Cálculo del Volumen en Dimensión Alta

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El Plan

- Part I. Intro to high dimension and convexity
 - Volume distribution, logconcavity
 - Ellipsoids
 - Lower bounds
- Part 2. Algorithms
 - Rounding
 - Volume/Integration
 - Optimization
 - Sampling
- Part 3. Probability
 - Markov chains
 - Conductance
 - Mixing of ball walk
 - Mixing of hit-and-run
- Part 4. Geometry
 - Isoperimetry
 - Concentration
 - Localization and applications
- Open problems

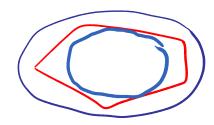
Volumen: Segundo intento: Elipsoides

Ellipsoid #1: John ellipsoid of a convex body K:

E = maximum volume ellipsoid contained in K.

Thm. For any convex body K, the John ellipsoid satisfies

$$E \subseteq K \subseteq nE$$
.

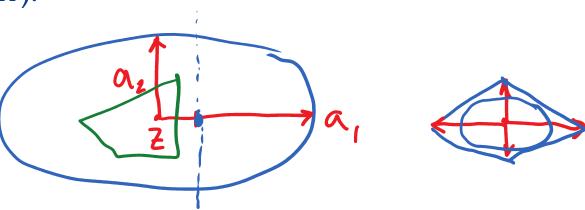


For any centrally-symmetric K, $E \subseteq K \subseteq \sqrt{n}E$.

Exercise 2: Encuentre un ejemplo ajustado.

Elipsoide de John Aproximado

- Variant of the Ellipsoid algorithm:
 - suppose current center is z and axes are $a_1, a_2, ..., a_n$.
 - ▶ Check if $z \pm \frac{a_i}{n} \in K$. If so, output current ellipsoid.
 - If not, then intersect E with halfspace H not containing $z + \frac{a_i}{n}$ and continue algorithm (replace E with min volume ellipsoid containing $E \cap H$).



▶ Thm.Algorithm outputs E satisfying $E \subseteq K \subseteq n^{1.5}E$.

Volumen por John elipsoide

Using the Ellipsoid algorithm, in polytime

$$E \subseteq K \subseteq n^{1.5}E$$

Then

$$vol(E) \le vol(K) \le n^{1.5n} \ vol(E)$$

Polytime, exponential approximation

Elipsoide #2: Elipsoide inertial

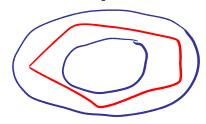
For a convex body K, matrix of inertia:

$$M = E_K ((x - \bar{x})(x - \bar{x})^T)$$

Inertial ellipsoid: $E = \{y \in R^n: y^T M^{-1} y \le 1\}$

Thm (KLS95).
$$\sqrt{\frac{n+1}{n}}E \subseteq K \subseteq \sqrt{n(n+1)}E$$

- \blacktriangleright Also a factor n sandwiching, but a different ellipsoid.
- Shown earlier up to constants by Milman-Pajor.



Posición Isotropico

- For any distribution with bounded second moments, there is an affine transformation to make it isotropic.
- Applying this to a convex body K:

$$E_K(x) = 0, \qquad E_K(xx^T) = I_n.$$

- Thus K "looks like a ball" up to second moments.
- How close is it really to a ball?
- K lies between two balls with radii within a factor of n.

Volumen por aproximación elipsoidal

- The Inertial ellipsoid can be approximated to within any constant factor (we'll see how)
- Therefore:

$$E \subseteq K \subseteq 2n E \Rightarrow vol(E) \leq vol(K) \leq (2n)^n vol(E)$$
.

- Polytime algorithm, $O(n)^n$ approximation
- Can we do better?

Elipsoide #3: Elipsoide de Milman

- For two compact sets A, B,
- N(A,B) = #translates of A needed to cover B.

Thm (Milman). For any convex body K, there is an ellipsoid E s.t., $N(K, E), N(E, K) \leq 2^{O(n)}$

Many important consequences in convex geometry.

Thm (Dadush-V.). Deterministic complexity of computing a Milman ellipsoid is $2^{\mathcal{O}(n)}$.

- \triangleright 2^{O(n)} time, 2^{O(n)} approximation.
- Can we do better?!

Complejidad de Volumen

Thm [E86, BF87]. For any deterministic algorithm that uses at most n^a membership calls to the oracle for a convex body K and computes two numbers A and B such that $A \le vol(K) \le B$, there is some convex body for which the ratio B/A is at least

$$\left(\frac{cn}{a\log n}\right)^{\frac{11}{2}}$$

where c is an absolute constant.

Thm [DF88]. Computing the volume of an explicit polytope $Ax \le b$ is #P-hard, even for a totally unimodular matrix A and rational b.

Estimación determinista

Thm [BF]. For deterministic algorithms:

oracle calls

approximation factor

$$n^a$$

$$\left(\frac{cn}{a\log n}\right)^{\frac{n}{2}}$$

$$\left(\frac{1}{\epsilon}\right)^{n}$$

$$(1+\epsilon)^n$$

Thm [Dadush-V.13].

Approximation factor of $(1 + \epsilon)^n$ in time $\left(\frac{1}{\epsilon}\right)^{O(n)} \operatorname{poly}(n)$.

Un Limite Inferior

- [Elekes]
- Membership oracle answers "YES" for points in unit ball, "No" for points outside.
- After m queries, volume of K is between volume of convex hull and volume of unit ball.
- ▶ Lemma. $vol(conv\{x_1, x_2, ..., x_m\}) \le \frac{m}{2^n}. vol(B^n)$
- Need exponentially many queries!

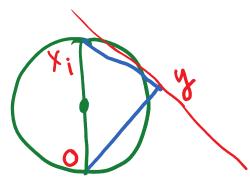
Un Limite Inferior

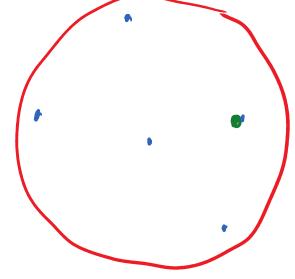
Lemma. $vol(conv\{x_1, x_2, ..., x_m\}) \le \frac{m}{2^n} \cdot vol(B^n)$

Proof. Let $B_i = \text{ball of radius } \frac{||x_i||}{2} \text{ around } \frac{x_i}{2}$.

Claim I. $\sum_{i} vol(B_i) \leq m \cdot \frac{vol(B^n)}{2^n}$.

Claim 2. $conv\{x_1, x_2, ..., x_m\} \subset \bigcup_i B_i$.





 $y \notin B_i \Rightarrow \angle 0yx_i$ is acute, i.e., 0 and x_i are on the same side of orthogonal hyperplane through y.

Hence, $y \notin conv\{x_1, x_2, ..., x_n\}$.

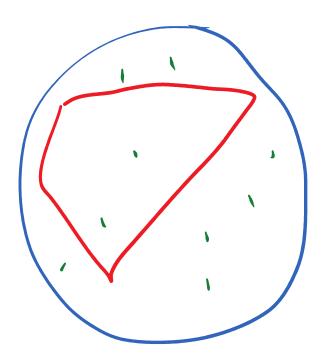
Volumen/Integración Aleatoria

[DFK89]. Polytime randomized algorithm that estimates volume to within relative error $(1+\epsilon)$ with probability at least $1-\delta$ in time poly $(n,\frac{1}{\epsilon},\log\left(\frac{1}{\delta}\right))$.

[Applegate-K91]. Polytime randomized algorithm to estimate integral of any (Lipshitz) logconcave function.

Volumen: Tercer intento: Muestreo

- Pick random samples from ball/cube containing K.
- ▶ Compute fraction c of sample in K.
- Output c.vol(outer ball).

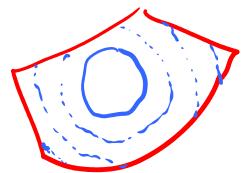


Need too many samples!

Volumen por Muestreo [DFK89]

$$B \subseteq K \subseteq RB$$
.

Let
$$K_i = K \cap 2^{i/n}B$$
, $i = 0, 1, ..., m = n \log R$.



$$vol(K) = vol(B) \cdot \frac{vol(K_1)}{vol(K_0)} \cdot \frac{vol(K_2)}{vol(K_1)} \cdot \dots \cdot \frac{vol(K_m)}{vol(K_{m-1})}.$$

Estimate each ratio with random samples. (Markov Chain Monte-Carlo method)

Volumen por Muestreo

$$K_i = K \cap 2^{i/n}B$$
, $i = 0, 1, ..., m = n \log R$.

$$\operatorname{vol}(K) = \operatorname{vol}(B) \cdot \frac{\operatorname{vol}(K_1) \operatorname{vol}(K_2)}{\operatorname{vol}(K_0) \operatorname{vol}(K_1)} \dots \frac{\operatorname{vol}(K_m)}{\operatorname{vol}(K_{m-1})}.$$

Claim. $vol(K_{i+1}) \le 2. vol(K_i)$.

$$K_{i+1} \subseteq 2^{1/n} (K \cap 2^{i/n} B) = 2^{1/n} K_i$$

Varianza de la estimación [DF91]

$$K_i = K \cap 2^{i/n}B$$
, $i = 0, 1, ..., m = n \log R$.

$$\operatorname{vol}(K) = \operatorname{vol}(B) \cdot \frac{\operatorname{vol}(K_1)}{\operatorname{vol}(K_0)} \frac{\operatorname{vol}(K_2)}{\operatorname{vol}(K_1)} \dots \frac{\operatorname{vol}(K_m)}{\operatorname{vol}(K_{m-1})}$$

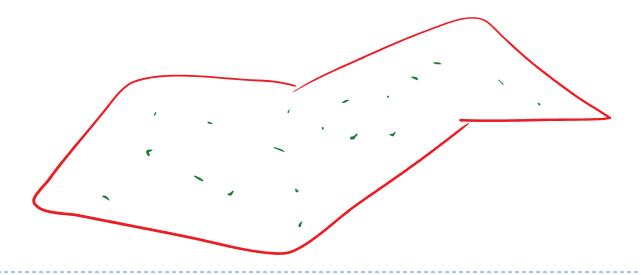
$$\frac{Var(Y_1Y_2...Y_m)}{E(Y_1Y_2...Y_m)^2} = \prod_{i} \frac{E(Y_i^2)}{E(Y_i)^2} - 1 = \prod_{i} \left(1 + \frac{Var(Y_i)}{E(Y_i)^2}\right) - 1$$

- $\frac{Var(Y_i)}{E(Y_i)^2} \le \frac{c}{k} \text{ using k samples in each phase.}$
- So $k = \frac{m}{\epsilon^2}$ samples in each phase suffice.
- Total number of samples $= m \cdot \frac{m}{\epsilon^2} = O^*(n^2)$.
- But, how to sample?

Muestreo

Input: function $f: \mathbb{R}^n \to \mathbb{R}_+$ specified by an oracle, point x with f(x)>0, error parameter ε .

Output: A point y from a distribution within distance ε of distribution with density proportional to f.



Aplicaciónes

Given a blackbox for sampling logconcave densities, we get efficient algorithms for:

- Rounding
- Convex Optimization
- Volume Computation/Integration
- some Learning problems

Redondear por Muestreo

- Sample m random points from K;
- 2. Compute sample mean and sample covariance matrix

3. Output $B = A^{-\frac{1}{2}}$.

B(K-z) is nearly isotropic.

Thm. $C(\epsilon)$.n random points suffice to get $E(||A-I||_2) \le \epsilon$. [Adamczak et al; improving on Bourgain, Rudelson]

I.e., for any unit vector v, $1 - \epsilon \le E\left(\left(v^T x\right)^2\right) \le 1 + \epsilon$.

Complejidad de Muestreo

Thm. [KLS97] For a convex body, the ball walk with an M-warm start reaches a nearly independent, nearly random point in poly(n, R, M) steps.

$$M = \sup \frac{Q_0(S)}{Q(S)}$$
 or $M = E_{Q_0}\left(\frac{Q_0(x)}{Q(x)}\right)$

Thm. [LV03]. Same holds for arbitary logconcave density functions. Complexity is $O^*(M^2n^2R^2)$.

Isotropic transformation makes $R=O(\sqrt{n})$; M can be kept at O(1).

KLS'97 volume algorithm:
$$n \times n \times n^3 = n^5$$

Progreso en el Cálculo del Volumen

	Power	New aspects
Dyer-Frieze-Kannan 89	23	everything
Lovász-Simonovits 90	16	localization
Applegate-K 90	10	logconcave integration
L 90	10	ball walk
DF 91	8	error analysis
LS 93	7	multiple improvements
KLS 97	5	speedy walk, isotropy
LV 03,04	4	annealing, wt. isoper.
LV 06	4	integration, local analysis
Cousins-V. 13, 15	3	Gaussian cooling