

SOME QUICK FORMULAS FOR THE VOLUMES  
OF AND THE NUMBER OF INTEGER POINTS IN  
HIGHER-DIMENSIONAL POLYHEDRA

ALEXANDER BARVINOK, BASED JOINT WORKS WITH J.A.  
HARTIGAN AND MARK RUDELSON

August 2023

# The problem

Let  $P \subset \mathbb{R}^n$  be a polyhedron defined by the system of linear equations  $Ax = b$  and inequalities  $x \geq 0$ . Here  $A$  is an  $m \times n$  matrix with  $\text{rank } A = m < n$ .

Suppose that  $P$  is bounded and has a non-empty relative interior, that is, contains a point  $x = (x_1, \dots, x_n)$  where  $x_j > 0$  for  $j = 1, \dots, n$ .

Our goal is to estimate quickly  $\text{vol } P$ , the  $(n - m)$ -dimensional volume of  $P$ . When  $A$  and  $b$  are integer, we also want to estimate quickly  $|P \cap \mathbb{Z}^n|$ , the number of integer points in  $P$ .

# The entropy maximization problem

We define  $f : \mathbb{R}_+^n \rightarrow \mathbb{R}$  by

$$f(x) = n + \sum_{j=1}^n \ln x_j \quad \text{where } x = (x_1, \dots, x_n)$$

and find the necessarily unique  $z \in P$ ,  $z = (z_1, \dots, z_n)$ , such that

$$f(z) = \max_{x \in P} f(x).$$

The point  $z$  is called the *analytic center* of  $P$ . Since  $\text{relint } P \neq \emptyset$ , we have  $z_j > 0$  for  $j = 1, \dots, n$ .

# The formula

Given a bounded polyhedron  $P$  defined by the system  $Ax = b$ ,  $x \geq 0$ , we compute its analytic center  $z = (z_1, \dots, z_n)$ . Let  $B$  be the  $m \times n$  matrix obtained by multiplying the  $j$ -th column of  $A$  by  $z_j$  for  $j = 1, \dots, n$ . Then

$$\mathcal{E}(A, b) = e^{f(z)} \frac{\sqrt{\det AA^T}}{\sqrt{\det BB^T}} = e^n z_1 \cdots z_n \frac{\sqrt{\det AA^T}}{\sqrt{\det BB^T}}$$

approximates  $\text{vol } P$  within a multiplicative factor of  $\gamma^m$ , where  $\gamma > 0$  is an absolute constant.

Note that it scales correctly:

$$\mathcal{E}(A, \tau b) = \tau^{n-m} \mathcal{E}(A, b) \quad \text{for } \tau > 0.$$

## Example

Suppose that  $P$  is defined by

$$\sum_{j=1}^n a_j x_j = n \quad \text{and} \quad x_j \geq 0 \quad \text{for} \quad j = 1, \dots, n.$$

We must have  $a_j > 0$  for  $j = 1, \dots, n$ . Then

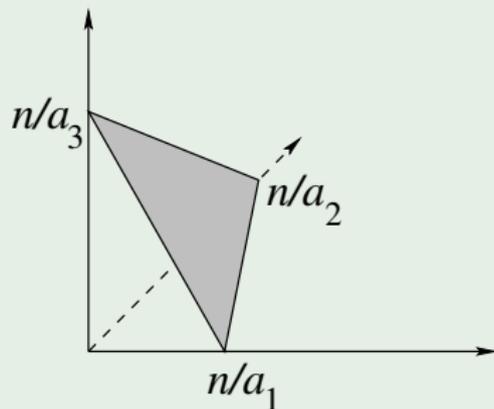
$$z = \left( \frac{1}{a_1}, \dots, \frac{1}{a_n} \right) \quad \text{and} \quad \mathcal{E}(A, b) = \frac{e^n}{a_1 \cdots a_n} \frac{\sqrt{a_1^2 + \dots + a_n^2}}{\sqrt{n}}.$$

On the other hand,

$$\text{vol } P = \frac{n^n}{n! a_1 \cdots a_n} \sqrt{a_1^2 + \dots + a_n^2}.$$

# Example: simplex

## Example



Since

$$n! = \sqrt{2\pi n} e^{-n} n^n (1 + o(1)) \quad \text{as } n \rightarrow +\infty,$$

we get

$$\text{vol } P = \frac{1}{\sqrt{2\pi}} \mathcal{E}(A, b) (1 + o(1)) \quad \text{as } n \rightarrow +\infty.$$

# Example: doubly stochastic matrices

## Example

Consider the polytope  $P_r$  of  $r \times r$  doubly stochastic matrices  $X = (x_{ij})$ :

$$\sum_{j=1}^r x_{ij} = 1 \quad \text{for } i = 1, \dots, r, \quad \sum_{i=1}^r x_{ij} = 1 \quad \text{for } j = 1, \dots, r$$

and  $x_{ij} \geq 0$  for  $i, j = 1, \dots, r$ .

*	*	*	*
*	*	*	*
*	*	*	*
*	*	*	*

# Example: doubly stochastic matrices

## Example

We have  $\dim P_r = (r - 1)^2$ . By symmetry, the analytic center is

$$z_{ij} = \frac{1}{r} \quad \text{for } i, j = 1, \dots, r \quad \text{and hence} \quad \mathcal{E}(A, b) = \frac{e^{r^2}}{r^{(r-1)^2}}.$$

Canfield and McKay (2009) proved that

$$\text{vol } P_r = e^{1/3} \frac{e^{r^2}}{(\sqrt{2\pi})^{2r-1} r^{(r-1)^2}} (1 + o(1)) \quad \text{as } r \rightarrow +\infty.$$

In Barvinok and Hartigan (2010), we called

$$\text{vol } P \approx \frac{\mathcal{E}(A, b)}{(2\pi)^{m/2}}$$

*Gaussian approximation* and showed that it holds under some conditions (more on this later).

# Example: 3-way planar transportation polytopes

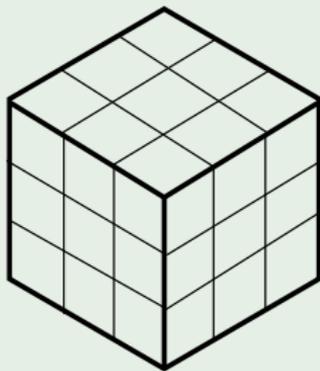
## Example

Consider the polytope  $P_r$  of  $r \times r \times r$  arrays (tensors)  $X = (x_{ijk})$  such that

$$\begin{aligned}\sum_{i=1}^r x_{ijk} &= 1 \quad \text{for } j, k = 1, \dots, r, \\ \sum_{j=1}^r x_{ijk} &= 1 \quad \text{for } i, k = 1, \dots, r, \\ \sum_{k=1}^r x_{ijk} &= 1 \quad \text{for } i, j = 1, \dots, r \quad \text{and} \\ x_{ijk} &\geq 0 \quad \text{for } i, j, k = 1, \dots, r.\end{aligned}$$

# Example: 3-way planar transportation polytopes

## Example



Then  $\dim P_r = (r - 1)^3$ . By symmetry,

$$z_{ijk} = \frac{1}{r} \quad \text{for } i, j, k = 1, \dots, r \quad \text{and hence} \quad \mathcal{E}(A, b) = \frac{e^{r^3}}{r^{(r-1)^3}}$$

approximates  $\text{vol } P_r$  within a factor of  $e^{O(r^2)}$  as  $r \rightarrow +\infty$ .

# The main theorem (with M. Rudelson)

## Theorem

- Let  $\alpha_0 \approx 1.398863726$  be the necessarily unique number in the interval  $(1, +\infty)$  satisfying

$$\frac{1}{2\pi} \int_{-\infty}^{+\infty} (1 + s^2)^{-\alpha_0/2} ds = 1.$$

Then

$$\text{vol } P \leq \alpha_0^{m/2} \mathcal{E}(A, b) \leq (1.183)^m \mathcal{E}(A, b).$$

- We have

$$\begin{aligned} \text{vol } P &\geq \frac{2\Gamma\left(\frac{m+2}{2}\right)}{\pi^{m/2} e^{(m+2)/2} (m+2)^{m/2}} \mathcal{E}(A, b) \\ &\approx \left(\frac{1}{e\sqrt{2\pi}}\right)^m \approx (0.14)^m \mathcal{E}(a, b). \end{aligned}$$

# The main theorem

In fact, we can prove

$$\text{vol } P \geq \gamma^m \mathcal{E}(A, b)$$

for any

$$\gamma < \frac{1}{\sqrt{2\pi e}} \approx 0.24$$

and sufficiently large  $m$ . The proof requires thin shell estimates (Klartag 2007, Chen 2021, Klartag and Lehec 2022), although pretty much any non-trivial estimate will do.

# Ideas of the proof: the maximum entropy distribution

Recall that a random variable  $X$  is standard exponential, if its density is

$$p_X(t) = \begin{cases} e^{-t} & \text{if } t > 0 \\ 0 & \text{if } t \leq 0. \end{cases}$$

The following lemma was proved in Barvinok and Hartigan (2010):

## Lemma

*Let  $X_1, \dots, X_n$  be independent standard exponential random variables and let  $z = (z_1, \dots, z_n)$  be the analytic center of  $P$ . Then the density of the random vector  $(z_1 X_1, \dots, z_n X_n)$  is constant on  $P$  and equal to*

$$e^{-f(z)} = \frac{e^{-n}}{z_1 \cdots z_n}.$$

# Ideas of the proof: the maximum entropy distribution

The proof is an exercise with Lagrange multipliers. A “deeper” reason why it works is that the distribution of  $(z_1 X_1, \dots, z_n X_n)$  is the maximum entropy distribution among all distributions supported on  $\mathbb{R}_+^n$  and with expectation in the affine subspace  $Ax = b$ .

## Corollary

Let  $a_1, \dots, a_n$  be the columns of  $A$ , so  $A = [a_1, \dots, a_n]$  and let

$$Y = \sum_{j=1}^n z_j X_j a_j = \sum_{j=1}^n X_j b_j \quad \text{where} \quad B = [b_1, \dots, b_n].$$

Then

$$\text{vol } P = e^{f(z)} \sqrt{\det AA^T} p_Y(b),$$

where  $p$  is the density of  $Y$ .

Note that

$$\mathbf{E} Y = b \quad \text{and} \quad \mathbf{Cov} Y = BB^T.$$

# Example: Simplex

## Example

Suppose that  $P$  is defined by

$$\sum_{j=1}^n a_j x_j = n \quad \text{and} \quad x_j \geq 0 \quad \text{for} \quad j = 1, \dots, n.$$

We have  $z_j = \frac{1}{a_j}$  for  $j = 1, \dots, n$  and  $Y = \sum_{j=1}^n X_j$ .

Hence

$$p_Y(t) = \begin{cases} \frac{t^n}{n!} e^{-t} & \text{if } t > 0 \\ 0 & \text{if } t \leq 0. \end{cases}$$

Then

$$e^{f(z)} \sqrt{\det AA^T} p_Y(b) = \frac{n^n}{n! a_1 \cdots a_n} \sqrt{a_1^2 + \cdots + a_n^2} = \text{vol } P.$$

# Ideas of the proof: log-concave isotropic densities

The density  $p_Y$  of  $Y$  is log-concave, and we are interested in  $p_Y(b)$  where  $\mathbf{E} Y = b$ . Furthermore, there is some freedom in choosing  $A$ :

$$A \mapsto WA, \quad b \mapsto Wb \quad \text{and} \quad B \mapsto WB,$$

where  $W$  is an  $m \times m$  invertible matrix. Then

$$AA^T \mapsto W(AA^T)W^T, \quad B \mapsto W(BB^T)W^T$$

and

$$\frac{\sqrt{\det AA^T}}{\sqrt{\det BB^T}}$$

does not change. Hence we can assume that  $BB^T = I$  and

$$\mathbf{Cov} Y = I.$$

# Ideas of the proof: log-concave isotropic densities

The proof for the lower bound of  $p_Y(b)$ : applies to all log-concave isotropic densities.

The proof for the upper upper bound of  $p_Y(b)$  uses the formula for the characteristic function of  $Y$ :

$$\phi_Y(t) = \prod_{j=1}^n \frac{1}{1 - \sqrt{-1} \langle b_j, t \rangle}$$

and is inspired by the proof of Ball (1989) of the upper bound for the volume of a section of the cube (but easier).

# The Gaussian formula

Recall the corollary: if  $X_1, \dots, X_n$  are independent standard exponential,

$$Y = \sum_{j=1}^n z_j X_j a_j = \sum_{j=1}^n X_j b_j,$$

then  $\text{vol } P = e^{f(z)} \sqrt{\det AA^T} p_Y(b)$ . In addition,

$$\mathbf{E} Y = b \quad \text{and} \quad \mathbf{Cov} Y = BB^T.$$

It stands to reason that, being a sum of independent random variables,  $Y$  is close to Gaussian, and hence

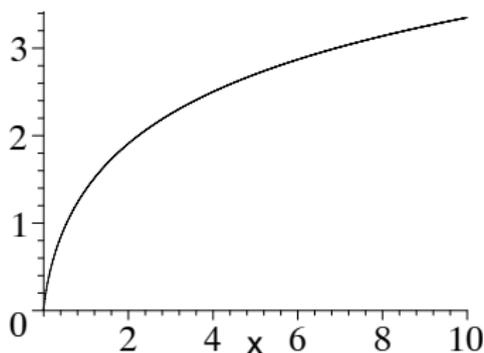
$$p_Y(b) \approx \frac{1}{(2\pi)^{m/2} \sqrt{\det BB^T}} \quad \text{and} \quad \text{vol } P \approx \frac{e^{f(z)} \sqrt{\det AA^T}}{(2\pi)^{m/2} \sqrt{\det BB^T}}.$$

Barvinok and Hartigan (2010, 2012) showed that this indeed holds asymptotically for some families of polyhedra, sometimes with the “Edgeworth correction” factor (like  $e^{1/3}$  for the polytope of doubly stochastic matrices).

# Counting integer points: the Gaussian formula

Suppose we want to count integer points in  $P = \{x \geq 0 : Ax = b\}$  (assume that  $A$  and  $b$  are integer). Consider the function

$$g(x) = (x + 1) \ln(x + 1) - x \ln x \quad \text{for } x \geq 0.$$



Remark:  $g(x)$  is the maximum entropy of a probability distribution (necessarily geometric) on  $\mathbb{Z}_+$  with expectation  $x$ :

$$\mathbf{P}(X = k) = pq^k \quad \text{for } k = 0, 1, \dots;$$

$$\mathbf{E} X = \frac{q}{p} := x, \quad \mathbf{var} X = \frac{q}{p^2} = x + x^2.$$

# Counting integer points: the Gaussian formula

In Barvinok and Hartigan (2010), we prove:

## Lemma

Let  $z = (z_1, \dots, z_n)$  be the necessarily unique point where the concave function

$$g(x) = \sum_{j=1}^n g(x_j) \quad \text{for } x = (x_1, \dots, x_n)$$

attains its maximum on  $P$ . Let  $X = (X_1, \dots, X_n)$  be the vector of independent geometric random variables with

$$\mathbf{E}(X_j) = z_j \quad \text{for } j = 1, \dots, n.$$

Then the probability mass function of  $X$  is constant on the points  $P \cap \mathbb{Z}^n$  and equal to  $e^{-g(z)}$ .

# Counting integer points: the Gaussian formula

The distribution of  $X$  is the maximum entropy distribution supported on  $\mathbb{Z}_+^n$  and with expectation in the affine subspace  $Ax = b$ .

Let  $a_1, \dots, a_n$  be the columns of  $A$ . We let

$$Y = \sum_{j=1}^n X_j a_j$$

and conclude that

$$|P \cap \mathbb{Z}^n| = e^{g(z)} \mathbf{P}(Y = b).$$

Given an  $m \times n$  matrix  $A = (a_{ij})$  with  $\text{rank } A = m < n$ , we compute the  $m \times m$  matrix  $B = (b_{ij})$  by

$$b_{ij} = \sum_{k=1}^n a_{ik} a_{jk} (z_k + z_k^2),$$

so that  $\mathbf{E} Y = b$  and  $\mathbf{Cov} Y = B$ .

# Counting integer points: the Gaussian formula

Assuming that  $Y$  is close to Gaussian, we get the following estimate for  $|P \cap \mathbb{Z}^n|$ , where  $P = \{x \geq 0 : Ax = b\}$ :

$$\mathcal{E}_I = \frac{e^{g(z)} \det \Lambda}{(2\pi)^{m/2} \sqrt{\det B}},$$

where  $\Lambda \subset \mathbb{Z}^m$  is the lattice generated by the columns of  $A$ . In a similar way, we can get an estimate for the number of 0-1 points in  $P$ . The function  $g$  is replaced by

$$h(x) = x \ln \frac{1}{x} + (1-x) \ln \frac{1}{1-x} \quad \text{for } 0 \leq x \leq 1$$

and  $B$  is computed as follows:

$$b_{ij} = \sum_{k=1}^n a_{ik} a_{jk} (z_k - z_k^2).$$

# The Gaussian formula for integer points: example

## Example

The number of  $4 \times 4$  non-negative integer matrices with row sums  $[220, 215, 93, 64]$  and column sums  $[108, 286, 71, 127]$  is  $1,225,914,276,768,514 \approx 1.2 \times 10^{15}$  (Diaconis and Efron, 1985). The value of  $\mathcal{E}_I(A, b)$  approximates it within relative error of 0.06 (De Loera, 2009).

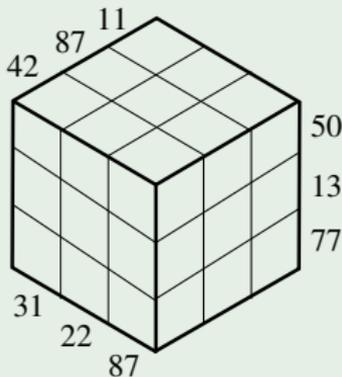
	108	286	71	127
220	*	*	*	*
215	*	*	*	*
93	*	*	*	*
64	*	*	*	*

Here  $Y$  is a sum of 16 independent 7-vectors.

# The Gaussian formula for integer points: example

## Example

The number of  $3 \times 3 \times 3$  non-negative integer arrays with slice sums  $[31, 22, 87]$ ,  $[50, 13, 77]$  and  $[42, 97, 11]$  is  $8,846,838,772,161,591 \approx 8.8 \times 10^{15}$ . The value of  $\mathcal{E}_I(A, b)$  approximates it within relative error 0.002 (De Loera 2009).



Here  $Y$  is the sum of 27 independent 7-vectors.