

On optimization on the Euclidean unit sphere

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Optimization without Borders

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Nesterov's 60th and Protasov's 50th birthdate

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Based on :

[Homogeneous polynomials and spurious local minima on the unit sphere](#)

[arXiv:2010.07066](#)

[Optimization on the Euclidean unit sphere](#)

[hal-03284041](#)

- **Homogeneous** optimization on \mathbb{S}^{n-1}

- ☞ Simple and complete characterization of first and second-order optimality conditions

- **Sparse** optimization on \mathbb{S}^{n-1}

- ☞ (when the criterion to minimize is a function of a few linear forms)

I. Homogeneous polynomials & spurious local minima on the unit sphere

Let \mathbb{S}^{n-1} be the Euclidean unit sphere $\{\mathbf{x} : \|\mathbf{x}\| = 1\} \subset \mathbb{R}^n$, and \mathcal{E}_n the Euclidean unit ball $\{\mathbf{x} : \|\mathbf{x}\| \leq 1\}$.

Consider the optimization problem

$$\mathbf{P} : \quad f^* = \min \{f(\mathbf{x}) : \mathbf{x} \in \mathbb{S}^{n-1}\}$$

where f is a **homogeneous** polynomial of degree t .

👉 Problem **P** is **NP-hard** in general with several important applications, and in particular for some well-known combinatorial optimization problems.

- Finding the **maximal cardinality** $\alpha(G)$ of a stable set in a graph G reduces to minimizing a **cubic form** on \mathbb{S}^{n-1} .
- Deciding **convexity** of an n -variate form reduces to minimizing a form on \mathbb{S}^{n-1} .
- Deciding **nonnegativity** of an even-degree form reduces to minimizing this form on \mathbb{S}^{n-1} .
- Deciding **copositivity** of a symmetric matrix reduces to check whether some associated **quartic form** is nonnegative on \mathbb{S}^{n-1} .
- In **quantum information**, the **Best Separable State problem** also relates to homogeneous polynomial optimization on \mathbb{S}^{n-1} (Fawzi et al.)

In the first part of the talk, f is a form of degree $t > 2$.

This talk

A **complete** & **simple** characterization of Second-Order Necessary Optimality conditions (SONC) at $\mathbf{x}^* \in \mathbb{S}^{n-1}$ solely in terms of

- $f(\mathbf{x}^*)$
- The first two **smallest eigenvalues** $\lambda_1(\nabla^2 f(\mathbf{x}^*))$ and $\lambda_2(\nabla^2 f(\mathbf{x}^*))$ of the Hessian $\nabla^2 f$ at $\mathbf{x}^* \in \mathbb{S}^{n-1}$.

First-Order Necessary Optimality Conditions (FONC)

A point $\mathbf{x}^* \in \mathbb{S}^{n-1}$ satisfies (FONC) if and only if

$$\nabla f(\mathbf{x}^*) = t f(\mathbf{x}^*) \mathbf{x}^*$$

Equivalently, if and only if

$$\|\nabla f(\mathbf{x}^*)\|^2 = t^2 f(\mathbf{x}^*)^2.$$

Démonstration.

KKT-optimality conditions yield

$$\nabla f(\mathbf{x}^*) = 2 \lambda^* \mathbf{x}^*, \quad \text{for some } \lambda^*$$

Euler's identity for homogeneous functions yields

$$t f(\mathbf{x}^*) = \langle \mathbf{x}^*, \nabla f(\mathbf{x}^*) \rangle = 2 \lambda^* \|\mathbf{x}^*\|^2 = 2 \lambda^*.$$

$$\Rightarrow \nabla f(\mathbf{x}^*) = t f(\mathbf{x}^*) \mathbf{x}^* \quad \text{and} \quad \|\nabla f(\mathbf{x}^*)\|^2 = t^2 f(\mathbf{x}^*)^2.$$



Démonstration.

(Continued) Conversely, suppose that $\|\nabla f(\mathbf{x}^*)\|^2 = t^2 f(\mathbf{x}^*)^2$. Then

$$\begin{aligned} \|\nabla f(\mathbf{x}^*) - t f(\mathbf{x}^*) \mathbf{x}^*\|^2 &= \|\nabla f(\mathbf{x}^*)\|^2 - \underbrace{2t f(\mathbf{x}^*) \langle \nabla f(\mathbf{x}^*), \mathbf{x}^* \rangle}_{=-2t^2 f(\mathbf{x}^*)^2} \\ &\quad + t^2 f(\mathbf{x}^*)^2 \|\mathbf{x}^*\|^2 \\ &= \|\nabla f(\mathbf{x}^*)\|^2 - t^2 f(\mathbf{x}^*)^2 = 0 \\ \Rightarrow \nabla f(\mathbf{x}^*) &= t f(\mathbf{x}^*) \mathbf{x}^*, \end{aligned}$$

that is, **(FONC)** holds with $2\lambda^* = t f(\mathbf{x}^*)$. □

Given $\mathbf{x} \in \mathbb{R}^n$, let

$$\mathbf{x}^\perp := \{ \mathbf{u} \in \mathbb{S}^{n-1} : \mathbf{u} \perp \mathbf{x}^* \}.$$

Second-Order Necessary Optimality Conditions (SONC)

Definition : A point $\mathbf{x}^* \in \mathbb{S}^{n-1}$ which satisfies (FONC) satisfies (SONC) if

$$\langle \mathbf{u}, (\nabla^2 f(\mathbf{x}^*) - 2\lambda^* \mathbf{I}) \mathbf{u} \rangle \geq 0, \quad \forall \mathbf{u} \perp \mathbf{x}^*.$$

Equivalently, if and only if

$$\langle \mathbf{u}, \nabla^2 f(\mathbf{x}^*) \mathbf{u} \rangle \geq 2\lambda^* (= tf(\mathbf{x}^*)), \quad \forall \mathbf{u} \in (\mathbf{x}^*)^\perp.$$

Lemma

If $\mathbf{x}^* \in \mathbb{S}^{n-1}$ satisfies **(FONC)** then \mathbf{x}^* is an eigenvector of $\nabla^2 f(\mathbf{x}^*)$ with associated eigenvalue $t(t-1)f(\mathbf{x}^*)$.

Démonstration.

Observe that $\mathbf{x} \mapsto \partial f(\mathbf{x})/\partial x_i$ is homogeneous of degree $t-1$, for every $i = 1, \dots, n$, and therefore by Euler's identity

$$\nabla^2 f(\mathbf{x}) \mathbf{x} = (t-1) \nabla f(\mathbf{x}), \quad \forall \mathbf{x} \in \mathbb{R}^n.$$

So if $\mathbf{x}^* \in \mathbb{S}^{n-1}$ satisfies **(FONC)** then

$$\nabla^2 f(\mathbf{x}^*) \mathbf{x}^* = (t-1) \nabla f(\mathbf{x}^*) = t(t-1)f(\mathbf{x}^*) \mathbf{x}^*.$$



Let

$$\tau(\mathbf{x}^*) := \min \{ \langle \mathbf{u}, (\nabla^2 f(\mathbf{x}^*) \mathbf{u}) \rangle : \mathbf{u} \in (\mathbf{x}^*)^\perp \},$$

so that if $\mathbf{x}^* \in \mathbb{S}^{n-1}$ then

$$(\mathbf{SONC}) \Leftrightarrow \tau(\mathbf{x}^*) \geq t f(\mathbf{x}^*).$$

Lemma

If $\mathbf{x}^* \in \mathbb{S}^{n-1}$ satisfies **(FONC)** then

$$\lambda_1(\nabla^2 f(\mathbf{x}^*)) = \min [t(t-1)f(\mathbf{x}^*), \tau(\mathbf{x}^*)].$$

Démonstration.

Observe that any $\mathbf{z} \in \mathbb{S}^{n-1}$ reads

$$\mathbf{z} = \alpha \mathbf{x}^* \oplus \beta \mathbf{u} : \mathbf{u} \in (\mathbf{x}^*)^\perp ; \alpha^2 + \beta^2 = 1$$

and observe that if $\mathbf{x}^* \in \mathbb{S}^{n-1}$ satisfies **(FONC)**

$$\langle \mathbf{u}, \nabla^2 f(\mathbf{x}^*) \mathbf{x}^* \rangle = t(t-1)f(\mathbf{x}^*) \langle \mathbf{u}, \mathbf{x}^* \rangle = 0.$$

□

Démonstration.

Hence

$$\begin{aligned}
 \lambda_1(\nabla^2 f(\mathbf{x}^*)) &= \min \{ \langle \mathbf{z}, \nabla^2 f(\mathbf{x}^*) \mathbf{z} \rangle : \mathbf{z} \in \mathbb{S}^{n-1} \} \\
 &= \min \{ \langle (\alpha \mathbf{x}^* + \beta \mathbf{u}), \nabla^2 f(\mathbf{x}^*) (\alpha \mathbf{x}^* + \beta \mathbf{u}) \rangle : \alpha^2 + \beta^2 = 1 \} \\
 &= \min \{ \alpha^2 t(t-1)f(\mathbf{x}^*) + \beta^2 \tau(\mathbf{x}^*) : \alpha^2 + \beta^2 = 1 \} \\
 &= \min [t(t-1)f(\mathbf{x}^*), \tau(\mathbf{x}^*)].
 \end{aligned}$$

□

In particular

If $\mathbf{x}^* \in \mathbb{S}^{n-1}$ satisfies **(FONC)** then :

$$\lambda_1(\nabla^2 f(\mathbf{x}^*)) = t(t-1)f(\mathbf{x}^*) \Rightarrow \tau(\mathbf{x}^*) = \lambda_2(\nabla^2 f(\mathbf{x}^*))$$

$$\text{and (SONC)} \Leftrightarrow \lambda_2(\nabla^2 f(\mathbf{x}^*)) \geq tf(\mathbf{x}^*) = \frac{\lambda_1(\nabla^2 f(\mathbf{x}^*))}{t-1}.$$

Theorem

Let $\mathbf{x}^* \in \mathbb{S}^{n-1}$ satisfy **(FONC)**. Then \mathbf{x}^* satisfies **(SONC)** if and only if

$$\begin{aligned} \lambda_1(\nabla^2 f(\mathbf{x}^*)) &\geq t f(\mathbf{x}^*) && \text{if } f(\mathbf{x}^*) \geq 0 \\ \lambda_2(\nabla^2 f(\mathbf{x}^*)) &\geq t f(\mathbf{x}^*) && \text{if } f(\mathbf{x}^*) < 0. \end{aligned}$$

So all **(SONC)** points $\mathbf{x}^* \in \mathbb{S}^{n-1}$ are characterized by :

- the value $f(\mathbf{x}^*)$, and
- The first and second smallest eigenvalues of $\nabla^2 f$ at \mathbf{x}^* .

In particular

If $\mathbf{x}^* \in \mathbb{S}^{n-1}$ satisfies **(FONC)** and $f(\mathbf{x}^*) < 0$ then :

$$\text{(SONC)} \Leftrightarrow \lambda_2(\nabla^2 f(\mathbf{x}^*)) \geq \frac{\lambda_1(\nabla^2 f(\mathbf{x}^*))}{t - 1}$$

and \mathbf{x}^* is the eigenvector associated with $\lambda_1(\nabla^2 f(\mathbf{x}^*))$.

☞ $\lambda_2(\nabla^2 f(\mathbf{x}^*))$ is significantly larger than $\lambda_1(\nabla^2 f(\mathbf{x}^*))$.

The case of odd degree forms

The only interesting local minima are negative since if $\mathbf{x} \in \mathbb{S}^{n-1}$ with $f(\mathbf{x}) > 0$ then $\mathbf{u} := -\mathbf{x} \in \mathbb{S}^{n-1}$ with value $f(\mathbf{u}) = -f(\mathbf{x}) < 0$.

So in this case

a negative local minimizer $\mathbf{x}^* \in \mathbb{S}^{n-1}$ is necessarily the eigenvector of the Hessian $\nabla^2 f(\mathbf{x}^*)$ associated with the **SMALLEST EIGENVALUE**

$$\lambda_1(\nabla^2 f(\mathbf{x}^*)) = t(t-1)f(\mathbf{x}^*).$$

Moreover

all negative local minima of f on \mathbb{S}^{n-1} are all negative local minima of f on the Euclidean ball \mathcal{E}_n .

It is then much easier to minimize f on the convex set \mathcal{E}_n rather than on the “nasty” non-convex set \mathbb{S}^{n-1} .

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The case of cubic forms

- ☞ For instance if $t = 3$ (i.e., f is a cubic form) then
- $\nabla^2 f(\mathbf{x}^*)$ is a matrix whose entries are **linear forms**, and so
 - $\mathbf{x} \mapsto \lambda_1(\nabla^2 f(\mathbf{x}))$ is a **CONCAVE** function
 - $\mathbf{x} \mapsto \lambda_1(\nabla^2 f(\mathbf{x})) + \lambda_2(\nabla^2 f(\mathbf{x}))$ is also a **CONCAVE** function.

Hence the (SONC) condition

$$\lambda_2(\nabla^2 f(\mathbf{x}^*)) \geq \frac{\lambda_1(\nabla^2 f(\mathbf{x}^*))}{t-1}$$

is equivalent to the condition

$$\lambda_1(\nabla^2 f(\mathbf{x}^*)) + \lambda_2(\nabla^2 f(\mathbf{x}^*)) \geq \frac{3 \lambda_1(\nabla^2 f(\mathbf{x}^*))}{2}$$

Theorem

An odd degree- t form f (with $t > 1$) has *no spurious negative local minimum* if the system

$$\begin{aligned}\nabla^2 f(\mathbf{x}) \mathbf{x} &= t(t-1)f(\mathbf{x}) \mathbf{x} \\ \lambda_2(\nabla^2 f(\mathbf{x})) &\geq \frac{\lambda_1(\nabla^2 f(\mathbf{x}))}{t-1}\end{aligned}$$

has a unique solution \mathbf{x} with $f(\mathbf{x}) < 0$

One may also relate the critical points of f on \mathbb{S}^{n-1} with the sub-varieties of a certain gradient ideal.

Let $f \in \mathbb{R}[\mathbf{x}]$ be homogeneous of degree t , and define $g \in \mathbb{R}[\mathbf{x}]$ by :

$$\mathbf{x} \mapsto g(\mathbf{x}) := f(\mathbf{x}) \left(1 - \frac{t \|\mathbf{x}\|^2}{t+2}\right), \quad \mathbf{x} \in \mathbb{R}^n.$$

Proposition

$$\text{On } \mathbb{S}^{n-1} : \quad \nabla g(\mathbf{x}) = 0 \quad \Leftrightarrow \quad \nabla f(\mathbf{x}) = t f(\mathbf{x}) \mathbf{x}$$

and so all (FONC) points of f are critical points of g and conversely.

$$\begin{aligned} V_{grad}(g) &:= \{\mathbf{z} \in \mathbb{C}^n : \nabla g(\mathbf{x}) = 0\} \\ &= W_0 \cup W_1 \dots \cup W_p \end{aligned}$$

where each W_i is an irreducible subvariety and g is **constant** on each W_i .

☞ Hence f has no spurious local minimum on \mathbb{S}^{n-1} if all the (SONC) points belong to a **single** $W_j \cap \mathbb{S}^{n-1}$ for some index j^* .

☞ an algebraic characterization

II. Sparse optimization on \mathbb{S}^{n-1}

Consider the problem

$$\mathbf{P} : \quad f^* = \min \{ h(\mathbf{x}) : \mathbf{x} \in \mathbb{S}^{n-1} \}$$

$$\text{where } h(\mathbf{x}) = f((\ell_1 \cdot \mathbf{x}), (\ell_2 \cdot \mathbf{x}), \dots, (\ell_m \cdot \mathbf{x}))$$

- for some m linear forms $\ell_1, \dots, \ell_m : \mathbb{R}^n \rightarrow \mathbb{R}$, and
- some function $f : \mathbb{R}^m \rightarrow \mathbb{R}$.

☞ If $m \ll n$ then \mathbf{P} can be viewed as a **sparse** optimization problem as in h , the coupling of variables only occurs through the m linear forms $(\ell_j)_{j \in [m]}$.

☞ Sometimes h is said to be **low-rank**

☞ However the constraint $\mathbf{x} \in \mathbb{S}^{n-1}$ is not expressed through the ℓ_j 's.

Take home message

Problem **P** is in fact equivalent to an m variables problem on the Euclidean unit ball $\mathcal{E}_m := \{\mathbf{x} \in \mathbb{R}^m : \|\mathbf{x}\| \leq 1\}$ of \mathbb{R}^m .

- Let $\ell \in \mathbb{R}^{m \times n}$ be the real matrix with rows $(\ell_j)_{j \in [m]}$.
- $\mathcal{L} := \ell \ell^T \in \mathbb{R}^{m \times m}$, and $\mathbf{L} := \mathcal{L}^{1/2}$,

and consider the problem

$$\mathbf{Q} : \quad \min_{\mathbf{y}} \{ f((\mathbf{L}_1 \cdot \mathbf{y}), \dots, (\mathbf{L}_m \cdot \mathbf{y})) : \mathbf{y} \in \mathcal{E}_m \}.$$

Theorem

Assume that the ℓ_j are linearly independent.

(i) Let $\mathbf{x}^* \in \mathbb{S}^{n-1}$ satisfy (SONC) for problem \mathbf{P} . Then there exists $\mathbf{y}^* \in \mathcal{E}_m$ which satisfies (SONC) for problem \mathbf{Q} and with same value

$$f((\mathbf{L}_1 \cdot \mathbf{y}^*), \dots, (\mathbf{L}_m \cdot \mathbf{y}^*)) = f(\ell \mathbf{x}^*) = h(\mathbf{x}^*).$$

(ii) Conversely, let $\mathbf{y}^* \in \mathcal{E}_m$ satisfy (SONC) for problem \mathbf{Q} . Then there exists $\mathbf{x}^* \in \mathbb{S}^{n-1}$ which satisfies (SONC) for problem \mathbf{P} and with same value

$$h(\mathbf{x}^*) = f(\ell \mathbf{x}^*) = f((\mathbf{L}_1 \cdot \mathbf{y}^*), \dots, (\mathbf{L}_m \cdot \mathbf{y}^*)).$$

- Let $\ell \in \mathbb{R}^{m \times n}$ be the real matrix with rows $(\ell_j)_{j \in [m]}$.
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$$h(\mathbf{x}^*) = f(\ell \mathbf{x}^*) = f((\mathbf{L}_1 \cdot \mathbf{y}^*), \dots, (\mathbf{L}_m \cdot \mathbf{y}^*)).$$

Key observation

The **KKT-optimality conditions** at $\mathbf{x}^* \in \mathbb{S}^{n-1}$ read :

$$\ell^T \nabla f((\ell_1 \cdot \mathbf{x}^*), \dots, (\ell_m \cdot \mathbf{x}^*)) = 2 \lambda^* \mathbf{x}^*,$$

for some λ^* .

In other words, whenever $\lambda^* \neq 0$

any candidate local minimizer $\mathbf{x}^* \in \mathbb{S}^{n-1}$ necessarily satisfies

$$\mathbf{x}^* \in \text{Span}(\ell_1, \dots, \ell_m)$$

☞ It is enough to search in $\text{Span}(\ell_1, \dots, \ell_m) \cap \mathbb{S}^{n-1}$!

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☞ It is enough to search in $\text{Span}(\ell_1, \dots, \ell_m) \cap \mathbb{S}^{n-1}$!

(i) Let $\mathbf{x}^* \in \mathbb{S}^{n-1}$ be such that $\lambda^* \neq 0$. Then letting $\mathbf{z} = (z_j)$,

$$\mathbf{x}^* = \sum_{j=1}^m z_j \boldsymbol{\ell}_j \quad \text{and} \quad \mathbf{y}^* := \mathbf{L} \mathbf{z} \Rightarrow \|\mathbf{y}^*\| = 1,$$

so that $\mathbf{y}^* \in \mathcal{E}_n$ and $f((\mathbf{L}_1 \cdot \mathbf{y}^*), \dots, (\mathbf{L}_m \cdot \mathbf{y}^*)) = h(\mathbf{x}^*)$.

(ii) If $\lambda^* = 0$ then $\nabla f(\boldsymbol{\ell} \mathbf{x}^*) = 0$.

- Write $\mathbf{x}^* = \boldsymbol{\ell}^T \mathbf{u} \oplus \mathbf{v}$ with $\mathbf{v} \in \text{Ker}(\boldsymbol{\ell})$, so that $\boldsymbol{\ell}^T \mathbf{u} \perp \mathbf{v}$.
- $1 = \|\mathbf{x}^*\| \Rightarrow \|\boldsymbol{\ell}^T \mathbf{u}\| \leq 1$, and $\mathbf{y}^* := \mathbf{L} \mathbf{u}$ implies $\|\mathbf{y}^*\| \leq 1$, so that $\mathbf{y}^* \in \mathcal{E}_m$.
- $\boldsymbol{\ell} \mathbf{x}^* = \boldsymbol{\ell} \boldsymbol{\ell}^T \mathbf{u} = \mathbf{L} \mathbf{L} \mathbf{u} = \mathbf{L} \mathbf{y}^*$, and therefore

$$h(\mathbf{x}^*) = f(\boldsymbol{\ell} \mathbf{x}^*) = f(\mathbf{L} \mathbf{y}^*), \quad \text{with } \mathbf{y}^* \in \mathcal{E}_m.$$

For the converse, similar calculations yield the desired result.

Hence

solving **P** on \mathbb{S}^{n-1} is equivalent to solving **Q** on \mathcal{E}_m and the latter problem is lower-dimensional on the **CONVEX SET** \mathcal{E}_m , a significant progress.

The case $m = 1$

If $m = 1$ (so that $\ell \in \mathbb{R}^n$) then Problem **P** reduces to the easy to solve univariate problem

$$\mathbf{Q} : f^* = \min_y \{ f(\|\ell\|y) : y \in [-1, 1] \}$$

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The case $m = 1$ (continued)

If $m = 1$ and h is a **quasi-convex polynomial** then

$$f^* = \min [f(\|\ell\|), f(-\|\ell\|)]$$

and so h has no spurious local minimum on \mathbb{S}^{n-1} .

☞ h quasi-convex implies $h(\mathbf{x}) = f(\ell \cdot \mathbf{x})$ for some $\ell \in \mathbb{R}^n$ and some **monotonic univariate polynomial** f (Ahmadi et al. (2013), Math. Program.).

Finally if h has the low-rank formulation

$$h(\mathbf{x}) = f(\boldsymbol{\ell} \mathbf{x}), \quad \mathbf{x} \in \mathbb{R}^n,$$

for some *hidden* $\boldsymbol{\ell} \in \mathbb{R}^{m \times n}$ then by sufficiently many evaluations of ∇f at randomly chosen points $(\mathbf{x}(i))_{i \in J}$ (e.g. $\mathbf{x}(i) \in \mathbb{S}^{n-1}$) one may recover $\boldsymbol{\ell}$.

Happy Birthday !