

Recall the setting of Scenario 2:

$$\hat{\theta} \in \operatorname{Argmin}_{\theta \in \mathbb{R}^d} \left\{ F(\theta) \triangleq h(A\theta) + R(\theta) \right\} \quad (*)$$

$\mathbb{R}^{n \times d}$
 Strongly convex on compact sets, $\forall h$ Lipschitz
 norm with polyhedral epigraph

As before, \hat{v} is the optimal value and Θ is the optimal solution set.

Local Error Bound Condition

For any $v \geq \hat{v}$, there exist $\mu, \varepsilon > 0$ s.t.

$$\operatorname{dist}(\theta, \Theta) \leq \mu \cdot \|E(\theta)\|_2 \quad \text{--- (EB)}$$

for any $\theta \in \mathbb{R}^d$ satisfying $F(\theta) \leq v$, $\|E(\theta)\|_2 \leq \varepsilon$.

Proposition 1: There exists a $\bar{y} \in \mathbb{R}^n$ such that for all $\hat{\theta} \in \Theta$,

$$A\hat{\theta} = \bar{y}, \quad \nabla \mathcal{L}(\hat{\theta}) = A^T \nabla h(A\hat{\theta}) = A^T \nabla h(\bar{y}) \triangleq \bar{g}$$

In particular,

$$\Theta = \left\{ \theta \in \mathbb{R}^d : A\theta = \bar{y}, \quad -\bar{g} \in \partial R(\theta) \right\}$$

Proof: Let $\theta_1, \theta_2 \in \Theta$ and set $\bar{y}_1 = A\theta_1$, $\bar{y}_2 = A\theta_2$.

Since h is strongly convex on compact sets, if $\bar{y}_1 \neq \bar{y}_2$,

then

$$h\left(\frac{\bar{y}_1 + \bar{y}_2}{2}\right) < \frac{1}{2} h(\bar{y}_1) + \frac{1}{2} h(\bar{y}_2).$$

$$\Leftrightarrow \mathcal{L}\left(\frac{\theta_1 + \theta_2}{2}\right) < \frac{1}{2} \mathcal{L}(\theta_1) + \frac{1}{2} \mathcal{L}(\theta_2) \quad \text{--- (1)}$$

By convexity of R ,

$$R\left(\frac{\theta_1 + \theta_2}{2}\right) \leq \frac{1}{2} R(\theta_1) + \frac{1}{2} R(\theta_2) \quad \text{--- (2)}$$

Adding (1) and (2), $F\left(\frac{\theta_1 + \theta_2}{2}\right) < \frac{1}{2} F(\theta_1) + \frac{1}{2} F(\theta_2) = \hat{v}$,

$\Downarrow \quad \Downarrow$

which is a contradiction. v v

Consider the structure of Θ . We can write

$$\Theta = \Theta_L \cap \Theta_R,$$

where $\Theta_L = \{ \theta \in \mathbb{R}^d : A\theta = \bar{y} \}$, $\Theta_R = \{ \theta \in \mathbb{R}^d : -\bar{g} \in \partial R(\theta) \}$.

Observe: Θ_L is polyhedral

It turns out that Θ_R is also polyhedral. This relies on the following fact:

Fact (Rockafellar: Convex Analysis)

(1) (Theorem 19.2) If R has polyhedral epigraph, so does its conjugate \tilde{R} (recall: $\tilde{R}(y) = \sup_{\theta} \{ \theta^T y - R(\theta) \}$)

(2) (Corollary 23.5.1) $\partial \tilde{R} = (\partial R)^{-1}$; i.e.,

$$\partial \tilde{R}(y) = (\partial R)^{-1}(y) = \{ \theta \in \mathbb{R}^d : y \in \partial R(\theta) \}$$

Hence, $\Theta_R = (\partial R)^{-1}(-\bar{g}) = \partial \tilde{R}(-\bar{g})$.

(3) (Theorem 23.10) If R has polyhedral epigraph and $R(\theta)$ is finite, then $\partial R(\theta)$ is a polyhedron.

By (2), $\Theta_R = \partial \tilde{R}(-\bar{g})$. By (1), since R has polyhedral epigraph, so does \tilde{R} . By (3) (taking $R = \tilde{R}$), we know that $\partial \tilde{R}(-\bar{g})$ is polyhedral if $\tilde{R}(-\bar{g})$ is finite. $\theta = -\bar{g}$

To prove the finiteness of $\tilde{R}(-\bar{g})$, we use the assumption that R is a norm.

Fact: Given a norm R , its conjugate \tilde{R} is

$$\tilde{R}(y) = \begin{cases} 0 & \text{if } R^*(y) \leq 1, \\ \infty & \text{otherwise} \end{cases}$$

$$\tilde{R}(Y) = \begin{cases} 0 & \text{if } R^*(Y) \leq 1, \\ +\infty & \text{o/w;} \end{cases}$$

$\xrightarrow{\text{dual norm}}$

i.e., \tilde{R} is the indicator of the unit ball of R^* .

Since $\Theta \neq \emptyset$, there exists an $\hat{\Theta} \in \Theta_R = \partial \tilde{R}(-\bar{g})$. Hence,

$$\tilde{R}(g) \geq \tilde{R}(-\bar{g}) + \hat{\Theta}^T (g + \bar{g}) \quad \forall g \in \mathbb{R}^d$$

Taking $g=0$, we get $0 \geq \tilde{R}(-\bar{g}) + \hat{\Theta}^T \bar{g}$, which implies

$$\tilde{R}(-\bar{g}) \leq -\hat{\Theta}^T \bar{g} < +\infty. \quad \uparrow \tilde{R}(0) = 0 \text{ since } R^*(0) = 0 \leq 1.$$

Summary: $\Theta = \Theta_L \cap \Theta_R$,

$$\Theta_L = \{ \Theta \in \mathbb{R}^d : A\Theta = \bar{y} \}, \quad \Theta_R = \{ \Theta \in \mathbb{R}^d : -\bar{g} \in \partial R(\Theta) \}$$

polyhedral *polyhedral*

Since we are interested in bounding $\text{dist}(\Theta, \Theta)$, the above motivates us to consider point-polyhedron distance.

Theorem 1 (Hoffman error bound)

Let $P = \{ z \in \mathbb{R}^n : Az \leq b \}$ be a non-empty polyhedron.

Then, there exists a $c > 0$, which depends only on A , s.t.

$$\text{dist}(x, P) \leq c \cdot \| (Ax - b)_+ \|_2 \quad \forall x \in \mathbb{R}^n$$

where $(v)_+ = \max\{v, 0\}$.

Corollary 1: Let $\{P_1, P_2, \dots, P_M\}$ be a finite collection of

polyhedra. Suppose that $P = \bigcap_{i=1}^M P_i \neq \emptyset$. Then, there exists

an $\alpha > 0$ s.t.

$$\text{dist}^2(x, P) \leq \alpha \cdot \sum_{i=1}^M \text{dist}^2(x, P_i) \quad \forall x \in \mathbb{R}^n.$$

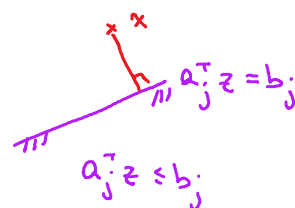
(Thus, $\{P_1, \dots, P_M\}$ is linearly regular.)

Proof of Corollary 1: Let $H_j = \{z \in \mathbb{R}^n : a_j^T z \leq b_j\}$ for $j=1, \dots, L$

and $\{K_1, \dots, K_M\}$ be a partition of $\{1, \dots, L\}$ s.t.

$$P_i = \bigcap_{j \in K_i} H_j. \text{ Observe}$$

(Exercise) \triangleleft $\text{dist}(x, H_j) = \frac{(a_j^T x - b_j)_+}{\|a_j\|_2}$

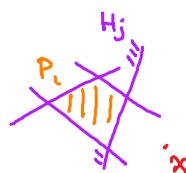


Hence,

$$\text{dist}^2(x, P) \leq c' \sum_{j=1}^L \text{dist}^2(x, H_j) \quad (\text{by Theorem 1})$$

and \triangleleft

$$= c' \sum_{i=1}^M \sum_{j \in K_i} \text{dist}^2(x, H_j)$$



$$\leq c'' \sum_{i=1}^M \text{dist}^2(x, P_i)$$

($\because \text{dist}(x, H_j) \leq \text{dist}(x, P_i)$
for $j \in K_i$)

By the corollary,

$$\text{dist}(\Theta, \Theta) \leq c \cdot [\text{dist}(\Theta, \Theta_L) + \text{dist}(\Theta, \Theta_R)]$$

for some constant $c > 0$. By Theorem 1,

$$\text{dist}(\Theta, \Theta_L) \leq c' \cdot \|A\Theta - \bar{y}\|_2.$$

Next tasks:

① The RHS of the error bound is in terms of $\|E(\Theta)\|_2$. Hence, we need to relate $\|A\Theta - \bar{y}\|_2$ to $\|E(\Theta)\|_2$.

② We cannot apply the same trick to bound $\text{dist}(\Theta, \Theta_R)$, since we do not have an explicit description of Θ_R .

Thus, some new tools are needed.