq c\}$$



Definition: A Polyhedron is an intersection of a finite number of halfspaces.

$$IR^n = \{x : \bar{a}^T x \geq 0\}$$

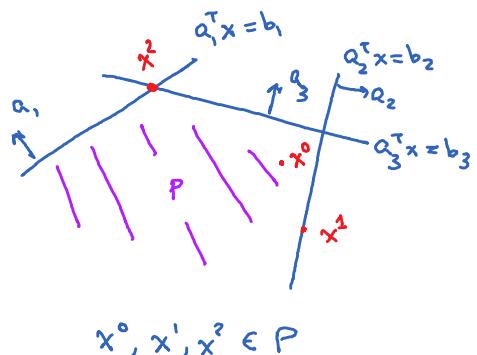
$$P = \bigcap_{d \in IR^n} \{x : d^T x \leq 1\}$$

not a polyhedron

Representation:

$$P = \{x \in IR^n : a_i^T x \leq b_i, i=1, \dots, m\} = \{x \in IR^n : Ax \leq b\}$$

$$A = \begin{bmatrix} -a_1^T \\ \vdots \\ -a_m^T \end{bmatrix} \in IR^{m \times n}$$



$$1) a_i^T x^0 < b_i, \forall i \quad I(x^0) = \emptyset$$

$$2) a_1^T x^1 < b_1, \quad a_2^T x^1 = b_2 \\ a_3^T x^1 < b_3, \quad (\text{active constraint})$$

$$3) a_1^T x^2 = b_1, \quad a_3^T x^2 = b_3, \quad a_2^T x^2 < b_2 \\ (\text{active constraints}) \quad I(x^2) = \{1, 3\}$$

Consider $\bar{x} \in P$. Define $I(\bar{x}) = \{i : a_i^T \bar{x} = b_i\}$ to be the active index set of \bar{x} .

Theorem: Let $\bar{x} \in P \subseteq IR^n$, $I(\bar{x})$ be its active index set. Then, the following are equivalent:

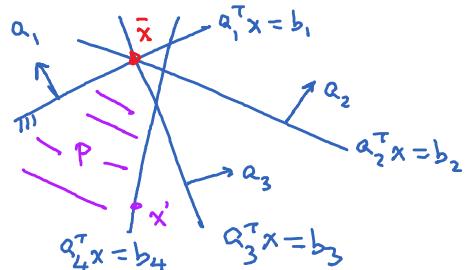
(1) $\exists n$ linearly independent vectors in $\{a_i : i \in I(\bar{x})\}$

(2) \bar{x} is the unique solution to the linear system

$$a_i^T x = b_i, \quad i \in I(\bar{x})$$

e.g.

\mathbb{R}^2 :



$$I(\bar{x}) = \{1, 2, 3\}$$

$\{a_1, a_2, a_3\}$. Any 2 are linearly independent

$$I(x') = \{4\}$$

$$\begin{cases} a_1^T x = b_1 \\ a_2^T x = b_2 \\ a_3^T x = b_3 \end{cases}$$

$\rightarrow \bar{x}$ is the unique solution

$$\{a_4\} \leftarrow \# 2 \text{ linearly indep. vectors} \quad \hookrightarrow \quad a_i^T \bar{x} = b_i, \quad i \in I(\bar{x})$$

x' is a solution to

$$a_i^T x = b_i, \quad i \in I(x')$$

but is not unique.