

projected gradient descent

- projection onto a convex set
- gradient projection method

orthogonal projection onto convex set

for $C \subseteq \mathbb{R}^n$ closed convex,

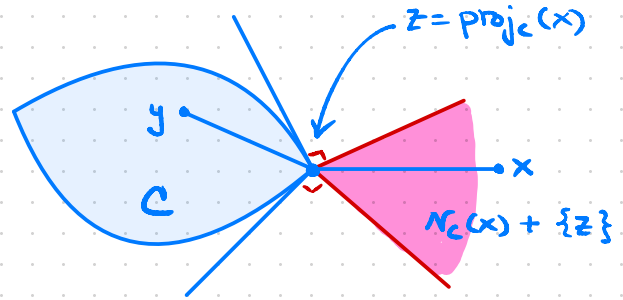
$$\text{proj}_C(x) := \underset{z \in C}{\text{argmin}} \frac{1}{2} \|z - x\|^2$$

properties

- if $x \in C \Rightarrow \text{proj}_C(x) = x$
- $\text{proj}_C(z)$ is unique (because objective is strictly convex)
- $z = \text{proj}_C(x) \Leftrightarrow z \in C$ and $(x - z)^T (y - z) \leq 0 \quad \forall y \in C$ (*)

Proof: let $g(x) := \frac{1}{2} \|x - z\|^2$. By optimality,

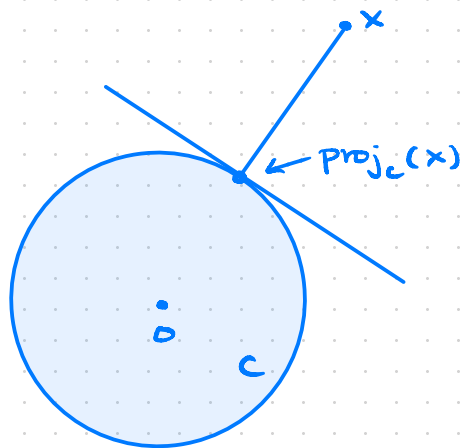
$$z = \text{proj}_C(x) \Leftrightarrow -\nabla g(x) = x - z \in N_C(x) \Leftrightarrow (*)$$



example: Projection onto 2-norm ball

$$C = \{x \mid \|x\|_2 \leq \alpha\} = \alpha B_2$$

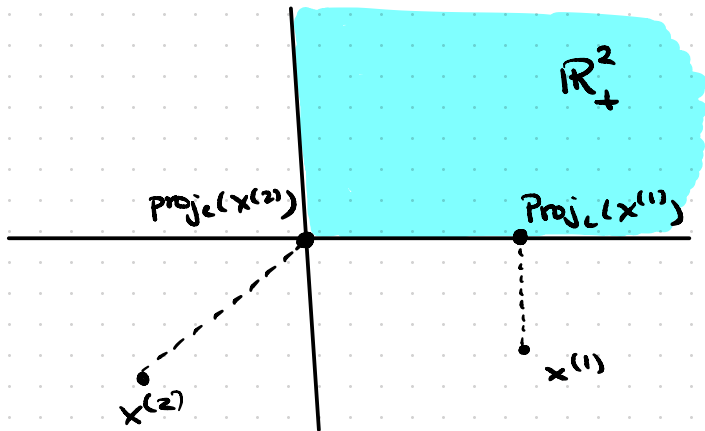
$$\text{proj}_C(x) = \begin{cases} x & \text{if } \|x\|_2 \leq \alpha \\ \alpha \frac{x}{\|x\|_2} & \text{otherwise} \end{cases}$$



example : projection onto nonnegative orthant

$$C = \{x \mid x \geq 0\} = \mathbb{R}_+^n$$

$$\text{proj}_C(x) = \left[\max \{0, x_j\} \right]_{j=1}^n$$



stationarity of projected gradient

$x^* \in \operatorname{argmin}_{x \in C} f(x)$ with $C \subseteq \mathbb{R}^n$ closed convex, $f: \mathbb{R}^n \rightarrow \mathbb{R}$ convex diff'1 iff

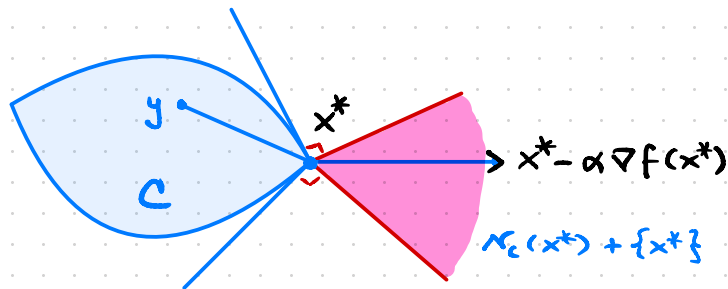
$$x^* = \operatorname{proj}_C(x^* - \alpha \nabla f(x^*)) \quad \forall \alpha > 0$$

by projection theorem:

$$(x^* - \alpha \nabla f(x^*) - x^*)^T (x - x^*) \leq 0 \quad \forall x \in C$$

$$\iff -\nabla f(x^*)^T (x - x^*) \leq 0 \quad \forall x \in C$$

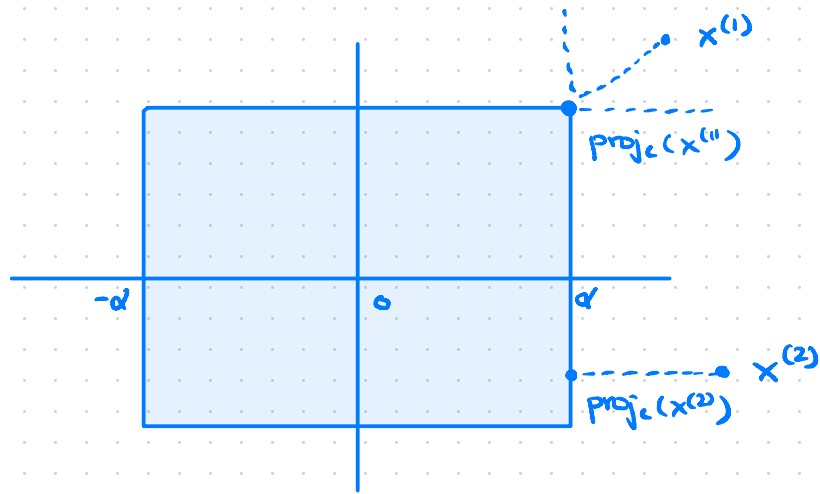
$$\iff -\nabla f(x^*)^T \in \mathcal{N}_C(x^*) \quad (\text{optimality})$$



example: projection onto inf-norm ball

$$C = \{x \mid \|x\|_\infty \leq \alpha\} \quad \|x\|_\infty = \max_{j=1 \dots n} |x_j|$$

$$\text{proj}_C(x) = \left[\text{sign}(x_j) \cdot \min\{\alpha, |x_j|\} \right]_{j=1}^n$$

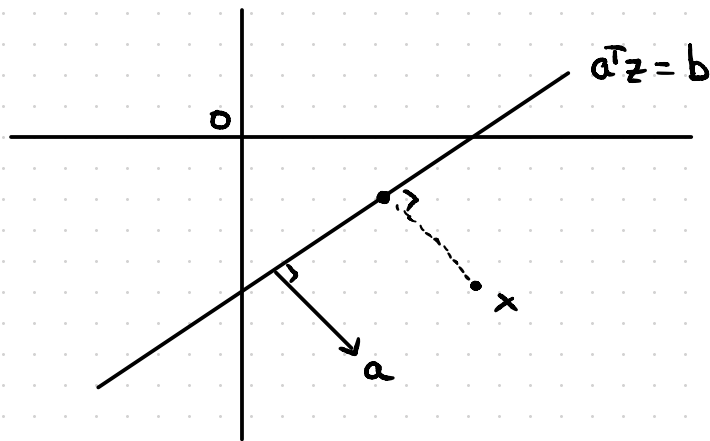


example : projection onto Affine set

$$C = \{x \mid Ax = b\} \quad A = \boxed{\begin{array}{|} \hline / / / \\ \hline \end{array}} \quad \text{full-row rank}$$

$$\text{proj}_C(x) = \underset{z}{\text{argmin}} \left\{ \frac{1}{2} \|z - x\|^2 \mid Az = b \right\}$$

Claim : $x - \text{proj}_C(x) \in \text{?}$



example: de-biasing

$$C = \{ x \mid e^T x = 0 \}$$

$$\text{proj}_C(x) = \underset{z}{\text{argmin}} \left\{ \frac{1}{2} \|z - x\|^2 \mid e^T z = 0 \right\}$$

by optimality, $x - \text{proj}_C(x) \in \text{range}(e)$

$$\Rightarrow x - \text{proj}_C(x) = \alpha e \quad \text{for some } \alpha \in \mathbb{R}$$

$$\Rightarrow \text{proj}_C(x) = x - \alpha e$$

to find α : $0 = e^T \text{proj}_C(x) = e^T (x - \alpha e) = e^T x - \alpha n$

$$\Rightarrow \alpha = \frac{1}{n} e^T x$$

projected gradient descent

solve the differentiable convex optimization problem

$$\min_{x \in C} f(x)$$

$$f: \mathbb{R}^n \rightarrow \mathbb{R} \text{ diff'1 convex}$$

$$C \subseteq \mathbb{R}^n \text{ convex}$$

iteration :

$$x_0 \in C \text{ arbitrary}$$

$$\text{for } k = 0, 1, 2, \dots$$

choose α_k (eg, Armijo, constant, decreasing)

$$x_{k+1} = \text{proj}_C (x_k - \alpha_k \nabla f(x_k))$$

stop if $\|x_k - x_{k+1}\| \leq \epsilon$