

# Understanding $X$ -nonnegative signomials, by way of $X$ -circuits.

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# What are signomials?

Start with “monomial” basis functions, for  $\alpha \in \mathbb{R}^n$

$$e^\alpha : \mathbb{R}^n \rightarrow \mathbb{R}_{++} \quad \text{takes values} \quad e^\alpha(\mathbf{x}) = \exp(\alpha^\top \mathbf{x}).$$

A signomial is a linear combination

$$f = \sum_{\alpha \in \mathcal{A}} c_\alpha e^\alpha.$$

For modeling reasons, signomials are usually written in *geometric form*

$$\mathbf{y} \mapsto \sum_{\alpha \in \mathcal{A}} c_\alpha \prod_{i=1}^n y_i^{\alpha_i} \quad \text{where} \quad y_i = \exp x_i.$$

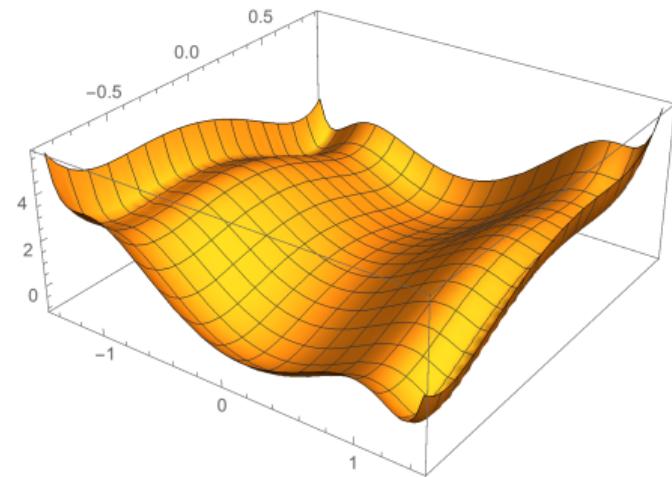
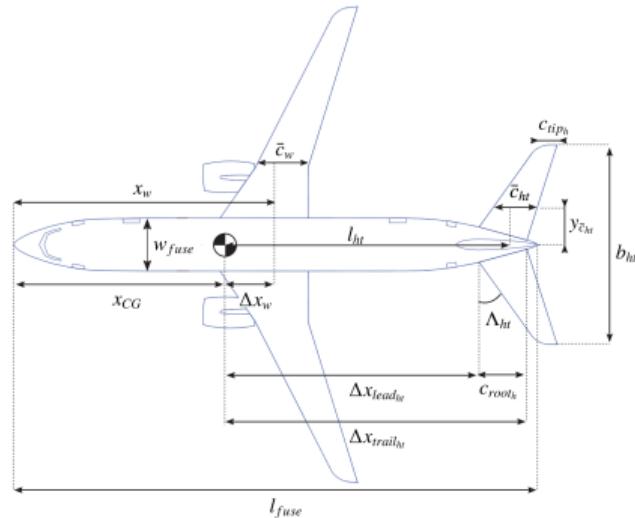
If a signomial has all nonnegative coefficients, call it a *posynomial*.

# Signomial applications in optimization

A *signomial program* (SP) is an optimization problem stated with signomials, e.g.

$$\inf_{\mathbf{x} \in \mathbb{R}^n} \{ f(\mathbf{x}) : g_i(\mathbf{x}) \leq 1 \text{ for all } i \text{ in } [k] \}.$$

**Major** applications in aircraft design [1, 2, 3, 4, 5] and structural engineering [6, 7, 8, 9].  
 Additional applications in EE [10], communications [11], and ML [12].



# Signomials are probably useful for you, too!

Consider the polynomial

$$p(t) = 1 + t - t^3 + t^4.$$

Suitably constructed (geometric-form) signomials can ...

- (a) exactly mimic the polynomial on positive reals [13, 14]

$$a(y) = 1 + y - y^3 + y^4.$$

- (b) produce a lower-bounding function [15, 16, 17, 18]

$$b(y) = 1 - y - y^3 + y^4.$$

- (c) perfectly capture zeroth-order behavior

$$c(y) = 1 + \left(y - \frac{1}{y}\right) - \left(y - \frac{1}{y}\right)^3 + \left(y - \frac{1}{y}\right)^4.$$

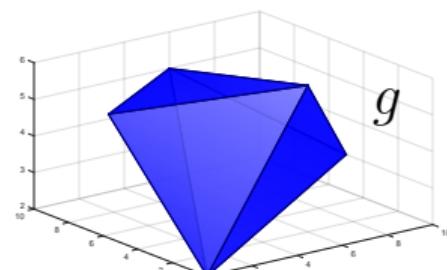
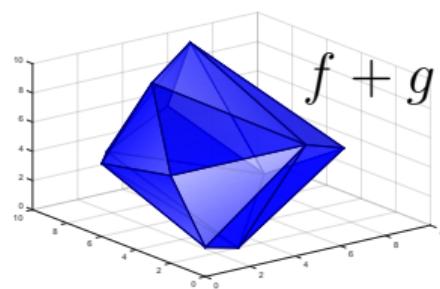
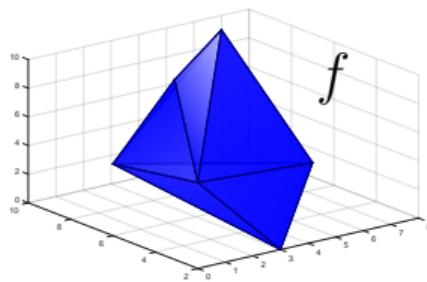
## Newton polytopes

Descartes' Rule of Signs: Given real  $\alpha_1 < \alpha_2 < \dots < \alpha_m$ , the number of positive roots of

$$y \mapsto c_1 y^{\alpha_1} + c_2 y^{\alpha_2} + \dots + c_m y^{\alpha_m}$$

is bounded above by the number of sign alternations in  $c_1, c_2, \dots, c_m$ .

In higher dimensions, consider “Newton polytopes”: convex hulls of exponent vectors.



Infer properties of polynomials over  $\mathbb{R}_{++}^n$ , signomials over  $\mathbb{R}^n$  (remember  $y_i = \exp x_i$ ).

# What are $\mathbb{R}^n$ -circuits?

A **circuit** is a minimal affinely dependent  $A \subset \mathbb{R}^n$ .

A circuit is **simplicial** if  $\text{conv } A$  has  $|A| - 1$  extreme points.

For a finite ground set  $\mathcal{A} \subset \mathbb{R}^n$ , define

$$\mathbb{R}^{\mathcal{A}} := \{\text{real } |\mathcal{A}|\text{-tuples indexed by } \alpha \in \mathcal{A}\},$$

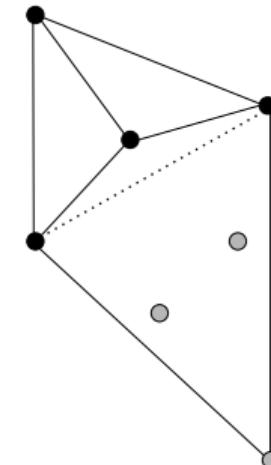
so we can also understand  $\mathcal{A}$  as an operator

$$\mathcal{A} : \mathbb{R}^{\mathcal{A}} \rightarrow \mathbb{R}^n, \quad \mathcal{A}\nu = \sum_{\alpha \in \mathcal{A}} \alpha \nu_{\alpha}.$$

Circuits  $A \subset \mathcal{A}$  are in 1-to-1 correspondence with lines

$$\{\nu \in \mathbb{R}^{\mathcal{A}} : \mathbf{1}^T \nu = 0, \text{ and } \text{supp } \nu \text{ minimal among } \nu \in \ker \mathcal{A}\}.$$

For simplicial circuits,  $\{\alpha : \nu_{\alpha} > 0\} = \text{ext conv } A$ .



# Definitions from convex analysis

A set convex set  $K$  is called a **cone** if

$$\mathbf{x} \in K \Rightarrow \lambda \mathbf{x} \in K \quad \text{for all } \lambda > 0;$$

the **dual cone** to  $K$  is

$$K^* = \{\mathbf{y} : \mathbf{y}^\top \mathbf{x} \geq 0 \text{ for all } \mathbf{x} \text{ in } K\}.$$

A convex set  $X$  induces a **support function**

$$\sigma_X(\boldsymbol{\lambda}) = \sup\{\boldsymbol{\lambda}^\top \mathbf{x} : \mathbf{x} \text{ in } X\}.$$

# This presentation

Content from arXiv:2006:06811, joint work with Thorsten Theobald and Helen Naumann.

- Goal of that paper: better understand constrained signomial nonnegativity.
- Along the way: generalize “circuit” to the constrained setting.

## Outline of remaining presentation

- Signomial nonnegativity on  $X \subset \mathbb{R}^n$  via Sums-of-AM/GM-Exponentials.
- For  $X \subset \mathbb{R}^n$  convex and  $\mathcal{A} \subset \mathbb{R}^n$  finite, define simplicial  $X$ -circuits.
- Explain some properties of these simplicial  $X$ -circuits.
- Explain how simplicial  $X$ -circuits uniquely construct  $X$ -SAGE cones.

# Sums of AM/GM-Exponentials

*Definition.* An **AM/GM-Exponential** or “**AGE function**” is an  $\mathbb{R}^n$ -nonnegative signomial, which has at most one negative coefficient [19].

*Example.* Let  $f = e^{\alpha_1} + e^{\alpha_2} + e^{\alpha_3} - 3e^{\alpha_4}$ , for

$$\alpha_1 = (2, 4, 0), \quad \alpha_2 = (4, 2, 0), \quad \alpha_3 = (0, 0, 6), \quad \alpha_4 = (2, 2, 2).$$

Use  $e^\alpha(x) = \exp(\alpha^T x) = e^x(\alpha)$  and convexity to bound the negative term

$$\alpha_4 = \frac{1}{3}\alpha_1 + \frac{1}{3}\alpha_2 + \frac{1}{3}\alpha_3 \quad \Rightarrow \quad 3e^{\alpha_4} \leq e^{\alpha_1} + e^{\alpha_2} + e^{\alpha_3}.$$

Historical note on nomenclature: convexity of  $\exp$  is equivalent to the AM/GM inequality

$$\mathbf{u} \in \mathbb{R}_{++}^m, \quad \boldsymbol{\lambda} \in \mathbb{R}_+^m, \quad \boldsymbol{\lambda}^T \mathbf{1} = 1 \quad \Rightarrow \quad \prod_{i=1}^m u_i^{\lambda_i} \geq \sum_{i=1}^m u_i \lambda_i.$$

## SAGE for constrained problems

An  **$X$ -AGE function** is an  $X$ -nonnegative signomial, with at most one negative coefficient.

Introduce symbols for **AGE cones** and **SAGE cones**

$$C_X(\mathcal{A}) = \sum_{\beta \in \mathcal{A}} \overbrace{\left\{ f : \mathbf{c}_{\setminus \beta} \geq \mathbf{0}, f = \sum_{\alpha \in \mathcal{A}} c_{\alpha} e^{\alpha}, f \geq 0 \text{ on } X \right\}}^{C_X(\mathcal{A}, \beta)}$$

**Theorem ([20])**

Fix  $\beta \in \mathcal{A}$ , and let  $f = \sum_{\alpha \in \mathcal{A}} c_{\alpha} e^{\alpha}$ . If  $X$  is convex, then  $f \in C_X(\mathcal{A}, \beta)$  if and only if

$$\exists \boldsymbol{\nu} \in \mathbb{R}^{\mathcal{A}} \quad \text{where} \quad \sigma_X(-\mathcal{A}\boldsymbol{\nu}) + D(\boldsymbol{\nu}_{\setminus \beta}, e\mathbf{c}_{\setminus \beta}) \leq c_{\beta} \quad \text{and} \quad \mathbf{1}^T \boldsymbol{\nu} = 0.$$

Special aspects of  $X = \mathbb{R}^n$

Immediate:  $\boldsymbol{\nu}$  must satisfy  $\mathcal{A}\boldsymbol{\nu} = \mathbf{0}$ .

Nontrivial: If  $f$  is extremal, then  $\text{supp } \mathbf{c} \subset \mathcal{A}$  is a simplicial  $\mathbb{R}^n$ -circuit.

# Definition of $X$ -circuits

For  $\beta \in \mathcal{A}$ , abbreviate  $M_\beta = \{\nu \in \mathbb{R}^{\mathcal{A}} : \mathbf{1}^\top \nu = 0, \nu_{\setminus \beta} \geq \mathbf{0}, \nu_\beta = -1\}$ .

*Definition.* A vector  $\lambda^* \in M_\beta$  is a normalized  $X$ -circuit if

1.  $\sigma_X(-\mathcal{A}\lambda^*) < +\infty$ , and
2. strict local-sublinearity holds:

If  $L \subset M_\beta$  is a segment properly containing  $\lambda^*$ , then  $\sigma_X(-\mathcal{A}\lambda)$  is nonlinear on  $L$ .

Defined for *any* closed convex set  $X$ .

Easy to characterize when  $X$  is a cone.

Can't recover  $\lambda^*$  given only information on  $\text{supp } \lambda^* = \{\alpha : \lambda_\alpha^* \neq 0\}$ .

Let  $\Lambda_X(\mathcal{A}, \beta)$  denote circuits in  $M_\beta$ , and aggregate

$$\Lambda_X(\mathcal{A}) = \bigcup_{\beta \in \mathcal{A}} \Lambda_X(\mathcal{A}, \beta).$$

# Circuits induced by polyhedral $X$

For a face  $F$  of a polyhedron  $P$ , have the [outer normal cone](#)

$$\mathsf{N}_P(F) = \{\mathbf{w} : \mathbf{z}^\top \mathbf{w} = \sigma_P(\mathbf{z}) \forall \mathbf{z} \in F\}.$$

The [outer normal fan](#) aggregates the normal cones

$$\mathcal{O}(P) = \{\mathsf{N}_P(F) : F \text{ is a face of } P\}.$$

Normal fans provide a useful decomposition

$$\bigcup_{K \in \mathcal{O}(P)} \text{relint } K = \{\mathbf{z} : \sigma_P(\mathbf{z}) < +\infty\}.$$

## Theorem ([21])

If  $X$  is polyhedral, then every circuit  $\lambda \in \Lambda_X(\mathcal{A}, \beta)$  generates a ray in the normal fan

$$\mathcal{O}(-\mathcal{A}^\top X - N_\beta^*)$$

where  $N_\beta = \{\boldsymbol{\nu} \in \mathbb{R}^{\mathcal{A}} : \mathbf{1}^\top \boldsymbol{\nu} = 0, \boldsymbol{\nu}_{\setminus \beta} \geq \mathbf{0}\}$ .

# X-circuits for AGE functions

In order for  $f = \sum_{\alpha \in \mathcal{A}} c_\alpha e^\alpha$  to be  $X$ -AGE with  $c_\beta < 0$  we need

$$\exists \boldsymbol{\nu} \in \mathbb{R}^{\mathcal{A}} \quad \text{where} \quad \sigma_X(-\mathcal{A}\boldsymbol{\nu}) + D(\boldsymbol{\nu}_{\setminus \beta}, e\mathbf{c}_{\setminus \beta}) \leq c_\beta \quad \text{and} \quad \mathbf{1}^\top \boldsymbol{\nu} = 0.$$

Fix  $\boldsymbol{\lambda} \in M_\beta$ , restrict  $\boldsymbol{\nu} = s\boldsymbol{\lambda}$  with scale  $s \geq 0$ , and optimize over  $s$ . We get

$$C_X(\mathcal{A}, \boldsymbol{\lambda}) := \left\{ \mathbf{c} \in \mathbb{R}^{\mathcal{A}} : \prod_{\alpha \neq \beta} \left[ \frac{c_\alpha}{\lambda_\alpha} \right]^{\lambda_\alpha} \geq -c_\beta \exp(\sigma_X(-\mathcal{A}\boldsymbol{\lambda})) \quad \text{and} \quad \mathbf{c}_{\setminus \beta} \geq 0 \right\}.$$

## Theorem ([21])

If  $X$  is a closed convex set,  $X$ -AGE cones admit the representation

$$C_X(\mathcal{A}, \boldsymbol{\beta}) = \text{conv}(\cup \{C_X(\mathcal{A}, \boldsymbol{\lambda}) : \boldsymbol{\lambda} \in \Lambda_X(\mathcal{A}, \boldsymbol{\beta})\}).$$

For  $\lambda \in \Lambda_X(\mathcal{A})$ , denote  $\phi_\lambda = (\lambda, \sigma_X(-\mathcal{A}\lambda)) \in \mathbb{R}^{\mathcal{A}} \times \mathbb{R}$ .

We call  $\lambda^*$  a *reduced circuit* if  $\phi_{\lambda^*}$  is an edge generator of

$$\text{cone}(\{\phi_\lambda : \lambda \in \Lambda_X(\mathcal{A})\} \cup \{(0, 1)\}).$$

### Theorem

Let  $R \subset \mathbb{R}^{\mathcal{A}}$  denote the set of reduced circuits for  $(\mathcal{A}, X)$ . If  $X$  is polyhedral, then

$$C_X(\mathcal{A}) = \sum_{\lambda \in R} C_X(\mathcal{A}, \lambda)$$

and moreover there is no proper subset  $\Lambda \subsetneq R$  for which  $C_X(\mathcal{A}) = \sum_{\lambda \in \Lambda} C_X(\mathcal{A}, \lambda)$ .

## Conclusion

Example lines of future work:

- If  $X$  is polyhedral: formal connection to matroid theory?
- Analyze “non-simplicial”  $X$ -circuits.
- Define “circuits” for product space of symmetric matrices. E.g.,

$$X \subset \mathbb{S}^n, \quad \mathcal{A} = \{\mathbf{A}_i \in \mathbb{S}^n\}_{i=1}^m, \quad \text{and} \quad \underbrace{(\mathbf{V}_i)_{i=1}^m \mapsto \sigma_X \left( - \sum_{i=1}^m \mathbf{A}_i \circ \mathbf{V}_i \right)}_{\text{require local strict-sublinearity}}.$$

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