

On volume of sublevel sets of polynomials

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Consider the compact set $\Omega_g \subset \mathbf{B} = (-1, 1)^n$ defined by :

$$\Omega_g := \{ \mathbf{x} \in \mathbb{R}^n : g(\mathbf{x}) \leq 1 \}$$

for some **nonnegative homogeneous polynomial** $g \in \mathbb{R}[\mathbf{x}]$.

Compute

$$\rho = \text{vol}(\Omega_g) = \int_{\Omega_g} d\mathbf{x}$$

... and possibly the moments

$$\rho_\alpha = \int_{\Omega_g} \mathbf{x}^\alpha d\mathbf{x}, \quad \alpha \in \mathbb{N}^n,$$

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Motivation

Let g be a **nonnegative homogeneous polynomial** of degree d and let $\Omega_g = \{\mathbf{x} : g(\mathbf{x}) \leq 1\}$.

Then :

$$\text{vol}(\Omega_g) = \int_{\Omega_g} d\mathbf{x} = \frac{1}{\Gamma(1 + n/d)} \int_{\Omega_g} \exp(-g(\mathbf{x})) d\mathbf{x}.$$

see e.g. **Morozov & Shakirov**, *Introduction to integral discriminants*, **J. High Energy physics**

I.  $\int_{\Omega_g} \exp(-g(\mathbf{x})) d\mathbf{x}$, called an **integral discriminant**, is ubiquitous in **statistical and quantum Physics**.

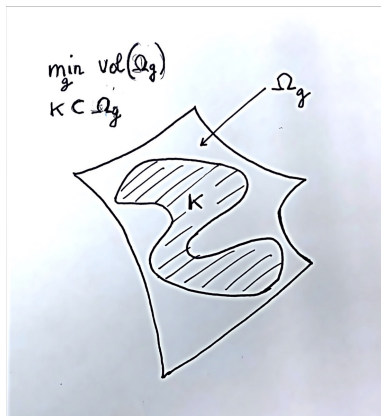
II. From the above formula it follows that

☞ $\text{vol}(\Omega_g)$ is a **strictly CONVEX** function of the **coefficients** of the polynomial g .

☞ very useful for solving Problem **P** :

P : Compute g **nonnegative homogeneous** of degree $2d$ such that $\mathbf{K} \subset \Omega_g$ and Ω_g has **minimum volume**.

where $\mathbf{K} \subset \mathbb{R}^n$ is a given compact (not necessarily convex) set.



Theorem

Problem **P** is a **CONVEX** problem with a *unique optimal solution* g^*

☞ $d = 2$ (quadratic case) : Ω_{g^*} is the celebrated Löwner-John ellipsoid

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Hence if one obtains good approximations of moments ρ_α , $|\alpha| = 2d$, then one may evaluate the function $g \mapsto \text{vol}(\Omega_g)$ and its **gradient** and **Hessian** because :

$$\frac{\partial \text{vol}(\Omega_g)}{\partial g_\alpha} = \frac{-\Gamma(1 + (n + |\alpha|)/2d)}{\Gamma(1 + n/2d)} \underbrace{\int_{\Omega_g} \mathbf{x}^\alpha d\mathbf{x}}_{\rho_\alpha}.$$

$$\frac{\partial^2 \text{vol}(\Omega_g)}{\partial g_\alpha \partial g_\beta} = \frac{-\Gamma(1 + (n + |\alpha + \beta|)/2d)}{\Gamma(1 + n/2d)} \underbrace{\int_{\Omega_g} \mathbf{x}^{\alpha+\beta} d\mathbf{x}}_{\rho_{\alpha+\beta}}.$$

☞ one may approximate the optimal g^* by a standard gradient descent algorithm (or even Newton's method if desired).

Computing $\text{vol}(\Omega)$

Let λ be the Lebesgue probability measure on a box $\mathbf{B} \supset \Omega_g$.

General approach

(i) Either approximate $\text{vol}(\Omega_g)$ by Monte-Carlo : λ -sample on \mathbf{B} and **COUNT** points that fall into Ω_g . This provides a (random) estimate of $\text{vol}(\Omega_g)$.

(ii) Or **SOLVE**[†] (or **approximate**)

$$\text{vol}(\Omega_g) = \max_{\phi} \{ \phi(\Omega_g) : \phi \leq \lambda \}$$

where the “max” is over measures ϕ supported on Ω_g .



† Henrion D., Lasserre J.B., Savorgnan C. (2009) Approximate volume and integration for basic semi-algebraic sets. SIAM Review 51, pp. 722–743

(i) 📌 simple method that can handle potentially relatively large dimensions. On the other hand, it only provides a **(random) estimate** of $\text{vol}(\Omega_g)$.

(ii) 📌 $\phi^* := \lambda_{\Omega_g}$ is the unique optimal solution and applying the **Moment-SOS hierarchy** provides a **monotone sequence of upper bounds** $(\rho_d)_{d \in \mathbb{N}} \downarrow \text{vol}(\Omega_g)$ as $d \rightarrow \infty$.


- Additional linear constraints coming from **Stokes' theorem** applied to ϕ^* **significantly accelerate** the (otherwise slow) convergence.
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Stokes' theorem

With vector field $X = x$ and $\alpha \in \mathbb{N}^n$ arbitrary :

$$\begin{aligned}
 0 &= \int_{\Omega_g} \text{Div}(X \cdot \mathbf{x}^\alpha (1 - g)) dx = \int \text{Div}(X \cdot \mathbf{x}^\alpha (1 - g)) d\phi^* \\
 &= \int \underbrace{\mathbf{x}^\alpha [(n + |\alpha|)(1 - g) - \langle \mathbf{x}, \nabla g \rangle]}_{p_\alpha(\mathbf{x})} d\phi^* \\
 &= \int p_\alpha(\mathbf{x}) d\phi^* \quad \text{a moment constraint on } \phi^*
 \end{aligned}$$

Hence one may equivalently solve :

$$\text{vol}(\Omega_g) = \max_{\phi \in \mathcal{M}(\Omega_g)} \{ \phi(\Omega_g) : \phi \leq \lambda; \int p_\alpha d\phi = 0, \alpha \in \mathbb{N}^n \}$$

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A simple transformation

Let the measure $\#\lambda$ on \mathbb{R} be the **pushforward** of λ by the mapping $g : \mathbf{B} \rightarrow \mathbb{R}$. That is :

$$\#\lambda(B) = \lambda(g^{-1}(B)), \quad \forall B \in \mathcal{B}(\mathbb{R}).$$

Let $I := g(\mathbf{B}) \subset \mathbb{R}$. Notice that :

All moments γ_k of $\#\lambda$ are obtained in closed form. That is :

$$\gamma_k := \int_I z^k d\#\lambda(z) = \int_{\mathbf{B}} g(\mathbf{x})^k \lambda(d\mathbf{x}), \quad k = 0, 1, \dots$$

Next, observe that

$$g(\Omega_g) = \{z \in I : 0 \leq z \leq 1\}.$$

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Then :

$$\#\lambda([0, 1]) = \int_{0 \leq z \leq 1} \#\lambda(dz) = \lambda(g^{-1}([0, 1])) = \lambda(\Omega_g)$$

That is, computing the n -dimensional volume ρ is computing the one-dimensional measure of the interval $[0, 1]$ for the measure $\#\lambda$ on $\mathbb{R} \dots$

☞ Therefore Jasour et al.[†] et al. suggest to solve :

$$\rho = \max_{\phi} \{ \phi([0, 1]) : \phi \leq \#\lambda; \text{supp}(\phi) = [0, 1] \}$$

Indeed $\phi^* = 1_{[0,1]}(z) d\#\lambda(z)$ is the unique optimal solution.

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Hence

One has replaced computation of the n -dimensional Lebesgue-volume of Ω_g by computation of the 1-dimensional $\#\lambda$ -volume of the interval $[0, 1]$

The value ρ can be approximated as closely as desired by solving appropriate SDP relaxations associated with the Moment-SOS hierarchy.

Problem :

- ☞ Convergence $(\rho_d)_{d \in \mathbb{N}} \downarrow \rho$ is typically **VERY SLOW** !
- ☞ One cannot use Stokes constraints because one does not know the density of $\#\lambda$.

The homogeneous case

Take home message

When g is homogeneous then one can do much better !

$$\text{Let } \phi_j^* = \int_{[0,1]} z^j d\#\lambda(z), \quad j = 0, 1, \dots$$

so that $\rho = \lambda(\Omega_g) = \phi_0^*$.

Suppose that g is **NONNEGATIVE** and **HOMOGENEOUS** of degree t . Then by Stokes' Theorem with vector field $X = \mathbf{x}$:

$$\begin{aligned}
 0 &= \int_{\Omega_g} [n(1 - g(\mathbf{x})^j) + \langle \mathbf{x}, \nabla(1 - g(\mathbf{x})^j) \rangle] d\lambda(\mathbf{x}) \\
 &= n\lambda(\Omega) - (n + jt) \int_{\Omega} g(\mathbf{x})^j d\lambda(\mathbf{x}) \\
 &= n\lambda(\Omega) - (n + jt) \int_{g(\Omega)} z^j d\# \lambda(z) \\
 &= n\phi_0^* - (n + jt)\phi_j^*, \quad j = 1, 2, \dots
 \end{aligned}$$

Theorem

Let $(\phi_j^*)_{j \in \mathbb{N}}$ be the moments of ϕ^* . Then :

$$\phi_j^* = \frac{n}{n+jt} \phi_0^*, \quad j = 1, 2, \dots$$

As a consequence the moment matrix $H_d(\phi^*)$ of ϕ^* , is just $\phi_0^* H_d^*$ with :

$$H_d^* = \begin{bmatrix} 1 & \frac{n}{n+t} & \cdots & \frac{n}{n+dt} \\ \frac{n}{n+t} & \cdots & \cdots & \frac{n}{n+(d+1)t} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{n}{n+dt} & \cdots & \cdots & \frac{n}{n+2dt} \end{bmatrix}$$

 which is the moment matrix of the probability measure

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But then :

$$\rho = \max_{\phi} \{ \phi(\mathbb{R}) : \phi \leq \#\lambda; \text{supp}(\phi) = [0, 1] \}$$

can be approximated as closely as desired by

$$\begin{aligned} \tau_d &= \max_{\theta} \{ \theta : \theta H_d^* \preceq H_d(\#\lambda) \} \\ &= \lambda_{\min}(H_d(\#\lambda), H_d^*) \end{aligned}$$

a **GENERALIZED EIGENVALUE PROBLEM** associated with two **HANKEL** moment matrices.

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$$\tau_d \downarrow \rho \text{ as } d \rightarrow \infty.$$

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$$\tau_d \downarrow \rho \text{ as } d \rightarrow \infty.$$

To visualize & appreciate the simplicity of the approach, let $n = 2$ and $g = \|\mathbf{x}\|^2 = x_1^2 + x_2^2$, and $\mathbf{B} = [-1, 1]^2$, so that $\text{vol}(\Omega_g) = \pi$. Then :

$$H_1^* = \begin{bmatrix} 1 & 1/2 \\ 1/2 & 1/3 \end{bmatrix}; \quad H_1(\#\lambda) = \begin{bmatrix} 1 & 2/3 \\ 2/3 & 28/45 \end{bmatrix}$$

This yields $4 \cdot \tau_1 \approx 3.20$ which is already a good upper bound on π whereas $4 \cdot \rho_1 = 4$.

$$H_2^* = \begin{bmatrix} 1 & 1/2 & 1/3 \\ 1/2 & 1/3 & 1/4 \\ 1/3 & 1/4 & 1/5 \end{bmatrix}; \quad H_2(\#\lambda) = \begin{bmatrix} 1 & 2/3 & 2/9 \\ 2/3 & 28/45 & 2/9 \\ 2/9 & 2/9 & 2/9 + \dots \end{bmatrix}$$

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d	$d = 1$	$d = 2$	$d = 3$	$d = 4$	$d = 5$
ρ_d	12.19	11.075	9.163	8.878	8.499
τ_d	6.839	5.309	5.001	4.945	4.936

TABLE – $n = 4$, $\rho = 4.9348$; ρ_d versus τ_d

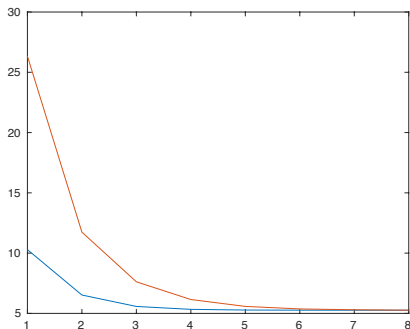
d	$d = 2$	$d = 3$	$d = 4$	$d = 5$	$d = 6$	$d = 7$	d
$2^n \tau_d$	15.04	7.97	5.569	4.639	4.272	4.133	4.
$\frac{(2^n \tau_d - \rho^*)}{\rho^*}$	270%	96%	37%	14%	5.26%	1.83%	0.

TABLE – $n = 8$, $\rho = 4.0587$; τ_d and relative error

Influence of the size of $\mathbf{B} = [-r, r]^n$

Introduction

$n = 8$ and τ_d with $r = 1.3$ (red above) and $r = 1$ (blue below)



Other moments

Suppose that one has already computed (or approximated) ϕ_0^* (and so all moments ϕ_j^*) of $\#\lambda$.

To compute the moment $\int_{\Omega_g} \mathbf{x}^\alpha dx$:

- Replace the measure λ on \mathbf{B} with the measure

$$d\lambda^\alpha := (1 - \mathbf{x}^\alpha)d\lambda \quad \text{on } \mathbf{B}, \text{ and}$$

- Use the pushforward $\#\lambda^\alpha$ of λ^α by the mapping g .
- Then again :

$$\begin{aligned} \Rightarrow \quad \lambda^\alpha(\Omega_g) &= \#\lambda^\alpha([0, 1]) = \int_{\Omega_g} (1 - \mathbf{x}^\alpha) d\mathbf{x} \\ &= \text{vol}(\Omega_g) - \int_{\Omega_g} \mathbf{x}^\alpha d\mathbf{x} \end{aligned}$$

So again the moments of $\#\lambda^\alpha$ are obtained in closed form

$$\#\lambda_j^\alpha = \int z^j d\#\lambda^\alpha(z) = \int_{\mathbf{B}} g(\mathbf{x})^j (1 - \mathbf{x}^\alpha) d\lambda(\mathbf{x}).$$

w.l.o.g. $\mathbf{B} = [-1, 1]^n$. From Stokes' theorem for the integral :

$$\int_{\Omega_g} \text{Div}(\mathbf{X} \cdot (1 - g_j)(1 - \mathbf{x}^\alpha)) d\mathbf{x},$$

the moments $(\phi_j^{\alpha*})_{j \in \mathbb{N}}$ of the restriction of $\#\lambda^\alpha$ to $[0, 1]$ satisfy :

$$\phi_j^{\alpha*} = \frac{n + |\alpha|}{n + |\alpha| + tj} \phi_0^{\alpha*} + \frac{|\alpha|}{n + |\alpha| + tj} (\phi_j^* - \phi_0^*), \quad \forall j \in \mathbb{N}.$$

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Quasi-homogeneous polynomials

Let $u \in \mathbb{Q}^n$:

A polynomial $p \in \mathbb{R}[\mathbf{x}]$ is **u -quasi-homogeneous** if

$$p(\lambda^{u_1} x_1, \dots, \lambda^{u_n} x_n) = \lambda p(\mathbf{x}), \quad \forall \lambda > 0, \mathbf{x} \in \mathbb{R}^n.$$

Euler's identity becomes :

$$\sum_{i=1}^n u_i \frac{\partial p(\mathbf{x})}{\partial x_i} x_i = p(\mathbf{x}), \quad \forall \mathbf{x} \in \mathbb{R}^n$$

Stokes' constraints also work for nonnegative such p :

Just use the vector field $X = (u_1 x_1, \dots, u_n x_n)$.

☞ and with $\mathbf{u} := \sum_i u_i$, one obtains :

$$\phi_j^* = \frac{\mathbf{u}}{\mathbf{u} + j} \phi_0^*, \quad j = 1, 2, \dots$$

Digression

If one use $\tilde{g} = g^{1/m}$ with $m \in \mathbb{N}$, then \tilde{g} is t/m -homogeneous (and not a polynomial anymore). In particular, with $s = \max_{\mathbf{x}} \{ \tilde{g}(\mathbf{x}) : \mathbf{x} \in \mathbf{B} \}$

$$\# \lambda_k = \int_0^s z^k d\# \lambda(z) = \int_{\mathbf{B}} g(\mathbf{x})^{k/m} d\mathbf{x}, \quad k = 0, 1, \dots$$

are not provided in closed-form anymore.

However, suppose that one may obtain $(\# \gamma_k)_{k \in \mathbb{N}}$ (e.g. by cubature formula on \mathbf{B} or by Monte-Carlo). Then again :

$$\begin{aligned} \tau_d &= \max_{\theta} \{ \theta : \theta H_d^* \preceq H_d(\# \lambda) (= H_d(\gamma)) \} \\ &= \lambda_{\min}(H_d(\gamma), H_d^*) \end{aligned}$$

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I. Extension to the non-homogeneous case

Again $\Omega_g = \{\mathbf{x} : 0 \leq g(\mathbf{x}) \leq 1\} \subset [-1, 1]^n$ but $g \in \mathbb{R}[\mathbf{x}]_t$ is not homogeneous.

Basic idea

- Write $g = \sum_{k=1}^t g_k$ with g_k being homogeneous of degree k .
- Use the pushforward measure $\#\lambda$ of λ w.r.t. the polynomial mapping

$$G : \mathbb{R}^n \rightarrow \mathbb{R}^t \quad \mathbf{x} \mapsto G(\mathbf{x}) = \begin{bmatrix} g_1(\mathbf{x}) \\ \cdots \\ \cdots \\ g_t(\mathbf{x}) \end{bmatrix}$$

$$I := G(\mathbf{B}) \subset \mathbb{R}^t.$$

- The moments of $\#\lambda$ are given by :

$$\begin{aligned} \gamma_\alpha &:= \int z_1^{\alpha_1} \cdots z_t^{\alpha_t} \#\lambda(d\mathbf{z}), \quad \alpha \in \mathbb{N}^t \\ &= \int_{\mathbf{B}} g_1(\mathbf{x})^{\alpha_1} \cdots g_t(\mathbf{x})^{\alpha_t} \lambda(d\mathbf{x}), \quad \alpha \in \mathbb{N}^t \end{aligned}$$

- $G(\Omega_g) = \{ \mathbf{z} \in I : 0 \leq \sum_{k=1}^t z_k \leq 1 \} =: \Theta.$

$$\rho = \max_{\phi} \{ \phi(\mathbb{R}^t) : \phi \leq \#\lambda; \text{supp}(\phi) = \Theta \}$$

☞ One has replaced a **Lebesgue-volume computation in \mathbb{R}^n** with a **$\#\lambda$ -volume computation in \mathbb{R}^t** ... Interesting if $t \ll n$.

Stokes' constraints

Recall that $g = \sum_{k=1}^t g_k$. For instance, with $t = 2$, Stokes' theorem yields :

$$0 = \int_{\Omega_g} [n g(1-g) g_1^i g_2^j + \langle \mathbf{x}, \nabla(g(1-g) g_1^i g_2^j) \rangle] \lambda(d\mathbf{x}),$$

that is :

$$\begin{aligned} 0 &= n \int \left[(n+i+2j) z_1^i z_2^j (1-z_1-z_2)(z_1+z_2) \right. \\ &\quad \left. + (z_1+2z_2) z_1^i z_2^j (1-2z_1-2z_2) \right] d\#\lambda \\ &= \int q_{ij}(\mathbf{z}) d\#\lambda \end{aligned}$$

Hence with every couple $(i, j) \in \mathbb{N}^2$ one obtains a linear moment constraint $L_{\phi^*}(q_{ij}) = 0$, where :

$$q_{ij}(\mathbf{z}) = (n + i + 2j) z_1^i z_2^j (1 - z_1 - z_2)(z_1 + z_2) \\ + (z_1 + 2z_2) z_1^i z_2^j (1 - 2z_1 - 2z_2)$$

Therefore with $h(\mathbf{z}) = (1 - z_1 - z_2)(z_1 + z_2)$, one solves the hierarchy of semidefinite programs :

$$\tau_d = \max_{\phi} \{ \phi(\mathbb{R}^t) : 0 \preceq \mathbf{M}_d(\phi) \preceq \mathbf{M}_d(\# \lambda) \\ \mathbf{M}_{d-1}(h \phi) \succeq 0 \\ L_{\phi}(q_{ij}) = 0, \quad \deg(q_{ij}) \leq 2d \}$$

II. Multi-homogeneous constraints

In this case $\Omega = \{\mathbf{x} : g_j(\mathbf{x}) \leq 1, \quad j = 1, \dots, t\} \subset [-1, 1]^n$, where each g_j is homogeneous of degree t_j . Again use the pushforward measure $\#\lambda$ of λ w.r.t. the polynomial mapping

$$G : \mathbb{R}^n \rightarrow \mathbb{R}^t \quad \mathbf{x} \mapsto G(\mathbf{x}) = \begin{bmatrix} g_1(\mathbf{x}) \\ \vdots \\ \vdots \\ g_t(\mathbf{x}) \end{bmatrix}$$

$$I := G(\mathbf{B}) \subset \mathbb{R}^t.$$

- The moments of $\#\lambda$ are given by :

$$\begin{aligned} \gamma_\alpha &:= \int z_1^{\alpha_1} \cdots z_t^{\alpha_t} \#\lambda(d\mathbf{z}), \quad \alpha \in \mathbb{N}^t \\ &= \int_{\mathbf{B}} g_1(\mathbf{x})^{\alpha_1} \cdots g_t(\mathbf{x})^{\alpha_t} \lambda(d\mathbf{x}), \quad \alpha \in \mathbb{N}^t \end{aligned}$$

- $G(\Omega) = \{\mathbf{z} \in I : z_k \leq 1, \quad k = 1, \dots, t\} =: \Theta.$

Again one may use Stokes' Theorem to provide additional linear constraints on the moments of ϕ^*

Thank You!