

## Ideas on presenting

- Knockout result : The audience clearly  
1. understands 1.1. How SP relate to Ent. Zone  
1.2. How to construct the His.  
2. To impress them
- High visual element
- "Applied to make audience"

20 min on part 1

5 min break

15 min on part 2

10 min break

30 min on part 3

5 min conclusion

85 min

# READING GROUP TALK: SIGNOMIAL OPTIMIZATION

## TABLE OF CONTENTS / OVERVIEW

### Part 1: AM-GM: Exponentials & Relative entropy

1. Definitions
2. Lemma  
→ Proof
3. Example  
↳ IMAGES

### Part 2: The SAGE-Cone

0. Idea
1. Definitions
2. Non-example of SAGE
3. Lemma (w/o proof)
4. Picture.  
(Draw by hand.)

### Part 3: Signomial Optimization.

#### Understand.

1.  $f_*$  to  $f_{\text{SAGE}}$
2. Compute  $f_{\text{SAGE}}$
3. Polygon type intervals
4. Observations

Proof new!

is it complete?

#### Compute.

1.  $f_*$
2.  $f_{\text{SAGE}}$
3.  $f_{\text{SAGE}}^{(\rho, q)}$

Proof new

is it complete?

#### Conclusion

## Definitions

SIGNOMIAL:  $g(x) := \sum_{j=1}^l c_j \exp(\alpha^{(j)^T} x)$

where  $c_j \in \mathbb{R}$ ,  $\alpha^{(j)} \in \mathbb{R}^n$  are parameters,  $j \in [l]$

## SIGNOMIAL OPTIMIZATION

$$\begin{array}{ll} \min & g(x) \\ \text{s.t.} & g_i(x) \geq 0 \quad \forall i \in [w] \\ & h_k(x) = 0 \quad \forall k \in [d] \end{array}$$

$g, g^2, \dots, g^m, h_1, \dots, h_k \in \text{SIGNOMIALS}$

## SPECIAL CASES

### AM/GM-EXPONENTIALS

- ① SIGNOMIAL  $g$
- ②  $g(x) \geq 0 \quad \forall x$
- ③  $c_j's > 0$  EXCEPT POSSIBLY  
for one Denoted

$$\therefore g(x) = b \exp(\alpha^T x) + \sum_{j=1}^l c_j \exp(\alpha^{(j)^T} x)$$

$b \in \mathbb{R}, c \in \mathbb{R}_{++}^l ; \alpha, \alpha^{(1)}, \dots, \alpha^{(l)} \in \mathbb{R}^n$

## RELATIVE ENTROPY

$$D: \mathbb{R}^n \times \mathbb{R}^n \ni (v, \lambda) \mapsto \sum_{j=1}^n v_j \ln\left(\frac{v_j}{\lambda_j}\right) \in \mathbb{R} \cup \{-\infty\}$$

## WEIGHTED AM/GM INEQUALITIES

$$\frac{w_1 x_1 + \dots + w_n x_n}{w} \geq \sqrt[w]{x_1^{w_1} \cdots x_n^{w_n}}$$

$$\frac{1}{w} \sum_{j=1}^n w_j x_j \geq \sqrt[w]{\prod_{j=1}^n x_j^{w_j}}$$

Where  $w_1, w_2, \dots, w_n > 0$  and  $w = \sum_{j=1}^n w_j$

Proof:  $x_1, x_2, \dots, x_n \geq 0$

$$\begin{aligned} \ln\left(\frac{1}{w} \sum_{j=1}^n w_j x_j\right) &\geq \sum_{j=1}^n \frac{w_j}{w} \ln x_j \quad \because \text{Jensen} \Rightarrow \ln \text{ is strictly concave} \\ &= \ln\left(\sqrt[w]{\prod_{j=1}^n x_j^{w_j}}\right) \end{aligned}$$

The result follows from applying exp on both sides which is valid since  $\ln$  is strictly inc.

□

CONVEX CONJUGATE:  $X$  a topo. space,  $X^*$  topo. dual  
 $\langle \cdot, \cdot \rangle : X \times X^* \rightarrow \mathbb{R}$  duality pair

$$f^*: X^* \ni x^* \mapsto \sup_{x \in X} \langle x^*, x \rangle - f$$

GENERALIZE TRANSFORM . . .

Recall:

SLATER'S CONDITION:  $\exists k$  (Efficient conditions for Strong Duality in Convex optimization problems)

Let  $A \in \mathbb{R}^{n \times k}$ ,  $b \in \mathbb{R}^k$ ,  $f_i(x)$  convex  $\forall i \in [m] \cup \{0\}$

$$\begin{aligned} & \min f_0(x) \\ \text{s.t. } & f_i(x) \leq 0 \quad \forall i \in [m] \\ & Ax = b \end{aligned}$$

Satisfy SLATER's Condition if

$$\exists x^* \in \bigcap_{i=0}^m \text{Dom}(f_i) \text{ s.t. } \begin{array}{l} f_i(x^*) < 0 \quad \forall i \in [m] \\ Ax^* = b \end{array}$$

Strictly feasible

If SLATER's Condition is satisfied then

STRONG Duality holds, i.e,

Claim: Signomial programming is NP-Hard.

## LEMMA 2

Let  $G \in \mathbb{R}^{n \times l}$ ,  $c \in \mathbb{R}_+^l$ ,  $b \in \mathbb{R}$ ,  $\alpha \in \mathbb{R}^n$

$$\textcircled{1} \quad g(x) := b \exp(\alpha^T x) + \sum_{j=1}^l c_j \exp(\alpha^{(j)T} x) \geq 0$$

$$\Leftrightarrow \textcircled{2} \quad \forall v \in \mathbb{R}_+^l \text{ s.t. } D(v, c) - b \leq 0 \quad (2.1)$$

$$[\alpha^{(1)}, \dots, \alpha^{(l)}]v = \sum_{j=1}^l v_j \alpha^{(j)} = (\mathbf{1}^T v) \alpha \quad (2.2)$$

Proof: (Via AM/GM)

" $\Leftarrow$ "

Suppose you are given a  $v$  satisfying (2)

$$\frac{1}{l} \sum_{j=1}^l \left( \frac{v_j / \mathbf{1}^T v}{v_j / \mathbf{1}^T v} \right) c_j \exp(\alpha^{(j)T} x) \geq \prod_{j=1}^l \left( \frac{c_j \exp(\alpha^{(j)T} x)}{v_j / \mathbf{1}^T v} \right)^{\frac{v_j / \mathbf{1}^T v}{l}}$$

•• Weighted AM/GM

$$= \prod_{j=1}^l \left( \frac{c_j \exp(\frac{v_j \alpha^{(j)T} x}{\mathbf{1}^T v})}{v_j / \mathbf{1}^T v} \right) = \prod_{j=1}^l \left( \frac{c_j}{v_j / \mathbf{1}^T v} \right)^{\frac{v_j / \mathbf{1}^T v}{l}} \exp(\alpha^T x)$$

$$\bullet \bullet \sum_{j=1}^l v_j \alpha^{(j)T} = \mathbf{1}^T v \alpha^T \quad (2.2)$$

Where

$$\prod_{j=1}^l \left( \frac{c_j}{v_j / \mathbf{1}^T v} \right)^{\frac{v_j / \mathbf{1}^T v}{l}} \geq b$$

•• Clever or next page

$$\prod_{j=1}^l \left( \frac{c_j}{v_j/\mathbb{I}^T v} \right)^{v_j/\mathbb{I}^T v} = \exp\{-D(\frac{v}{\mathbb{I}^T v}, c)\}$$

$\therefore$  Def. Rel. Ent.

$$\exp\{-D(\frac{v}{\mathbb{I}^T v}, c)\} \geq \xi [D(\frac{v}{\mathbb{I}^T v}, c) + \log(\xi) - 1] + \xi > 0$$

$\therefore$  Definition of Convex Conjugate:



1

$$f^*: X^* \ni x^* \mapsto \sup_{\xi \geq 0} \langle x^*, \xi \rangle - f(\xi)$$

Claim:  $\exp(-x)$  is the Conv-Conj of  $x \log x$

$$\exp(-p) = \sup_{\xi \geq 0} (1-p)\xi - \xi \log \xi$$

[Legendre Transfor] [Recall]

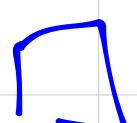
$$\begin{aligned} &= -\xi \left( D\left(\frac{v}{\mathbb{I}^T v}, c \right) + \log(\xi) - \log(e) \right) \\ &= -\xi \left( \sum_{j=1}^l \frac{v_j}{\mathbb{I}^T v} \log\left(\frac{v_j}{c_j \mathbb{I}^T v}\right) + \log\left(\frac{\xi}{e}\right) \right) \\ &= -\sum_{j=1}^l \xi \frac{v_j}{\mathbb{I}^T v} \log\left(\frac{\xi v_j}{\mathbb{I}^T v} \cdot \frac{1}{c_j e}\right) \end{aligned}$$

$$= -D\left(\frac{\xi v}{\mathbb{I}^T v}, ec\right)$$

$\therefore$  Def. Rel. Ent.

$$\geq -D(v, ec) \quad \text{choose } \xi := \mathbb{I}^T v$$

$$\geq -D(v, ec) \quad \text{by (2.1)}$$



" $\Leftrightarrow$ "

$$g(x) \geq 0$$

$\Leftrightarrow$

$$g(x) \exp(-\alpha^T x) \geq 0$$

$\Leftrightarrow$

$$\exp(-\alpha^T x) > 0$$

$$\sum_{j=1}^l c_j \exp((\alpha^{(j)^T} x)_j - \alpha^T x) \geq -b$$

$\circlearrowleft$  Def of  $g(x)$

Consider the problem

$$P := \inf_{\beta \in \mathbb{R}^n} c^T \epsilon$$

$$\text{s.t. } \exp(\alpha^{(j)^T} x - \alpha^T \beta) = \epsilon_j \quad \forall j \in [l]$$

We want  $P \geq -b$

$$P = \inf_{\beta \in \mathbb{R}^n, \epsilon \in \mathbb{R}^l} c^T \epsilon$$

$\leq$   $\because$  def of inf  
 $\geq$   $\because c, \epsilon \geq 0$

$$\text{s.t. } \exp(\alpha^{(j)^T} x - \alpha^T \beta) \leq \epsilon_j \quad \forall j \in [l]$$

$\circlearrowleft$  Definition of Lagrangian dual

$$\text{Sup}_{V \in \mathbb{R}_+^l} \inf_{\substack{x \in \mathbb{R}^n \\ \epsilon \in \mathbb{R}^l}} c^T \epsilon + \sum_{j=1}^l V_j (\exp(\alpha^{(j)^T} x - \alpha^T x) - \epsilon_j)$$

Define  $E(x) := \exp(\alpha^{(j)^T} x - \alpha^T x) \leq \epsilon$  then

$$\text{Sup}_{V \in \mathbb{R}_+^l} \inf_{\beta \in \mathbb{R}^n} \inf_{\epsilon \in \mathbb{R}^l} c^T \epsilon + V^T E(x) - V^T \epsilon$$

Note:

$\inf_{\gamma \in \mathbb{R}^n} v^\top E(\gamma)$  is attained when  $\nabla_x v^\top E(x) = 0$

$$\begin{aligned}\frac{\partial}{\partial \gamma_i} v^\top E(\gamma) &= \frac{\partial}{\partial x_j} \sum_{j=1}^l v_j \exp((\alpha^{(j)\top} - \alpha)x) \\ &= \sum_{j=1}^l v_j (\alpha^{(j)\top} - \alpha) \exp((\alpha^{(j)\top} - \alpha)x)\end{aligned}$$

$$\text{so } \nabla_x (v^\top E(x)) = \left( \sum_{j=1}^l (\alpha^{(j)} - \alpha) \cdot v_j \exp((\alpha^{(j)\top} - \alpha)x) \right)_{i=1}^n$$

$$\left( (\alpha^{(j)} - \alpha)_i \right)_{\substack{i \in [n] \\ j \in [l]}} \left( v_j \exp((\alpha^{(j)\top} - \alpha)x) \right)_{j \in [l]} = 0$$

choose  $v_j := v_j / \exp((\alpha^{(j)\top} - \alpha)x)$   $\forall j$  then

$$\left( (\alpha^{(j)} - \alpha)_i \right)_{\substack{i \in [n] \\ j \in [l]}} \left( \frac{v_j}{\exp((\alpha^{(j)\top} - \alpha)x)} \right)_{j \in [l]} = 0 \Leftrightarrow \boxed{\sum_j v_j \alpha^{(j)} = \Pi^\top v \alpha}$$

$$D = \sup_{v \in \mathbb{R}_+^l} \inf_{\epsilon \in \mathbb{R}_{++}^l} \inf_{x \in \mathbb{R}^m} c^T \epsilon + \sqrt{E(x) - \epsilon}$$

?

0  
0  
0  
0

$$-v^T \begin{bmatrix} \log(\frac{v_1}{e c_1}) \\ \vdots \\ \log(\frac{v_l}{e c_l}) \end{bmatrix} = -v^T \begin{bmatrix} \log(v_1) \\ \vdots \\ \log(v_l) \end{bmatrix} - \begin{bmatrix} \log(c_1) \\ \vdots \\ \log(c_l) \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}$$

$$\sum_{j=1}^l v_j \log \left( \frac{v_j}{e c_j} \right) = \sum_{j=1}^l v_j \log \left( \frac{v_j}{e c_j} \right)^{v_j} = \log \left( \prod_{j=1}^l \left( \frac{v_j}{e c_j} \right)^{v_j} \right)$$

Sees  
 $v \in \mathbb{R}_+^l$   
 s.e.

$$-\sum_{j=1}^l v_j \log \left( \frac{v_j}{e c_j} \right)$$

$$[\alpha^{(1)}, \alpha^{(2)}, \dots, \alpha^{(l)}] v = (\pi^T v) \propto$$

$\Leftrightarrow$

Sees  
 $v \in \mathbb{R}_+^l$   
 s.e.

$$-D(v, eC)$$

$$[\alpha^{(1)}, \alpha^{(2)}, \dots, \alpha^{(l)}] v = (\pi^T v) \propto$$

## Section 2: Characterizing the Cone of Sums of Ah/Gm Exponentials

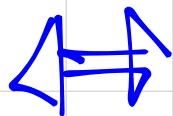
Exponents (fixed)

$$(\alpha, \alpha^{(1)}, \dots, \alpha^{(l)})$$

Coefficients ("Variable")

$$(b, c_1, \dots, c_l)$$

$$g(x) := b \exp(\alpha^T x) + \sum_{j=1}^l c_j \exp(\alpha^{(j)}^T x) \geq 0$$



$\forall v \in \mathbb{R}_+^l$

s.t.  $A v := \begin{bmatrix} 1 & 1 & \dots & 1 \\ \alpha^{(1)} & \alpha^{(1)} & \dots & \alpha^{(1)} \\ \vdots & \vdots & \ddots & \vdots \end{bmatrix} v = (1^T v) \alpha$

$$D(v, \alpha) - b \leq 0$$

} linear constraint on  $v$

} Entropy constraint on  $V$  and coefficients  $c, b$

What are we gonna do with this tool?

max  $b$

s.t.  $\sum_{j=1}^l c_j \exp(\alpha^{(j)}^T x) - b \geq 0$

$g(x)$  with

$$\alpha = 0$$

$$b \leq 0$$



s.t.  $\forall v \in \mathbb{R}_+^l$

s.t.  $A v := \begin{bmatrix} 1 & 1 & \dots & 1 \\ \alpha^{(1)} & \alpha^{(1)} & \dots & \alpha^{(1)} \\ \vdots & \vdots & \ddots & \vdots \end{bmatrix} v = 0$

$$D(v, \alpha) - b \leq 0$$

## Definitions

For a finite set of vectors  $M \subseteq \mathbb{R}^n$

$$\text{SAGE}(M) := \left\{ f = \sum_{i=1}^l f_i : \begin{array}{l} f_i : \text{AM/GM Expo} \\ \text{using Exponent. in } M \end{array} \right.$$

$$\text{So if } M = \{\alpha^{(j)}\}_{j=1}^l \text{ then}$$

$\text{SAGE}\left(\{\alpha^{(j)}\}_{j=1}^l\right) =$  The paper gives a description with only  $l$  terms..

SAGE  $\subseteq$  all Nonnegative Symmetric

Example

$$(\exp(x_1) - \exp(x_2) - \exp(x_3))^2 \geq 0$$

is not SAGE because ... Why

$$\sum_{i=1}^3 \exp(2e_i^\top \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}) + \exp([0, 1, 1]^\top x)$$

$$- \exp([1, 1, 0]^\top x) - \exp([0, 1, 1]^\top x)$$

$$Q = \begin{bmatrix} 2 & 0 & 0 & 0 \\ 0 & 2 & 0 & 1 \\ 0 & 0 & 2 & ? \end{bmatrix} \quad C = (1, 1, 1, 1) \quad b = -1 \quad b' = -1$$

$$\alpha = \begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix}$$

$$QV = \mathbb{I}^\top V \alpha$$

$$\alpha' = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} 2 & 0 \\ 0 & 2 \\ 0 & 0 \end{bmatrix} V = (V_1 + V_2) \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$$

$$V_1 \log\left(\frac{V_1}{\epsilon}\right) + V_2 \log\left(\frac{V_2}{\epsilon}\right) \leq -1$$

$$\frac{2V_1}{2V_1} = \frac{V_1 + V_2}{V_1 + V_2} \neq 1 \quad V_2 = V_1$$

$$\text{Example: } (\exp(x_1) - \exp(x_2) - \exp(x_3))^2 \geq 0$$

$$= \sum_{i=1}^3 \exp(2e_i^\top x) + 2\exp([0,1,1]x) \\ - 2\exp([1,1,0]x) - 2\exp([2,0,1]x)$$

is not in SAGE.

$$\text{Equation: } \alpha^{(j)} \text{'s} \quad \begin{bmatrix} 2 & 0 & 0 & 0 \\ 0 & 2 & 0 & 2 \\ 0 & 0 & 2 & 1 \end{bmatrix}$$

$$\text{Coefficients: } c_{j,i} \text{'s} \quad (1, 1, 1, 2) \quad b \text{'s} \quad -2, -2$$

$\alpha$ 's

$$\begin{bmatrix} 1 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix}$$

We are gonna use: the Lemma

↳ we need to clear 2 columns of A of lower integer

$$\begin{bmatrix} 2 & 0 \\ 0 & 2 \\ 0 & 0 \end{bmatrix} V = (V_1 + V_2) \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \Rightarrow V_1 = V_2$$

$$\begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 2 & 1 \end{bmatrix} W = (W_1 + W_2) \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \Rightarrow W_2 = W_1 + W_2 \\ W_1 = 0$$

$$W_2 \log\left(\frac{w_2}{e}\right) \leq -2$$

$$\log(w_2) - \log(e) \leq -\frac{2}{w_2}$$

$$\log(w_2) \leq 1 - \frac{2}{w_2}$$

Holds for no  $w_2$



$$C_{SAGE}(\{\alpha^{(j)}\}_{j=1}^l) := \left\{ c \in \mathbb{R}^l \mid \sum_{j=1}^l c_j \exp \{\alpha^{(j)}\} \in SAGE \right\}$$

"The SET of all coefficients that correspond to AM/GM-Expo's in exponent  $\{\alpha^{(j)}\}_{j=1}^l$ "

### Properties

$$C_{SAGE}(\{\alpha^{(j)}\}_{j=1}^l) = \left\{ c \in \mathbb{R}^l \mid \forall c^{(j)}, v^{(j)} \in \mathbb{R}^l \text{ s.t. } \sum_{j=1}^l c^{(j)} = c \right. \\ \left. \sum_{i=1}^l \alpha^{(i)} v_i^{(j)} = 0, v_j^{(j)} = -I^T v_{1j}^{(j)}, j \in [l] \right\}$$

$$D(v_{1j}^{(j)}, e c_{1j}^{(j)}) - c_j^{(j)} \leq 0, v_{1j}^{(j)} \in \mathbb{R}_+^{l-1} \quad ?$$


---

Counter Example

## SIGNOMIALS

$\text{CONE}$   
 $\text{of } \sigma^{\leq}-\text{signomials}$

$\text{SAGE}(\{\alpha^{(j)}\}_{j=1}^l)$

$*$

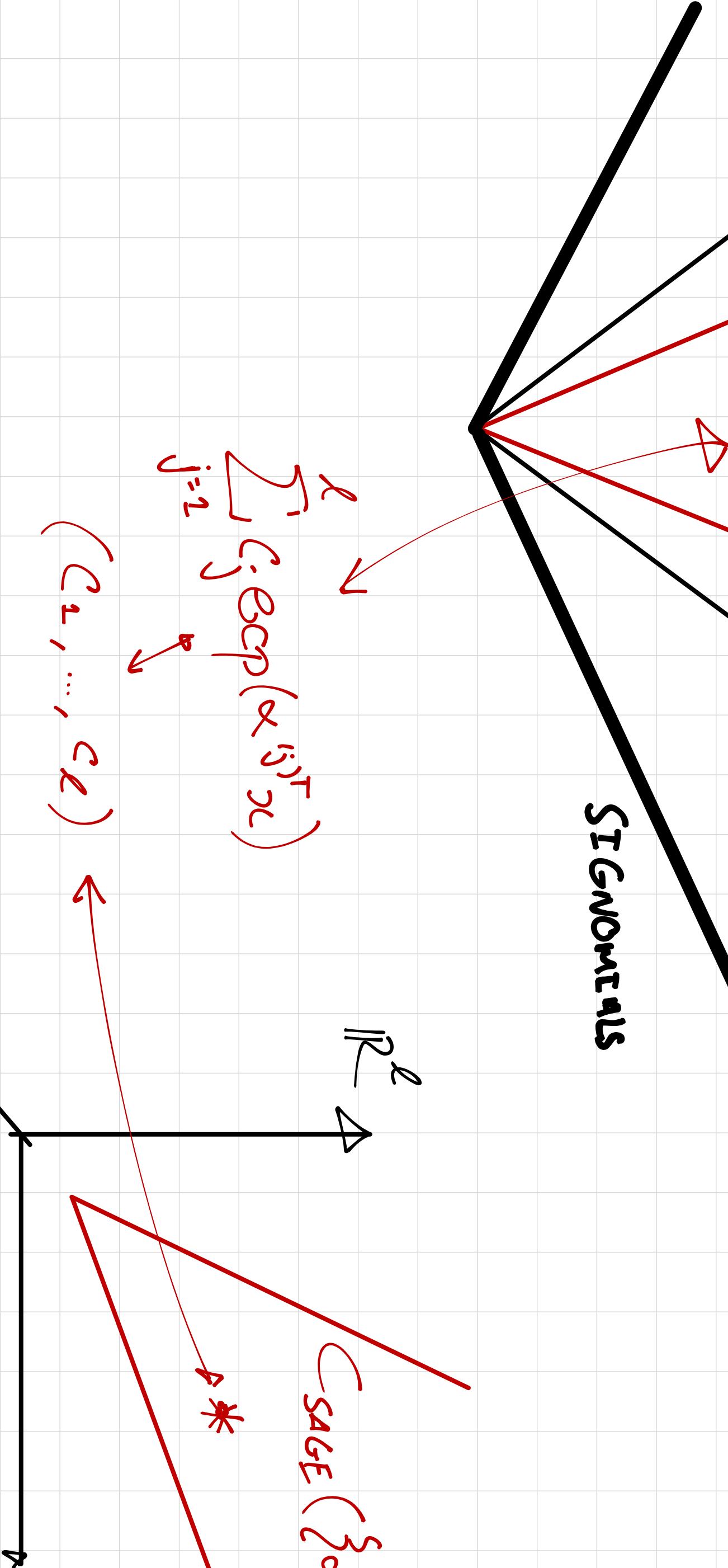
$\sum_{j=1}^l c_j \text{exp}(\alpha^{(j)T} x)$

$(c_1, \dots, c_l)$

$\mathbb{R}^l$

$\text{SAGE}(\{\alpha^{(j)}\}_{j=1}^l)$

$*$



# Sigmoidal Optimization (unconstrained)

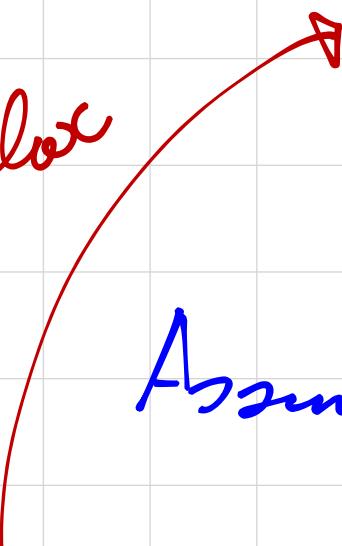
Let  $f$  be sigmoidal in  $x \in \mathbb{R}^n$  variables

## Unconstrained SP

$$f_* = \inf_{x \in \mathbb{R}^n} f(x)$$

$$\Leftrightarrow f_* = \sup_{\gamma \in \mathbb{R}} \gamma \quad \dots \quad (\text{U-SP})$$

s.t.  $f(x) - \gamma \geq 0$

*Relax*  

$\in$  "Nonnegative Sigmoidal"  
CONE

Assume w.l.o.g  $f(x) = \sum_{j=1}^l c_j \exp(\alpha^{(j)} \cdot x)$   
With  $\alpha^{(1)} = 0$  Then

$$f_{\text{SAGE}} = \sup_{\gamma \in \mathbb{R}} \gamma$$

s.t.  $f(x) - \gamma \in \text{SAGE}(\{\alpha^{(j)}\}_{j=2}^l)$

Clearly  $f_{\text{SAGE}} < f_*$   $\because \text{SAGE}(\{\alpha^{(j)}\}_{j=2}^l) \subseteq$  "Nonnegative Sigmoidal"  
CONE

$$f_{\text{SAGE}} = \sup_{\gamma \in \mathbb{R}} \gamma$$

$$\text{s.t. } (c_1 - \gamma, c_2, \dots, c_l) \in C_{\text{SAGE}}(0, \alpha^{(2)}, \dots, \alpha^{(l)})$$

This we can solve because the cone is full-dimensional

\* CVXPY

\* ECOS

# Where is the flaw? (1)

Idea is to use a P\'olya type argument

$$f^{(P)}$$

$$f_{\text{SAGE}} = \sum_{j=1}^l \alpha_j x_j$$

$$\text{s.t. } \left( \sum_{j=1}^l \exp \alpha_j x_j \right)^P (f(x) - \gamma) \in \text{SAGE} \left( E_{p+1} \left( \sum_{j=1}^l \alpha_j x_j \right) \right)$$

Where

$$E_p \left( \sum_{j=1}^l \alpha_j x_j \right) = \left\{ \sum_{j=1}^l \lambda_j \alpha_j x_j \mid \sum_{j=1}^l \lambda_j \leq p, \lambda_j \in \mathbb{Z}_+ \right\}$$

Recall P\'olya (1975)

$p(x) \in \mathbb{R}[x]$  homogeneous, positive on  $\mathbb{R}_+ \setminus \{0\}$   
 then for some  $n \in \mathbb{N}$ , all coefficients of  
 $\left( \sum_{i=1}^n x_i \right)^p p(x)$  are positive

!!

Just to recap the idea

- We check  $\left( \sum_{j=1}^l \exp \alpha_j x_j \right)^P (f(x) - \gamma) \in \text{SAGE} \left( E_{p+1} \left( \sum_{j=1}^l \alpha_j x_j \right) \right)$  for higher and higher values of  $P \in \mathbb{Z}_+$
- $\left( \sum_{j=1}^l \exp \alpha_j x_j \right)^P (f(x) - \gamma) \geq 0 \Rightarrow (f(x) - \gamma) \geq 0$   
 $\Rightarrow \left( \sum_{j=1}^l \exp \alpha_j x_j \right)^P > 0$

## Observations:

I)  $f_{\text{SAGE}}^{(p)} \leq f_* + p \in \mathbb{Z}_+ \quad (\textcircled{1} \text{ Previous Rec.})$

II)  $f_{\text{SAGE}}^{(0)} = f_{\text{SAGE}} \quad (\textcircled{2} \text{ By def})$

III)  $f_{\text{SAGE}}^{(p)} \leq f_{\text{SAGE}}^{(p+1)} \quad (\text{Lemma 3.1})$

Quick Proof:  $g_p(x) := \left( \sum_{j=1}^l \exp(\alpha^{(j)T} x) \right)^p (f(x) - \gamma)$

$$g_{p+1}(x) := \left( \sum_{j=1}^l \exp(\alpha^{(j)T} x) \right)^{p+1} (f(x) - \gamma)$$

Clearly:  $g_{p+1}(x) = \sum_{j=1}^l \exp(\alpha^{(j)T} x) g_p(x)$

$$g_p(x) \in E_p(\{\alpha^{(j)}\}) \Rightarrow \exp(\alpha^{(j)T} x) g_p(x) \in E_{p+1}(\{\alpha^{(j)}\})$$

$\Rightarrow g_{p+1}(x) \in E_{p+1}(\{\alpha^{(j)}\}) \quad \text{so closed under +}$

~ Is there a guarantee if  $p$  s.e. ~

IV)  $f_{\text{SAGE}}^{(p)} \rightarrow f_* \text{ as } p \rightarrow \infty$

For certain families of eigenvalues

~ To be elaborated on later. ~

# Sigmonial Optimization (Constrained)

Let  $f(x), g_1(x), \dots, g_m(x)$  be sigmonials in exponents  $\sum_{j=1}^m \alpha^{(j)}$

Let  $C := \{g_j(x) \mid j \in [m]\}$

$$K_C := \{x \in \mathbb{R}^n \mid g(x) \geq 0 \text{ for } g \in C\}$$

(I need a name for these domains)

Do we need a finite set of  $g$ 's?

Where do we need  $K$  constraints?

## Constrained SP

$$f_* = \sup_{\gamma \in \mathbb{R}} \gamma \quad (\text{CSP})$$

s.t.  $f(x) - \gamma \geq 0 \quad \forall x \in K$

Weak duality

$$f_{WD} = \sup_{\gamma \in \mathbb{R}, \mu \in \mathbb{R}_+^m} \gamma$$

s.t.  $f(x) - \gamma - \sum_{j=1}^m \mu_j g_j(x) \geq 0$

## Two problems:

1. Problem is still intractable to check  $\geq 0$

2. The problem is Non-convex

" $\nabla$ " No Strong duality  $\Rightarrow f_{\text{opt}} \leq f_*$

## Solutions:

1. Relax Nonnegativity with SAGE memb.

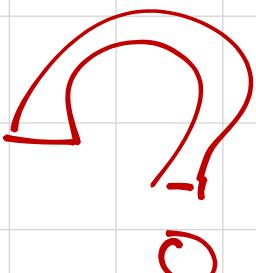
2. Add "redundant" constraints (how does that help?)  
↳ Another trick used a lot in PGP.

Def'n:  $R_q(C) := \left\{ \prod_{k=1}^q h_k \mid h_k \in \{1\} \cup C \right\}$

$$f^{(p,q)}_{\text{SAGE}} = \sup_{\gamma \in \mathbb{R}}$$

$$s_h(x) \in \text{SAGE}\left(E_p(\{x^{(j)}\}_{j=1}^l)\right)$$

$$\text{s.t. } f(x) - \gamma - \sum_{h(x) \in R_q(C)} s_h(x) h(x) \in \text{SAGE}\left(E_{p,q}(\{x^{(j)}\}_{j=1}^l)\right)$$



~~f~~  
Not strong

~~Why is it convex now?~~

~~Why is it monotonic now?~~

### Lemma 3.2

Let  $f(x), \{g_j(x)\}_{j=1}^l \in C$  be sigmoid.

w.r.t. f exponents  $\{\alpha^{(j)}\}_{j=1}^l \subset \mathbb{R}^n$  with  $\alpha^{(1)} = 0$

Then  $\underset{\text{SAGE}}{f^{(p,q)}} \leq \underset{\text{SAGE}}{f^{(p',q')}} \quad p \leq p' \quad p, p', q, q' \in \mathbb{Z}_+$   
 $q \leq q'$

Quick Proof:

$$\text{SAGE}(E_p) \subseteq \text{SAGE}(E_{p'})$$

$$R_q(C) \subseteq R_{q'}(C)$$

$$\text{SAGE}(E_{p+q}) \subseteq \text{SAGE}(E_{p'+q'})$$



Conclusion: