

# Error Bounds and Facial Residual Functions for Conic Linear Programs

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based on works with Scott B. Lindstrom, Tianxiang Liu,  
Ting Kei Pong, Vera Roshchina and James Saunderson

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OWOS

$$\begin{aligned} \min_x \quad & f(x) \\ \text{subject to} \quad & h(x) = 0 \end{aligned}$$

- Suppose I use my favourite solver and obtain  $x^*$ .
- The solver tells me that the KKT conditions are satisfied to  $\epsilon = 10^{-6}$ .
- It also tells me that  $\|h(x^*)\| \leq 10^{-7}$ .

### Question 1

Is  $x^*$  close to the set of **optimal** solutions?

### Question 2

Is  $x^*$  close to the set of **feasible** solutions?

Distance to a set  $C$ :  $\text{dist}(x, C) := \inf_{y \in C} \|x - y\|$ .

# An example by Sturm (SIOPT'00)

find  $x \in S^3$

subject to  $\begin{pmatrix} x_{11} & x_{33} & x_{13} \\ x_{33} & 0 & 0 \\ x_{13} & 0 & x_{33} \end{pmatrix} \succeq 0.$

- Feasible set: matrices  $\begin{pmatrix} x_{11} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$  with  $x_{11} \geq 0.$

# An example by Sturm

Let  $\epsilon > 0$

$$x_\epsilon := \begin{pmatrix} 3 & \sqrt{\epsilon} & \sqrt[4]{\epsilon} \\ \sqrt{\epsilon} & \epsilon & 0 \\ \sqrt[4]{\epsilon} & 0 & \sqrt{\epsilon} \end{pmatrix}$$

- The constraints are “ $x_{22} = 0$ ”, “ $x_{12} = x_{33}$ ” and “ $x \in \mathcal{S}_+^3$ ”.
- Suppose we measure the violation of constraints by  $x$  using

$$\text{Res}(x) := [x_{22}^2 + (x_{12} - x_{33})^2 + \max\{-\lambda_{\min}(x), 0\}^2]^{1/2}$$

( $\text{Res}(x) = 0 \Leftrightarrow x$  is feasible.)  $x_\epsilon$  does not seem a bad point:

$$\text{Res}(x_\epsilon) = \epsilon$$

But...

$$\text{dist}(x_\epsilon, \text{Feas}) \geq \sqrt[4]{\epsilon}.$$

If  $\epsilon = 10^{-4}$ , we have  $\text{Res}(x_\epsilon) = 10^{-4}$ , but  $\text{dist}(x_\epsilon, \text{Feas}) \geq 0.1$ .



$$\begin{aligned} \min_x \quad & f(x) \\ \text{subject to} \quad & h(x) = 0 \end{aligned}$$

- Suppose I use my favourite solver and obtain  $x^*$ .
- The solver tells me that the KKT conditions are satisfied to  $\epsilon = 10^{-6}$ .
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### Question 1

Is  $x^*$  close to the set of **optimal** solutions?

### Question 2

Is  $x^*$  close to the set of **feasible** solutions?

Answer: **Not necessarily!** Also  $\text{Res}(x_\epsilon) \rightarrow 0$  does not imply  $\text{dist}(x_\epsilon, \text{Feas}) \rightarrow 0 \dots$

# Conclusions

- Using solvers, we input the constraints one by one:  
 $h_1(x) = 0, \dots, h_n(x) = 0, g_1(x) \leq 0, g_2(x) \leq 0, \dots, g_m(x) \leq 0.$
- Solvers can only compute the residuals with respect the  $g_i$  and  $h_j$ .  
(**Backward error**)
  - Some measure of error using  $|h_j(x)|$ ,  $\max\{g_i(x), 0\}$ , or similar quantities are used
- The **true** distance to the feasible region is almost never computable.  
(**Forward error**)

**Backward Error:**  $\text{Res}(x) := [x_{22}^2 + (x_{12} - x_{33})^2 + \max\{-\lambda_{\min}(x), 0\}^2]^{1/2}$

**Forward Error:**  $\text{dist}(x, \text{Feas}).$

## Key point

**Forward error  $\neq O(\text{Backward Error})$**

- The same phenomenon happens for optimal sets: small KKT residual  $\not\Rightarrow$  the point is close to the optimal set.

# What next?

**Error bounds** provide relations between **Forward error** and **Backward error**.

**In this talk:** error bounds for problems involving cones.

# Feasibility problems over convex cones

Consider the following *feasibility problem over a convex cone*  $\mathcal{K}$ .

$$\begin{array}{ll} \text{find} & x \\ \text{subject to} & x \in (\mathcal{L} + a) \cap \mathcal{K} \end{array}$$

- $\mathcal{K}$ : closed convex cone contained in some space  $\mathcal{E}$ .
- $\mathcal{L}$ : subspace contained in  $\mathcal{E}$ .
- $a \in \mathcal{E}$ .

( $\mathcal{L} + a$  is an affine space)



# Motivation

Let  $\|\cdot\|$  be the Euclidean norm and fix  $x \in \mathcal{E}$ .

$$\text{dist}(x, \mathcal{L} + a) = \inf\{\|x - y\| \mid y \in \mathcal{L} + a\}$$

$$\text{dist}(x, \mathcal{K}) = \inf\{\|x - y\| \mid y \in \mathcal{K}\}$$

$$\text{dist}(x, (\mathcal{L} + a) \cap \mathcal{K}) = \inf\{\|x - y\| \mid y \in (\mathcal{L} + a) \cap \mathcal{K}\}$$

## Fundamental question

Can we estimate  $\text{dist}(x, (\mathcal{L} + a) \cap \mathcal{K})$  using  $\text{dist}(x, \mathcal{L} + a)$  and  $\text{dist}(x, \mathcal{K})$ ?



- **Backward error:**  $\text{dist}(x, \mathcal{L} + a) + \text{dist}(x, \mathcal{K})$
- **Forward error:**  $\text{dist}(x, (\mathcal{L} + a) \cap \mathcal{K})$

# Hölderian error bounds

$C_1, C_2$ : closed convex sets.  $C := C_1 \cap C_2$

## Definition (Hölderian error bound)

$C_1, C_2$  satisfy a **Hölderian error bound**  $\stackrel{\text{def}}{\iff}$  for every bounded set  $B$  there exist  $\theta_B > 0$ ,  $\gamma_B \in (0, 1]$  such that

$$\text{dist}(x, C) \leq \theta_B (\text{dist}(x, C_1) + \text{dist}(x, C_2))^{\gamma_B} \quad \forall x \in B.$$

If  $\gamma_B = \gamma \in (0, 1]$  for all  $B$ , the bound is **uniform**. If the bound is uniform with  $\gamma = 1$ , we call it a **Lipschitzian** error bound.

- $\text{ri } C_1 \cap \text{ri } C_2 \neq \emptyset \Rightarrow$  Lipschitzian
- $C_1, C_2$  are polyhedral  $\Rightarrow$  Lipschitzian (Hoffman's Lemma)
- $C_1$ : polyhedral,  $(\text{ri } C_2) \cap C_1 \neq \emptyset \Rightarrow$  Lipschitzian
- $C_1$ : affine space,  $C_2$ : PSD cone  $\Rightarrow$  Uniform Hölderian (Sturm's error bound, SIOPT'00)

# Beyond Sturm's error bound

## Today's goals

- Prove error bounds for general cones beyond  $\mathcal{S}_+^n$  as **tightly** as possible.



Scott B. Lindstrom; L. and Ting Kei Pong

Error bounds, facial residual functions and applications to the exponential cone  
[arXiv:2010.16391](https://arxiv.org/abs/2010.16391)



Scott B. Lindstrom; L. and Ting Kei Pong

Tight error bounds and facial residual functions for the  $p$ -cones and beyond  
[arXiv:2109.11729](https://arxiv.org/abs/2109.11729)



L.

Amenable cones: error bounds without constraint qualifications.

*Mathematical Programming*, 186:1–48, 2021. ([arxiv:1712.06221](https://arxiv.org/abs/1712.06221))



Not gonna lie, these papers are long...

But they are (30%–50% **framework**) + **computation of examples**.



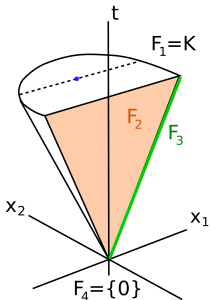
# Review of faces

- $\mathcal{K}$ : closed convex cone
- $\mathcal{F} \subseteq \mathcal{K}$ : closed convex cone

## Definition (Face of a cone)

$\mathcal{F}$  is a face of  $\mathcal{K} \Leftrightarrow$  if  $x + y \in \mathcal{F}$ , with  $x, y \in \mathcal{K}$ , then  $x, y \in \mathcal{F}$ .

If  $\mathcal{F} \subseteq \mathcal{K}$  is a face, we write  $\mathcal{F} \trianglelefteq \mathcal{K}$ .



# Ingredient 1 - Error bounds under a constraint qualification

$$\begin{array}{ll} \text{find} & x \\ \text{subject to} & x \in (\mathcal{L} + a) \cap \mathcal{K} \end{array} \quad (\text{CFP})$$

Proposition (An error bound for when a face satisfying a CQ is known)

Let  $\mathcal{F} \trianglelefteq \mathcal{K}$  be such that

- Ⓐ  $\mathcal{F} \cap (\mathcal{L} + a) = \mathcal{K} \cap (\mathcal{L} + a)$
- Ⓑ  $(\text{ri } \mathcal{F}) \cap (\mathcal{L} + a) \neq \emptyset$

Then, for every bounded set  $B$ , there exists  $\kappa_B > 0$  such that

$$\text{dist}(x, \mathcal{K} \cap (\mathcal{L} + a)) \leq \kappa_B (\text{dist}(x, \mathcal{F}) + \text{dist}(x, \mathcal{L} + a)), \quad \forall x \in B.$$

It is not an error bound with respect to  $\mathcal{L} + a$  and  $\mathcal{K}$ , but it is close.

# General strategy

**Goal:** We want to bound  $\text{dist}(x, (\mathcal{L} + a) \cap \mathcal{K})$  using  $\text{dist}(x, \mathcal{L} + a)$  and  $\text{dist}(x, \mathcal{K})$ .

- 1 Find  $\mathcal{F}$  such that
  - a  $\mathcal{F} \cap (\mathcal{L} + a) = \mathcal{K} \cap (\mathcal{L} + a)$
  - b  $(\text{ri } \mathcal{F}) \cap (\mathcal{L} + a) \neq \emptyset$

Therefore,

$$\text{dist}(x, \mathcal{K} \cap (\mathcal{L} + a)) \leq \kappa_B(\text{dist}(x, \mathcal{F}) + \text{dist}(x, \mathcal{L} + a)), \quad \forall x \in B. \quad (1)$$

- 2 Upper bound  $\text{dist}(x, \mathcal{F})$  using  $\text{dist}(x, \mathcal{K})$  and  $\text{dist}(x, \mathcal{L} + a)$ .
- 3 Plug the upper bound in (1).

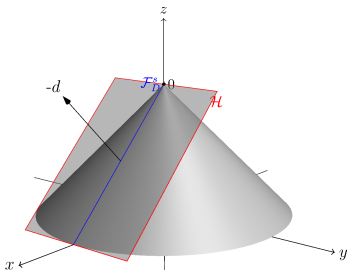
# How to find $\mathcal{F}$ ?

We want  $\mathcal{F}$  such that

- Ⓐ  $\mathcal{F} \cap (\mathcal{L} + a) = \mathcal{K} \cap (\mathcal{L} + a)$
- Ⓑ  $(\text{ri } \mathcal{F}) \cap (\mathcal{L} + a) \neq \emptyset$

**Idea:**

- 1 Let  $\mathcal{F}_1 = \mathcal{K}$  and  $i \leftarrow 1$ .
- 2 If  $(\mathcal{L} + a) \cap \text{ri } \mathcal{F}_i \neq \emptyset$ , we are done.
- 3 If  $(\mathcal{L} + a) \cap \text{ri } \mathcal{F}_i = \emptyset$ , we invoke a separation theorem.
  - There exists  $z_i \in \mathcal{F}_i^* \setminus \mathcal{F}_i^\perp$  and  $z_i \in \mathcal{L}^\perp \cap \{a\}^\perp$ .
  - Let  $\mathcal{F}_{i+1} \leftarrow \mathcal{F}_i \cap \{z_i\}^\perp$  and  $i \leftarrow i + 1$ . Go to Step 2.



# How to find $\mathcal{F}$ ? - Facial Reduction

## Theorem (The facial reduction theorem)

Suppose (CFP) is feasible. There is a chain of faces

$$\mathcal{F}_\ell \subsetneq \cdots \subsetneq \mathcal{F}_1 = \mathcal{K}$$

and vectors  $(z_1, \dots, z_{\ell-1})$  such that:

- ① For all  $i \in \{1, \dots, \ell - 1\}$ , we have

$$z_i \in \mathcal{F}_i^* \cap \mathcal{L}^\perp \cap \{a\}^\perp,$$

$$\mathcal{F}_{i+1} = \mathcal{F}_i \cap \{z_i\}^\perp.$$

- ②  $\mathcal{F}_\ell \cap (\mathcal{L} + a) = \mathcal{K} \cap (\mathcal{L} + a)$  and  $(\text{ri } \mathcal{F}_\ell) \cap (\mathcal{L} + a) \neq \emptyset$ .



L. M. Muramatsu and T. Tsuchiya.

Facial reduction and partial polyhedrality.

*SIAM Journal on Optimization*, 28(3), 2018 (<http://arxiv.org/abs/1512.02549>).



J. M. Borwein and H. Wolkowicz.

Regularizing the abstract convex program.

*Journal of Mathematical Analysis and Applications*, 83(2):495 – 530, 1981.



# General strategy

**Goal:** We want to bound  $\text{dist}(x, (\mathcal{L} + a) \cap \mathcal{K})$  using  $\text{dist}(x, \mathcal{L} + a)$  and  $\text{dist}(x, \mathcal{K})$ .

- 1 Find  $\mathcal{F}$  such that
  - a  $\mathcal{F} \cap (\mathcal{L} + a) = \mathcal{K} \cap (\mathcal{L} + a)$
  - b  $(\text{ri } \mathcal{F}) \cap (\mathcal{L} + a) \neq \emptyset$

Therefore,

$$\text{dist}(x, \mathcal{K} \cap (\mathcal{L} + a)) \leq \kappa_B(\text{dist}(x, \mathcal{F}) + \text{dist}(x, \mathcal{L} + a)), \quad \forall x \in B. \quad (1)$$

- 2 Upper bound  $\text{dist}(x, \mathcal{F})$  using  $\text{dist}(x, \mathcal{K})$  and  $\text{dist}(x, \mathcal{L} + a)$ .
- 3 Plug the upper bound in (1).

**Step 1 done!**

# Ingredient 2 - One-step Facial Residual Functions

Let

- $\mathcal{K}$ : closed convex cone.
- $z \in \mathcal{K}^*$

## Definition (1-FRF for $\mathcal{K}$ and $z$ )

If  $\psi_{\mathcal{K},z} : \mathbb{R}_+ \times \mathbb{R}_+ \rightarrow \mathbb{R}_+$  satisfies

- 1  $\psi_{\mathcal{K},z}$  is nonnegative, monotone nondecreasing in each argument and  $\psi(0, \alpha) = 0$  for every  $\alpha \in \mathbb{R}_+$ .
- 2 whenever  $x \in \text{span } \mathcal{K}$  satisfies the inequalities

$$\text{dist}(x, \mathcal{K}) \leq \epsilon, \quad \langle x, z \rangle \leq \epsilon,$$

we have:

$$\text{dist}(x, \mathcal{K} \cap \{z\}^\perp) \leq \psi_{\mathcal{K},z}(\epsilon, \|x\|).$$

# Main result

Theorem (Error bound based on  $\mathbb{1}$ -FRF, Lindstrom, L., Pong)

Let  $\mathcal{K}$  be a closed convex cone such that  $\mathcal{K} \cap (\mathcal{L} + \mathbf{a}) \neq \emptyset$ . Let

$$\mathcal{F}_\ell \subsetneq \cdots \subsetneq \mathcal{F}_1 = \mathcal{K}$$

be a chain of faces of  $\mathcal{K}$  together with  $z_i \in \mathcal{F}_i^* \cap \mathcal{L}^\perp \cap \{\mathbf{a}\}^\perp$  such that

$$(\mathcal{L} + \mathbf{a}) \cap \text{ri } \mathcal{F}_\ell \neq \emptyset.$$

and  $\mathcal{F}_{i+1} = \mathcal{F}_i \cap \{z_i\}^\perp$  for every  $i$ . Let  $\psi_i$  be a  $\mathbb{1}$ -FRF for  $\mathcal{F}_i$ ,  $z_i$ . Then, there is a suitable positively rescaled shift of the  $\psi_i$ , such that for every bounded  $B$  there are  $\kappa > 0$ ,  $M > 0$  such that

$$x \in B, \quad \text{dist}(x, \mathcal{K}) \leq \epsilon, \quad \text{dist}(x, \mathcal{L} + \mathbf{a}) \leq \epsilon,$$

implies

$$\text{dist}(x, (\mathcal{L} + \mathbf{a}) \cap \mathcal{K}) \leq \kappa(\epsilon + \varphi(\epsilon, M)),$$

where  $\varphi = \psi_{\ell-1} \diamond \cdots \diamond \psi_1$ , if  $\ell \geq 2$ . If  $\ell = 1$ , we let  $\varphi$  be the function satisfying  $\varphi(\epsilon, \|x\|) = \epsilon$ .

$$(f \diamond g)(a, b) := f(a + g(a, b), b).$$

## Main result

**Theorem (Error bound based on  $\mathbb{1}$ -FRF, Lindstrom, L., Pong)**

Let  $\mathcal{K}$  be a closed convex cone such that  $\mathcal{K} \cap (\mathcal{L} + a) \neq \emptyset$ . Let

$$\mathcal{F}_\ell \subsetneq \cdots \subsetneq \mathcal{F}_1 = \mathcal{K}$$

be a chain of faces of  $\mathcal{K}$  together with  $z_i \in \mathcal{F}_i^* \cap \mathcal{L}^\perp \cap \{a\}^\perp$  such that

$$(\mathcal{L} + a) \cap \text{ri } \mathcal{F}_\ell \neq \emptyset.$$

and  $\mathcal{F}_{i+1} = \mathcal{F}_i \cap \{z_i\}^\perp$  for every  $i$ . Let  $\psi_i$  be a  $\mathbb{1}$ -FRF for  $\mathcal{F}_i$ ,  $z_i$ . Then, there is a suitable positively rescaled shift of the  $\psi_i$ , such that for every bounded  $B$  there are  $\kappa > 0$ ,  $M > 0$  such that

$$x \in B, \quad \text{dist}(x, \mathcal{K}) \leq \epsilon, \quad \text{dist}(x, \mathcal{L} + a) \leq \epsilon,$$

implies

$$\text{dist}(x, (\mathcal{L} + a) \cap \mathcal{K}) \leq \kappa(\epsilon + \varphi(\epsilon, M)),$$

where  $\varphi = \psi_{\ell-1} \diamond \cdots \diamond \psi_1$ , if  $\ell \geq 2$ . If  $\ell = 1$ , we let  $\varphi$  be the function satisfying  $\varphi(\epsilon, \|x\|) = \epsilon$ .

$$(f \diamond g)(a, b) := f(a + g(a, b), b).$$

# The case of symmetric cones - L'21

- $\mathcal{K}$ : symmetric cone (psd matrices, second order cone and etc)
- $\mathbb{1}$ -FRF:  $\psi_{\mathcal{F},z}(\epsilon, t) = \kappa\epsilon + \kappa\sqrt{\epsilon t}$

Suppose  $(\mathcal{L} + a) \cap \mathcal{K} \neq \emptyset$ .

There exists  $\gamma \geq 0$  such that for every bounded  $B$ , there exists  $\kappa_B$  such that

$$\text{dist}(x, (\mathcal{L} + a) \cap \mathcal{K}) \leq \kappa_B (\text{dist}(x, \mathcal{L} + a) + \text{dist}(x, \mathcal{K}))^{(2^{-\gamma})}, \quad \forall x \in B$$

where  $\gamma$  is the number of facial reduction steps.

**Reminder:**  $z \in \mathcal{F}^*$  and

$$x \in \text{span } \mathcal{F}, \quad \text{dist}(x, \mathcal{F}) \leq \epsilon, \quad \langle x, z \rangle \leq \epsilon,$$

implies

$$\text{dist}(x, \mathcal{F} \cap \{z\}^\perp) \leq \psi_{\mathcal{F},z}(\epsilon, \|x\|).$$

# p-cones

Let  $\|\bar{x}\|_p := \sqrt[p]{|\bar{x}_1|^p + \dots + |\bar{x}_n|^p}$ .

- $\mathcal{K}_p^{n+1} := \{x = (x_0, \bar{x}) \in \mathbb{R}^{n+1} \mid x_0 \geq \|\bar{x}\|_p\}$
- Non-homogeneous, not self-dual even if the inner product is changed<sup>1</sup>
- $\mathbb{1}$ -FRF:  $\psi_{\mathcal{K}_p^{n+1}, z}(\epsilon, t) = \kappa\epsilon + \kappa(\epsilon t)^{\alpha_z}$

$$\alpha_z := \begin{cases} \frac{1}{2} & \text{if } |\bar{z}|_0 = n, \\ \frac{1}{p} & \text{if } |\bar{z}|_0 = 1 \text{ and } p < 2, \\ \min\left\{\frac{1}{2}, \frac{1}{p}\right\} & \text{otherwise,} \end{cases}$$

For every bounded  $B$ , there exists  $\kappa_B$  such that

$$\text{dist}(x, (\mathcal{L} + a) \cap \mathcal{K}_p^{n+1}) \leq \kappa_B (\text{dist}(x, \mathcal{L} + a) + \text{dist}(x, \mathcal{K}_p^{n+1}))^{\alpha_z}, \quad \forall x \in B$$

**Tight result:** the exponents cannot be improved.

<sup>1</sup>The automorphism group and the non-self-duality of p-cones, by Ito and L., JMAA'19

# Least squares with $p$ -norm regularization

$$\theta = \min_{x \in \mathbb{R}^n} g(x) := \frac{1}{2} \|Ax - b\|^2 + \sum_{i=1}^s \lambda_i \|x_i\|_p, \quad (\text{LS})$$

Conic reformulation:

$$\begin{aligned} \min_{t, u, w, y, x} \quad & 0.5t + \sum_{i=1}^s \lambda_i y_i \\ \text{s.t.} \quad & Ax - w = b, \quad u = 1 \\ & (t, u, w) \in \mathcal{Q}_r^{m+2}, \quad (y_i, x_i) \in \mathcal{K}_p^{n_i+1}, \quad i = 1, \dots, s. \end{aligned}$$

The **optimal set** is the intersection of

$$\mathcal{L} + \mathbf{a} = \left\{ v \mid 0.5t + \sum_{i=1}^s \lambda_i y_i = \theta, u = 1, Ax - w = b \right\}$$

with the cone

$$\mathcal{K} = \mathcal{Q}_r^{m+2} \times \mathcal{K}_p^{n_1+1} \times \dots \times \mathcal{K}_p^{n_s+1}.$$

$\Rightarrow g$  satisfies a Hölderian error bound condition with an **explicit** exponent<sup>2</sup>

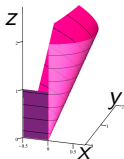
## Theorem (LLP'21)

Let  $x^*$  be an optimal solution to (LS). Under a mild condition,  $g$  satisfies the KL property at  $x^*$  with exponent  $1 - \alpha$ , where  $\alpha = \min\{0.5, 1/p\}$ .

<sup>2</sup>See *Kurdyka-Łojasiewicz Exponent via Inf-projection*, by Yu, Li, Pong, FoCM'21

# The exponential cone

$$K_{\text{exp}} := \left\{ (x, y, z) \mid y > 0, z \geq ye^{x/y} \right\} \cup \left\{ (x, y, z) \mid x \leq 0, z \geq 0, y = 0 \right\}.$$



- 1 Applications to entropy optimization, logistic regression, geometric programming and etc.
- 2 Available in Alfonso, Hypatia, Mosek, SCS.  
<https://docs.mosek.com/modeling-cookbook/expo.html>.



V. Chandrasekaran, P. Shah

Relative entropy optimization and its applications.

*Math. Program.* 161, 1–32 (2017)



# Error bounds for the exponential cone - LLP'20

$$\begin{aligned} & \text{find } x && \text{(CFP)} \\ & \text{subject to } x \in (\mathcal{L} + a) \cap K_{\text{exp}} \end{aligned}$$

Four types of error bounds are possible:

- Lipschitzian error bound
- Hölderian error bound with exponent 1/2
- **Entropic error bound:** for every bounded set  $B$ , there exists  $\kappa_B > 0$

$$\text{dist}(x, (\mathcal{L} + a) \cap K_{\text{exp}}) \leq \kappa_B g_{-\infty}(\max(\text{dist}(x, \mathcal{L} + a), \text{dist}(x, K_{\text{exp}}))), \quad \forall x \in B.$$

- **Logarithmic error bound:** for every bounded set  $B$ , there exists  $\kappa_B > 0$

$$\text{dist}(x, (\mathcal{L} + a) \cap K_{\text{exp}}) \leq \kappa_B g_{\infty}(\max(\text{dist}(x, \mathcal{L} + a), \text{dist}(x, K_{\text{exp}}))), \quad \forall x \in B,$$

where

$$g_{-\infty}(t) := -t \ln(t), \quad g_{\infty}(t) := -\frac{1}{\ln(t)}, \quad (\text{for } t \text{ small}).$$

The results above are **tight**.

# Some remarks

- More stuff in the papers! Ex: direct products, techniques for obtaining FRFs, for proving tightness and so on.



Scott B. Lindstrom; L and Ting Kei Pong

Error bounds, facial residual functions and applications to the exponential cone

[arXiv:2010.16391](https://arxiv.org/abs/2010.16391)



Scott B. Lindstrom; L and Ting Kei Pong

Tight error bounds and facial residual functions for the  $p$ -cones and beyond

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Other advertisement:



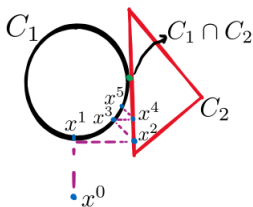
T. Liu and L.

Convergence analysis under consistent error bounds

[arXiv:2008.12968](https://arxiv.org/abs/2008.12968)



Error bounds provide information on the speed of algorithms



Lipschitzian error bound  $\implies$  **Linear** convergence :

$$\text{dist}(x^k, C_1 \cap C_2) \leq M\theta^k$$

Hölderian error bound  $\implies$  **Sublinear** convergence:

$$\text{dist}(x^k, C_1 \cap C_2) \leq Mk^{-\alpha}$$



J. M. Borwein, G. Li, and M. K. Tam.

Convergence rate analysis for averaged fixed point iterations in common fixed point problems.

*SIAM Journal on Optimization*, 27(1):1–33, 2017.

# Consistent error bounds

$C_1, \dots, C_m \subseteq \mathbb{R}^n$ : closed convex sets

## Definition (Consistent error bound functions)

$\Phi : \mathbb{R}_+ \times \mathbb{R}_+ \rightarrow \mathbb{R}_+$  is a (**strict**) **consistent error bound function** for  $C_1, \dots, C_m$  if:

i

$$\text{dist}(x, \cap_{i=1}^m C_i) \leq \Phi \left( \max_{1 \leq i \leq m} \text{dist}(x, C_i), \|x\| \right) \quad \forall x \in \mathbb{R}^n;$$

ii

$\forall b \geq 0$ ,  $\Phi(\cdot, b)$  is monotone (**increasing**) nondecreasing, right-continuous at 0 and  $\Phi(0, b) = 0$ ;

iii

$\forall a \geq 0$ ,  $\Phi(a, \cdot)$  is monotone nondecreasing.

Fact:  $\cap_{i=1}^m C_i \neq \emptyset \Rightarrow \exists \Phi$  a **strict consistent error bound function** for  $C_1, \dots, C_m$



T. Liu and L.

Convergence analysis under consistent error bounds

[arXiv:2008.12968](https://arxiv.org/abs/2008.12968) (Revised in 03/2022)

# Main convergence result

$C_1, \dots, C_m \subseteq \mathbb{R}^n$ : closed convex sets.  $C = \bigcap_{i=1}^m C_i$ .

$\Phi$ : *strict* consistent error bound function

$\{x^k\}$ : sequence by some reasonable algorithm

For  $\kappa > 0$  and  $\delta > 0$  define  $\phi_{\kappa, \Phi}(t) := (\Phi(\sqrt{t}, \kappa))^2$

$$\Phi_{\kappa}^{\spadesuit}(t) := \int_{\delta}^t \frac{1}{\phi_{\kappa, \Phi}^{-}(s)} ds$$

Then, the convergence of  $\{x^k\}$  is either finite or  $\exists \tau > 0$

$$\text{dist}(x^k, C) \leq \sqrt{(\Phi_{\hat{\kappa}}^{\spadesuit})^{-1}(L - \tau k)} \quad \forall k \geq 2l,$$

where  $\hat{\kappa} = \|x^0\| + 2 \text{dist}(0, C)$  and  $L = \Phi_{\hat{\kappa}}^{\spadesuit}(\text{dist}^2(x^0, C))$ .

Gee... that looks like hard.  How practical is that?

- For consistent error bound functions associated to Hölderian error bounds  $(\Phi_{\hat{\kappa}}^{\spadesuit})^{-1}$  has **closed form**.
- For other types of error bounds, there are upper bounds based on **Karamata theory**.

$f : (0, a] \rightarrow (0, \infty)$  is **regularly varying at 0** with index  $\rho$  if

$$\lim_{x \rightarrow 0_+} \frac{f(\lambda x)}{f(x)} = \lambda^\rho, \quad \lambda > 0,$$

- Asymptotic behavior of regularly varying functions under taking integrals, inverses, powers is **very** well-understood.



N. H. Bingham, C. M. Goldie, and J. L. Teugels.

*Regular Variation.*

Encyclopedia of Mathematics and its Applications. Cambridge University Press, 1987.

# Convergence rates under exotic error bounds - LL'20

Recall that

$$\text{dist}(x^k, C_1 \cap C_2) \leq \sqrt{(\Phi_{\kappa}^{\spadesuit})^{-1}(L - \tau k)} \quad \forall k \geq M,$$

Then,

- ④ **Entropic error bound:** The convergence rate is **almost linear**: for any  $r > 0$ , the following relations hold as  $s \rightarrow +\infty$

$$\sqrt{((\Phi_{\kappa}^{\spadesuit})^{-1}(-s))} = o(s^{-r}), \quad e^{-rs} = o\left(\sqrt{((\Phi_{\kappa}^{\spadesuit})^{-1}(-s))}\right).$$

- ④ **Logarithmic error bound:** The convergence rate is logarithmic

$$\eta_1\left(\frac{1}{\ln(s)}\right) \leq \sqrt{((\Phi_{\kappa}^{\spadesuit})^{-1}(-s))} \leq \eta_2\left(\frac{1}{\ln(s)}\right), \quad \forall s \geq N.$$

Blue and Red are upper and lower bounds, respectively

# Amenable cones

## Definition (Amenable cones)

$\mathcal{K}$  is **amenable** if for every face  $\mathcal{F}$  of  $\mathcal{K}$  there is  $\kappa > 0$  such that

$$\text{dist}(x, \mathcal{F}) \leq \kappa \text{dist}(x, \mathcal{K}), \quad \forall x \in \text{span } \mathcal{F}.$$

- Symmetric cones (e.g., PSD cone) are amenable ( $\kappa = 1$ )
- Polyhedral cones are amenable
- Strictly convex cones are amenable. ( $p$ -cones, second order cones and so on)
- Amenability is preserved under linear isomorphisms



L, V. Roshchina and J. Saunderson  
 Amenable cones are particularly nice.  
[arxiv:2011.07745](https://arxiv.org/abs/2011.07745)



L, V. Roshchina and J. Saunderson  
 Hyperbolicity cones are amenable.  
[arxiv:2102.06359](https://arxiv.org/abs/2102.06359)



L.  
 Amenable cones: error bounds without constraint qualifications.



# Facial exposedness

$$\mathcal{F} \text{ is a face of } \mathcal{K} \stackrel{\text{def}}{\iff} \mathcal{F} \trianglelefteq \mathcal{K}$$

① Projectionally exposed cone (BW'81)  $\stackrel{\text{def}}{\iff} \forall \mathcal{F} \trianglelefteq \mathcal{K}$  there exists a projection such that  $P\mathcal{K} = \mathcal{F}$ .

② Amenable cones (L'21)  $\stackrel{\text{def}}{\iff} \forall \mathcal{F} \trianglelefteq \mathcal{K}$  there is  $\kappa > 0$  such that


$$\text{dist}(x, \mathcal{F}) \leq \kappa \text{dist}(x, \mathcal{K}), \quad \forall x \in \text{span } \mathcal{F}.$$

③ Nice cone (P'07)  $\stackrel{\text{def}}{\iff} \forall \mathcal{F} \trianglelefteq \mathcal{K}, \quad \mathcal{F}^* = \mathcal{K}^* + \mathcal{F}^\perp.$

④ Facially exposed cone  $\stackrel{\text{def}}{\iff} \forall \mathcal{F} \trianglelefteq \mathcal{K}, \quad \exists z \in \mathcal{K}, \text{ s.t. } \mathcal{F} = \mathcal{K} \cap \{z\}^\perp.$

Other curious types of cones:

① Perfect cones (B'78)  $\stackrel{\text{def}}{\iff} \mathcal{K}$  is self-dual and every face  $\mathcal{F} \trianglelefteq \mathcal{K}$  is self-dual over  $\text{span } \mathcal{F}$ .

② Devious cones  (TW'12)  $\stackrel{\text{def}}{\iff} \mathcal{K} + \text{span } \mathcal{F}$  is not closed for  $\{0\} \neq \mathcal{F} \trianglelefteq \mathcal{K}$ .

# A comparison table

		Exposed	Nice	Amenable	Projectionally
Preserved under	finite intersections	✓	✓	✓	?
	direct product	✓	✓	✓	✓
	injective linear image	✓	✓	✓	✓
Symmetric cones		✓	✓(CT'08)	✓	✓L'21
Homogeneous cones		✓	✓(CT'08)	✓LRS'20	?
Hyperbolicity cones		✓(R'05)	✓	✓LRS'21	?

- Facially exposed  $\stackrel{P'13}{\Leftarrow}$  Nice  $\stackrel{L'21}{\Leftarrow}$  **Amenable**  $\stackrel{EPBR}{\Leftarrow}$  Projectionally exposed.
- There exists a 4D cone that is facially exposed but not nice (Vera, SIOPT'14).
- There exists a 4D cone that is nice but not amenable LRS'20
- In dimension 4 or less: Amenable  $\Leftrightarrow$  Projectionally exposed. LRS'20

# Open questions

- Is there an amenable cone that is not projectionally exposed?  
 ( $\dim \mathcal{K} \geq 5$  must hold!)
- Which cones are projectionally exposed?



L. V. Roshchina and J. Saunderson

Amenable cones are particularly nice.

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L. V. Roshchina and J. Saunderson

Hyperbolicity cones are amenable.

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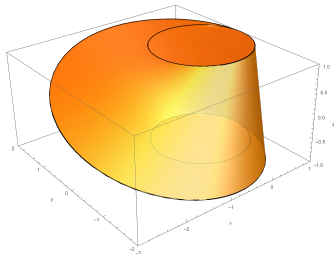
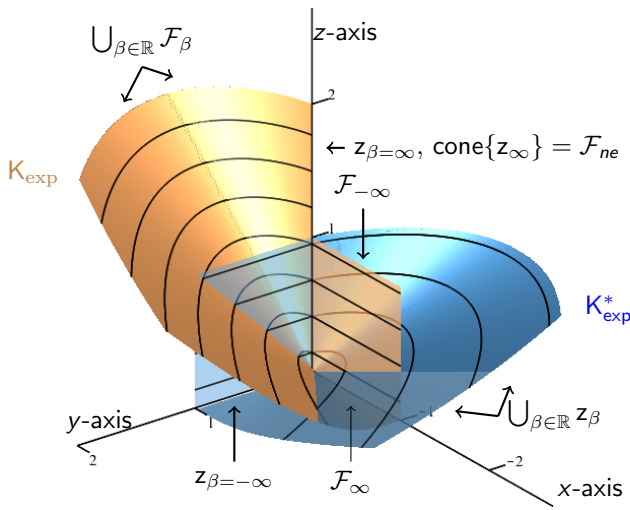


Figure: A 3D slice of a 4D convex cone that is nice but not amenable



**Figure:** The exponential cone and its dual, with faces and exposing vectors labeled according to our index  $\beta$ .

# Consequences for symmetric cone programming

$$\begin{aligned} \min_x \quad & c^T x \\ \text{subject to} \quad & Ax = b \\ & x \in \mathcal{K} \end{aligned}$$

Over a bounded set  $B$ :

**For the feasible set:**

- Under Slater: **Forward error** =  $O(\mathbf{Backward Error})$ .
- Without Slater: **Forward error** =  $O((\mathbf{Backward Error})^{2^{-\gamma}})$

**For the optimal set:**

- Strict complementarity holds:  $x^* + s^* \in \text{ri } \mathcal{K} \Leftrightarrow x^* \in \text{ri}(\mathcal{K} \cap \{s^*\}^\perp)$ 
  - $\text{Opt} = \{x \mid c^T x = \theta, Ax = b, x \in \mathcal{K}\}$  intersects  $\text{ri}(\mathcal{K} \cap \{s^*\}^\perp)$
  - Facial reduction finishes in 1 step.
- Under Strict complementarity:  
**Forward error** =  $O(\sqrt{\mathbf{Backward Error}})$