
HIGH-DIMENSIONAL CONVEX GEOMETRY

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Contents

1	Introduction	3
1.1	The Euclidean Ball	3
1.1.1	Finding the Volume	3
1.1.2	Some Surprising Results in Concentration	4
1.2	The Cube and other Polytopes	5
1.2.1	Banach-Mazur Distance and Spherical Caps	5
1.2.2	Bounds on Almost-Spherical Polytopes	7
1.3	Fritz John's Theorem	8
1.3.1	The Statement of the Theorem	8
1.3.2	Some Consequences of Fritz John's Theorem	8
1.3.3	The Proof	10
2	Volume Inequalities	14
2.1	Spherical Sections of Symmetric Bodies	14
2.2	The Prékopa-Leindler Inequality	17
2.2.1	Brunn's Theorem	17
2.2.2	The Brunn-Minkowski Inequality	17
2.2.3	The Prékopa-Leindler inequality	19
2.3	The Reverse Isoperimetric Problem	21
2.3.1	Volume Ratio Estimates and Young's Convolution Inequality	22
2.3.2	A Generalization	23
3	Concentration and Almost-Balls	25
3.1	Concentration in Geometry	25
3.1.1	The Chordal Metric	25
3.1.2	The Gaussian Metric	26
3.2	Dvoretzky's Theorem	28
3.2.1	Expressing the Result in Terms of the Median	28
3.2.2	Dvoretzky's Theorem for a Cross-Polytope under the Gaussian Measure	30
3.2.3	A Weaker Version of the Dvoretzky-Rogers Lemma	30
3.2.4	Bounding the Expectation	31
4	Computing Volume in High Dimensions	33
4.1	Sandwiching and Deterministic Algorithms	33
4.1.1	Oracles	33
4.1.2	Sandwiching	34
4.1.3	The Problem and Deterministic Attempts	36
4.1.4	The Bárány-Füredi Theorem	36
4.1.5	Bounding $V(n, m)$ and $S(n, m)$	37

4.2	Rapidly Mixing Random Walks	40
4.2.1	An Issue with High Dimensions and the Solution	40
4.2.2	Random Walks on Graphs	41
4.2.3	Conductance and Bounding the Speed of Convergence	42
4.2.4	An Overview of Random Walks for Uniform Distributions	45
4.3	A Modified Grid Walk that Runs in $\mathcal{O}^*(n^8)$	46
4.3.1	A Description of the Walk	46
4.3.2	Showing Rapid Mixing by Bounding Conductance	48
4.4	Measure-Theoretic Markov Chains and Conductance	49
4.4.1	Some Basic Definitions	49
4.4.2	Conductance	51
4.4.3	A Distance Function	52
4.4.4	Rapidly Mixing Markov Chains	54
4.4.5	An Important Inequality involving the operator M	55
4.4.6	Metropolis Chains	57
4.5	An Isoperimetric Inequality	58
4.5.1	Log-Concave Functions	58
4.5.2	An Improvement of a Past Result	58
4.6	An $\mathcal{O}^*(n^7)$ Algorithm using Ball-Step	66
4.6.1	Ball-Step and Bounding Conductance	66
4.6.2	The Walk	68
4.6.3	Better Sandwiching and Ignoring the Error Probability	72
4.6.4	Bringing Everything Together and a Final Analysis	73
5	The KLS Conjecture	79
5.1	An Isoperimetric Problem	79
5.1.1	Introduction	79
5.1.2	Needles and Localization Lemmas	80
5.1.3	Exponential Needles	81
5.1.4	An Example Using the Equivalences	83
5.1.5	Isotropy	84
5.1.6	The KLS Conjecture	86
5.2	A More Detailed Look	89
5.2.1	The Slicing Conjecture	89
5.2.2	The Thin-Shell Conjecture	90
5.3	Recent Bounds on the Isoperimetric Constant	90
5.3.1	A Look At Stochastic Localization	90
5.3.2	Towards a $n^{-1/4}$ Bound	92
5.3.3	Controlling A_t	94
5.3.4	Towards an Almost Constant Bound	96

§1. Introduction

Definition 1.1. A subset S of a Euclidean space is said to be *convex* if for any $u_1, \dots, u_r \in S$ and non-negative $\lambda_1, \dots, \lambda_r$ such that $\lambda_1 + \dots + \lambda_r = 1$, the *affine combination* $\sum_{i=1}^r \lambda_i u_i$ is in S as well.

We primarily consider convex bodies, that is, compact and convex subsets of Euclidean spaces here. To put it more succinctly, a convex body is something that “behaves a bit like a Euclidean ball”.

A few simple examples of convex bodies on \mathbb{R}^n are:

- the cube $[-1, 1]^n$. Here, the ratio of the radii of the circumscribed ball to the inscribed ball is \sqrt{n} , so it is not much like a Euclidean ball. We sometimes denote it by B_∞^n since it is the unit ball under the ℓ_∞ norm.
- the n -dimensional *regular solid simplex* which is the convex hull of $n + 1$ equally spaced points. Here, the ratio of the radii of the circumscribed ball to the inscribed ball is n . This ratio is “maximal” in some sense.
- the n -dimensional “octahedron” or *cross-polytope* which is the convex hull of the $2n$ points $(\pm 1, 0, \dots, 0)$, $(0, \pm 1, 0, \dots, 0)$, \dots , $(0, 0, \dots, 0, \pm 1)$. Note that this is the unit ball on the ℓ_1 norm on \mathbb{R}^n so we denote it as B_1^n . Here, the ratio of the radii of the circumscribed ball to the inscribed ball is \sqrt{n} .

More generally, a k -simplex is a k -dimensional polytope (Definition 1.4) which is the convex hull of its $k + 1$ vertices.

Definition 1.2. A *cone* in \mathbb{R}^n is the convex hull of a single point and a convex body of dimension $n - 1$. In \mathbb{R}^n , the volume of a cone of “height” h over a base of $(n - 1)$ -dimensional volume B is Bh/n .

Since B_1^n is made up of 2^n pieces similar to the piece with non-negative coordinates, which is a cone of height 1 with base analogous to the similar piece in \mathbb{R}^{n-1} , the volume of the non-negative section is $1/n!$. Therefore, the $\text{vol}(B_1^n) = 2^n/n!$.

1.1. The Euclidean Ball

The fourth and final example is the Euclidean ball itself, namely

$$B_2^n = \left\{ x \in \mathbb{R}^n : \sum_{i=1}^n x_i^2 \leq 1 \right\}.$$

1.1.1. Finding the Volume

Let us now attempt to calculate $v_n = \text{vol}(B_2^n)$. Note that we can easily get the “surface area” of the ball from the volume by splitting it into “thin” cones from 0 and observing that the volume of each cone is equal to $1/n$ times its base area. Therefore, the surface area of the ball is nv_n .

We perform integration in spherical polar coordinates using two variables - r , which denotes the distance from 0 and θ , which is a point on the unit ball that represents the direction of the point. We obviously have $x = r\theta$. The point θ carries the information of $n - 1$ coordinates.

We can then write the integral of a general function on \mathbb{R}^n by

$$\int_{\mathbb{R}^n} f = \int_{r=0}^{\infty} \int_{S^{n-1}} f(r\theta) r^{n-1} d\theta dr \quad (1.1)$$

Here, $d\theta$ represents the area measure on the sphere. From our earlier observation, its total mass is nv_n . The r^{n-1} factor appears because the sphere of radius r has r^{n-1} times that of the sphere of radius 1.

An important thing to note about the measure corresponding to $d\theta$ is that it is *rotation-invariant*. If A is a subset of the sphere and U is orthogonal to A , then UA has the same measure as A . Therefore, we often simplify integrals such as 1.1 by pulling out the nv_n factor to get

$$\int_{\mathbb{R}^n} f = nv_n \int_{r=0}^{\infty} \int_{S^{n-1}} f(r\theta) r^{n-1} d\sigma_{n-1}(\theta) dr \quad (1.2)$$

where σ_{n-1} is the rotation-invariant measure on \mathbb{R}^{n-1} of total mass 1. Now, to evaluate v_n , we choose a suitable f such that the integrals on either side can easily be calculated, namely

$$f : x \mapsto \exp\left(-\frac{1}{2} \sum_{i=1}^n x_i^2\right).$$

Then the integral on the left of 1.2 is

$$\int_{\mathbb{R}^n} f = \int_{\mathbb{R}^n} \prod_{i=1}^n \exp\left(-\frac{x_i^2}{2}\right) = \prod_{i=1}^n \int_{-\infty}^{\infty} \exp\left(-\frac{x_i^2}{2}\right) = (\sqrt{2\pi})^n$$

and the integral on the right is

$$nv_n \int_0^{\infty} \int_{S^{n-1}} e^{-r^2/2} r^{n-1} d\sigma_{n-1} dr = nv_n \int_0^{\infty} e^{-r^2/2} r^{n-1} dr = v_n 2^{n/2} \Gamma\left(\frac{n}{2} + 1\right).$$

Equating the two,

$$v_n = \frac{\pi^{n/2}}{\Gamma\left(\frac{n}{2} + 1\right)}$$

Using Stirling's Formula, we can approximate this slightly better as

$$v_n \approx \frac{\pi^{n/2}}{\sqrt{2\pi} e^{-n/2} \left(\frac{n}{2}\right)^{(n+1)/2}} \approx \left(\frac{2\pi e}{n}\right)^{n/2}.$$

This is quite small for large n . The radius of a ball of volume 1 would be approximately $\sqrt{n/2\pi e}$, which is very large!

1.1.2. Some Surprising Results in Concentration

This is possibly the first hint one should take that following your intuition is probably not a good idea when dealing with high dimensional spaces.

Let us now restrict ourselves to considering the ball of volume 1.

What is the $(n-1)$ -dimensional volume of a slice through the center of the ball? Since the slice is an $(n-1)$ dimensional ball, it is equal to

$$v_{n-1} r^{n-1} = v_{n-1} \left(\frac{1}{v_n}\right)^{(n-1)/n}.$$

This is approximately equal to \sqrt{e} (using Stirling's formula once again). More generally, the volume of the slice that is at distance x from the center of the ball is equal to

$$\sqrt{e} \left(\frac{\sqrt{r^2 - x^2}}{r}\right)^{n-1} = \sqrt{e} \left(1 - \frac{x^2}{r^2}\right)^{(n-1)/2} \approx \sqrt{e} \left(1 - \frac{2\pi e x^2}{n}\right)^{(n-1)/2} \approx \sqrt{e} \exp(-\pi e x^2)$$

Note that this is normally distributed but the variance $1/2\pi e$ *does not depend on n !* So despite the fact that the radius grows as \sqrt{n} , the distribution of the volume stays the same. For example, nearly all the volume (around 96%) is concentrated in the slab with $\|x_1\| \leq 1/2$.

This might lead us to believe that since the volume is concentrated around any such equator¹ around a subspace, the volume should be concentrated around the intersection of all such equators, which seems to suggest that it should be concentrated around the center. However, for large n , we obviously know that most of the volume should be concentrated on the surface of the sphere². These two points seem to be directly contradictory! However, as might

¹since we could have equally well taken something other than x_1 .

²the volume of a ball of radius dr ($d < 1$) is $d^n \ll 1$ times that of a ball of radius r .

be expected, this is once again because our intuition fails when dealing with high-dimensional spaces. The measure of unit ball is “concentrated” both near the surface *and* around the equator, for any equator. To make more sense of this³, while each x_i is small, the overall distance from 0 is quite large since the small individual coordinates are compensated by the large dimension n . The former leads to the point being close to the equator and the latter leads to the point being close to the surface of the ball.

Another fun⁴ thing to think about is the following. Consider the cube $[-1, 1]^n$. Construct a ball of radius $1/2$ at each of the 2^n vertices $(\pm 1, \dots, \pm 1)$. Now, construct the ball with center $(\frac{1}{2}, \dots, \frac{1}{2})$ that touches each of these 2^n balls. Then note that for $n = 4$, this ball touches (the center of each face of) the cube, and for $n \geq 5$, it actually goes *outside* the cube!

To conclude, let us write the volume of a general convex body K in spherical polar coordinates. Assume that K has 0 in its interior and for each direction $\theta \in S^{n-1}$, let $r(\theta)$ be the radius of K (in that direction). Then,

$$\text{vol}(K) = nv_n \int_{S^{n-1}} \int_0^{r(\theta)} s^{n-1} ds d\sigma = v_n \int_{S^{n-1}} r(\theta)^n d\sigma. \quad (1.3)$$

Definition 1.3. A convex body K is said to be (*centrally*) *symmetric* if $-x \in K$ whenever $x \in K$.

Any symmetric body (other than the trivial $\{0\}$) is the unit ball under some $\|\cdot\|_K$ on \mathbb{R}^n (for example, the octahedron was the unit ball under the ℓ_1 norm). For a general symmetric body K , the volume is given by

$$\text{vol}(K) = v_n \int_{S^{n-1}} \|\theta\|_K^{-n} d\sigma_{n-1}(\theta) \quad (1.4)$$

1.2. The Cube and other Polytopes

So for example. since the volume of the cube $[-1, 1]^n$ is 2^n , we can use it to estimate the average radius of the cube as

$$v_n \int_{S^{n-1}} r(\theta)^n = 2^n \implies \int_{S^{n-1}} r(\theta)^n \approx \left(\sqrt{\frac{2n}{\pi e}} \right)^n \text{ so the average radius is approximately } \sqrt{\frac{2n}{\pi e}}$$

That is, the volume of the cube is far more concentrated towards the corners (where the radius is closer to \sqrt{n}), rather than the middles of facets (where the radius is closer to 1).

It can actually be shown⁵ that the fraction of volume of the intersection of the cube and the ball is less than $\exp(-4n/45)$, which further emphasizes the point that nearly all the volume lies in the corners.

Definition 1.4. A body which is bounded by a finite number of flat facets is called a *polytope*.

A polytope is essentially the intersection of a finite number of half-spaces. Note that the cube is a polytope with $2n$ facets.

Earlier, we remarked that the cube is not much like a Euclidean ball. So a question that might come to mind is: If K is a polytope with m facets, how close can K be to the Euclidean ball?

1.2.1. Banach-Mazur Distance and Spherical Caps

Let us define this “closeness” more concretely.

Definition 1.5 (Banach-Mazur Distance). The *Banach-Mazur distance* $d(K, L)$ between symmetric convex bodies K and L is the least positive d for which there is a linear image \tilde{L} of L such that $\tilde{L} \subseteq K \subseteq d\tilde{L}$.

³The answers to [this mathoverflow question](#) might further aid understanding

⁴subject to debate

⁵Consider the random variable $z_i = x_i^2$ where x_i is drawn uniformly randomly from $[-1, 1]$. Show that $\mathbf{E}[z_i] = 1/3$ and $\mathbf{Var}[z_i] = 4/45$ and use the Chernoff bound to get a bound on $\Pr[\sum_i z_i \leq 1]$.

Henceforth, we refer to the Banach-Mazur distance as just *distance*.

This corresponds to the how we thought of inscribing/circumscribing a ball earlier, since the ratio of the two radii we considered is just this distance.

If we wanted to make this distance a metric, then we should consider $\log d$ instead of d (the current distance is multiplicative and for any K , $d(K, K) = 1$).

From what we mentioned earlier, we know that the distance between the cube and the Euclidean ball in \mathbb{R}^n is at most \sqrt{n} . We shall prove later that it is indeed equal to \sqrt{n} .

As might be expected, if we want a polytope that approximates the ball very well, we would need a very large number of facets.

Definition 1.6. For a fixed unit vector v and some $\varepsilon \in [0, 1)$, the set

$$C(\varepsilon, v) = \{\theta \in S^{n-1} : \langle \theta, v \rangle \geq \varepsilon\}$$

is called the ε -cap about v or more generally, a *spherical cap* (or just *cap*).

It is often better to write a cap in terms of its radius rather than in terms of ε . The *cap of radius r about v* is

$$\{\theta \in S^{n-1} : \|\theta - v\| \leq r\}$$

It is easy to see that a cap of radius r is a $(1 - \frac{r^2}{2})$ -cap.

As we shall see in the proof of Theorem 1.3, it is useful to know some upper and lower bounds on the area of an ε -cap.

Lemma 1.1 (Lower bound on the area of spherical caps). For $r \in [0, 2]$, a cap of radius r on S^{n-1} has measure (under σ_{n-1}) at least $\frac{1}{2}(r/2)^{n-1}$.

Proof. Suppose $n \geq 2$ and let $\alpha = 2 \sin^{-1}(r/2)$. We can assume that $\alpha \in [0, \frac{\pi}{2}]$ since we can prove the other case similarly. Then the measure of the cap is given by

$$\begin{aligned} A(n, \alpha) &= \int_0^\alpha \frac{(n-1)v_{n-1}}{nv_n} (\sin \theta)^{n-2} d\theta \\ &= \frac{(n-1)\Gamma(\frac{n}{2}+1)}{n\Gamma(\frac{n-1}{2}+1)\sqrt{\pi}} \int_0^\alpha \sin^{n-2}(\theta) d\theta \\ &= \frac{\Gamma(\frac{n}{2})}{\Gamma(\frac{n-1}{2})\sqrt{\pi}} \int_0^\alpha \sin^{n-2}(\theta) d\theta \\ &\geq \frac{1}{\sqrt{\pi}} \int_0^\alpha \left(\frac{2\theta}{\pi}\right)^{n-2} d\theta \\ &= \frac{1}{\sqrt{\pi}} \cdot \left(\frac{2}{\pi}\right)^{n-2} \frac{\alpha^{n-1}}{n-1} \\ &= \frac{4}{\sqrt{\pi}(n-1)} \left(\frac{4}{\pi}\right)^{n-2} \cdot \frac{1}{2} (\alpha/2)^{n-1} \\ &\geq \frac{4}{\sqrt{\pi}(n-1)} \left(\frac{4}{\pi}\right)^{n-2} \cdot \frac{1}{2} (r/2)^{n-1} \\ &= \frac{\sqrt{\pi}}{n-1} \left(\frac{4}{\pi}\right)^{n-1} \cdot \frac{1}{2} (r/2)^{n-1} \end{aligned}$$

It is easily shown that

$$\frac{\sqrt{\pi}}{n-1} \left(\frac{4}{\pi}\right)^{n-1} \geq 1$$

for all $n \geq 2$, thus proving the inequality. ■

Lemma 1.2 (Upper bound on the area of spherical caps). For $\varepsilon \in [0, 1]$, the cap $C(\varepsilon, u)$ on S^{n-1} has measure (under σ_{n-1}) at most $e^{-n\varepsilon^2/2}$.

Proof. Let $\alpha = \cos^{-1}(\varepsilon)$. We may assume that $\alpha \in [0, \pi/2]$. Instead of finding the fraction of area of the spherical cap, we shall instead find the fraction of volume subtended at the center by the cap.

When $\varepsilon \leq \frac{1}{\sqrt{2}}$, note that the entire volume is contained in the ball of radius $\sqrt{1 - \varepsilon^2}$ centered at εu . The fraction of volume of this ball is equal to $(\sqrt{1 - \varepsilon^2})^n \leq e^{-n\varepsilon^2/2}$.

On the other hand, when $\varepsilon > \frac{1}{\sqrt{2}}$, this entire volume is contained in the ball of radius $\frac{1}{2\varepsilon}$ centered at $\frac{1}{2\varepsilon}u$. The fraction of volume of this ball is equal to $(2\varepsilon)^{-n} \leq e^{-n\varepsilon^2/2}$. ■

1.2.2. Bounds on Almost-Spherical Polytopes

Theorem 1.3. Let K be a symmetric polytope in \mathbb{R}^n with $d(K, B_2^n) = d$. Then K has at least $\exp(n/2d^2)$ facets. On the other hand, for each n , there is a polytope with 4^n facets whose distance from the ball is at most 2.

Before proving the above theorem, let us reformulate what a symmetric polytope is in another way. Suppose you have a symmetric polytope K with m pairs of facets. Then it is basically the intersection of m slabs in \mathbb{R}^n each of the form $\{x : |\langle x, v_i \rangle| \leq 1\}$ for some $v_i \in \mathbb{R}^n$. That is,

$$K = \{x : |\langle x, v_i \rangle| \leq 1 \text{ for } 1 \leq i \leq m\} \quad (1.5)$$

We can then consider a linear map from $K \rightarrow \mathbb{R}^m$ given by

$$T : x \mapsto (\langle x, v_1 \rangle, \dots, \langle x, v_m \rangle)$$

This maps \mathbb{R}^n to a subspace of \mathbb{R}^m . By the formulation of K given in 1.5, the intersection of this subspace with the unit cube is just the image of K under T ! This is just an n -dimensional slice of $[-1, 1]^m$. Even conversely, any n -dimensional slice of $[-1, 1]^m$ is a convex body with at most m pairs of facets.

Proof. For the proof, let us write what it means for each v_i (following the above notation) if $B_2^n \subseteq K \subseteq dB_2^n$.

- The first inclusion just says that each v_i is of length at most 1 (otherwise, one could consider $v_i/\|v_i\|$, which would be in B_2^n but not in K).
- The latter says that if $\|x\| > d$, then there is some i for which $\langle x, v_i \rangle > 1$. That is, for any unit vector θ , there is some i such that

$$\langle \theta, v_i \rangle \geq \frac{1}{d}.$$

Since we want to minimize m while satisfying the above two conditions, we can clearly do no better than have $\|v_i\| = 1$ for each i . We want that every $\theta \in S^{n-1}$ is in one of the m $(1/d)$ -caps about the (v_i) .

- Obviously, to do this, we should attempt to estimate the area of a general ε -cap ($\varepsilon = 1/d$ here). Given Lemma 1.2, we get that

$$m \geq \frac{1}{\exp(-n\varepsilon^2/2)} = \exp\left(\frac{n}{2d^2}\right).$$

- To show that there exists a polytope with the given number of facets, it is enough to find $2 \cdot 4^{n-1}$ points v_1, \dots, v_m such that the caps of radius 1 centered at these points covers the sphere. Such a set is called a *1-net*. Now, suppose we choose a set of points on the sphere such that any two of them are at least distance 1 apart. Such a set is called a *1-separated set*.

Note that the caps of radius $1/2$ centered at each of the points in a 1-separated set are disjoint. Since the measure of a cap of radius $1/2$ is at least 4^{-n} (by Lemma 1.1), the number of points in a 1-separated set is at most 4^n .

It is then enough to choose a “maximal” 1-separated set (a 1-separated set S such that $S \cup x$ is not 1-separated for any $x \in S^{n-1}$) since it is then automatically a 1-net!

Therefore, there is a 1-net (and thus a corresponding polytope) with at most 4^n points. ■

1.3. Fritz John’s Theorem

At the very beginning, we had mentioned that the distance of the cube $[-1, 1]^n$ and the regular solid simplex are at distance at most \sqrt{n} and n from the ball respectively. However, how would one go about proving that the distances are *exactly* \sqrt{n} and n ?

1.3.1. The Statement of the Theorem

Fritz John’s Theorem aids us in this pursuit.

He considered ellipsoids inside convex bodies. If (e_i) is an orthonormal basis of \mathbb{R}^n and (α_i) are positive numbers, then the ellipsoid defined by

$$\left\{ x : \sum_{i=1}^n \frac{\langle x, e_i \rangle^2}{\alpha_i^2} \leq 1 \right\}$$

has volume equal to $v_n \prod_i \alpha_i$. The theorem states that there is a *unique* maximal ellipsoid contained in any convex body, and further, he characterized this ellipsoid! Also, if K is a symmetric convex body and \mathcal{E} is its maximal ellipsoid, then $K \subseteq \sqrt{n}\mathcal{E}$!

We can then use this characterization combined with an affine transformation to prove that the distance between the cube and the ball is \sqrt{n} .

We state John’s Theorem after performing the affine transformation, since it is easier to understand what’s going on then. Roughly, it says that there should be several points of contact between the ball and the boundary of K .

Theorem 1.4 (Fritz John’s Theorem). Each convex body K contains a unique ellipsoid of maximal volume. This ellipsoid is B_2^n iff $B_2^n \subseteq K$ and for some m , there are unit vectors $(u_i)_{i=1}^m$ on the boundary of K and positive numbers $(c_i)_{i=1}^m$ such that

$$\sum_i c_i u_i = 0 \tag{1.6}$$

and for each $x \in \mathbb{R}^n$,

$$\sum_i c_i \langle x, u_i \rangle^2 = \|x\|^2. \tag{1.7}$$

1.3.2. Some Consequences of Fritz John’s Theorem

Before proving the theorem, let us discuss some of its implications.

The first condition essentially says that the (u_i) are not all on one side of the body⁶. Intuitively, this makes sense because if the points were concentrated towards one side of the body, then we could move the ball a little bit in the opposite direction and then expand it a little to get a larger ellipsoid.

The second says that the (u_i) are something like an orthonormal basis, in that we can resolve the norm as a weighted sum of squares of inner products.

Equation (1.7) is equivalent to saying that for all $x \in \mathbb{R}^n$,

$$x = \sum_i c_i \langle x, u_i \rangle u_i.$$

⁶more than simple linear independence since the c_i are positive.

This ensures that the points do not lie close to a (proper) subspace of \mathbb{R}^n . This makes sense intuitively as well since if they did, we could contract the ellipsoid a bit in this direction and expand it orthogonally.

Equation (1.7) is written more compactly as

$$\sum_i c_i u_i \otimes u_i = I_n. \quad (1.8)$$

Here, $u_i \otimes u_i$ represents the (rank-1) orthogonal projection onto the span of u_i , the map given by $x \mapsto \langle x, u_i \rangle u_i$. Note that this map is just equal to $u_i u_i^\top$. This implies that the trace of this projection is equal to $\|u_i\|^2 = 1$ ⁷. Equating the traces of either side of Equation (1.8), we get

$$\sum_i c_i = n. \quad (1.9)$$

Finally, note that if K is a *symmetric* convex body, then the first condition is obsolete since we can just find any (u_i) satisfying the second condition and replacing each u_i with $+u_i$ and $-u_i$ with each having half the original weight.

Let us now consider a couple of examples to better understand the implications of the theorem.

- For the cube $[0, 1]^n$, the maximal ellipsoid is B_2^n as one would expect. The points of contact are the standard basis vectors $(e_i)_1^n$ of \mathbb{R}^n with their negatives, and they do indeed satisfy

$$\sum_i e_i \otimes e_i = I_n.$$

- A slightly more nuanced example is that of the regular solid simplex. Unfortunately, there is no simple or standard way to represent the n -dimensional simplex in n dimensions. It is, however, far more natural to represent it in \mathbb{R}^{n+1} by considering the convex hull of the $n+1$ standard basis vectors $(e_i)_1^{n+1}$. We also scale it up by a factor of $\sqrt{n(n+1)}$ (so that the ball contained is B_2^n) such that the $n+1$ points (p_i) we take the convex hull of to get the simplex are given by

$$p_i = \sqrt{n(n+1)} e_i.$$

This simplex can be parametrized as

$$K = \left\{ x \in \mathbb{R}^{n+1} : \sum_{i=1}^{n+1} x_i = \sqrt{n(n+1)} \text{ and } x_i \geq 0 \text{ for each } i \right\}.$$

Similar to the cube, the contact points of the maximal ellipsoid are the centers of each of the facets. More precisely, these $n+1$ endpoints are given by

$$u_i = \frac{\sqrt{n(n+1)}}{n} \left(\sum_{j=1}^{n+1} e_j - e_i \right).$$

Affinely shifting the hyperplane such that it passes through the origin (making $x_0 = \frac{\sqrt{n(n+1)}}{n+1} \sum_i e_i$ the new origin) and setting the constants c_i as $c = \frac{n}{n+1}$ for each i , for any x in the (unshifted) body,

$$\begin{aligned} \sum_i n(n+1)c_i \langle x - x_0, u_i - x_0 \rangle^2 &= c \sum_i \left(\sum_{j=1}^{n+1} \frac{x_j}{n} - \frac{x_i}{n} - \frac{2}{n+1} + \frac{1}{n+1} \right)^2 \quad \left(\langle x, x_0 \rangle = \langle x_0, u_i \rangle = \langle x_0, x_0 \rangle = \frac{1}{n+1} \right) \\ &= n^2 \sum_i \left(\frac{x_i}{n} - \frac{1}{n(n+1)} \right)^2 \\ &= \|x - x_0\|^2. \end{aligned}$$

⁷We could have also got this more directly by using the fact that the trace of (a matrix in some basis corresponding to) a linear transformation is the sum of its eigenvalues. For an orthogonal projection, this is just equal to the rank of the target space (which is 1 in this case).

It is easily shown that $\sum_i c_i(u_i - x_0) = 0$ and that each $(u_i - x_0)$ is of unit norm, thus proving that the ball touching the centers of the facets (which is an affine shift of B_2^n) is the maximal ellipsoid inside the n -dimensional simplex.

Now, let us prove one of the claims that we made at the beginning of the section.

Theorem 1.5. Suppose that K is a symmetric convex body and B_2^n is the maximal ellipsoid contained in K . Then $K \subseteq \sqrt{n}B_2^n$.

Suppose that K is a convex body and B_2^n is the maximal ellipsoid contained in K . Then $K \subseteq nB_2^n$.

Note that while we have stated the above assuming that B_2^n is the maximal ellipsoid, any convex body in general can be brought to this form by performing an affine shift.

Proof.

- Let x be an arbitrary point in the symmetric body K . Our aim is to show that $\|x\| \leq \sqrt{n}$. Let $(u_i)_1^m$ be the points as described in **Fritz John's Theorem**. We may assume that if u is in this set, then so is $-u$. Now, note that for any i , the tangent plane to K at u_i must coincide with the tangent plane to B_2^n at u_i (otherwise, we would get a contradiction to $B_2^n \subseteq K$). Then, since K is convex, any point in the body must be in the half-space defined by this tangent that contains 0 – this means that $\langle x, u_i \rangle \leq 1$ for each i . Then, for each i , we have $\langle x, u_i \rangle \leq 1$ and $\langle x, -u_i \rangle \leq 1$ (since we've assumed that if u is in the (u_i) , then so is $-u$). That is, $|\langle x, u_i \rangle| \leq 1$ for each i . Using the above along with Equation (1.7) and Equation (1.9), we now have

$$\|x\|^2 = \sum_i c_i \langle x, u_i \rangle^2 \leq \sum_i c_i = n,$$

which is exactly what we set out to prove!

- Let x be an arbitrary point in the convex body. From the first part, we already have that $\langle x, u_i \rangle \leq 1$ for each i . We also have $\langle x, u_i \rangle \geq -\|x\|$ (since $\|u_i\| = 1$). Then,

$$\begin{aligned} 0 &\leq \sum_i c_i (1 - \langle x, u_i \rangle) (\|x\| + \langle x, u_i \rangle) \\ \implies \sum_i c_i \langle x, u_i \rangle^2 &\leq \sum_i c_i \|x\| + (1 - \|x\|) \left\langle x, \sum_i c_i u_i \right\rangle \\ \implies \sum_i c_i \langle x, u_i \rangle^2 &\leq \sum_i c_i \|x\| && \text{(since } \sum_i c_i u_i = 0\text{)} \\ \implies \|x\| &\leq n. && \text{(by Equation (1.7) and Equation (1.9))} \end{aligned}$$

■

Let us now prove Fritz John's Theorem.

1.3.3. The Proof

Lemma 1.6 (Fritz John's Theorem Pt. 1). Let K be a convex body and for some integer m , let there be unit vectors $(u_i)_1^m$ in ∂K and positive reals $(c_i)_1^m$ satisfying Equation (1.6) and Equation (1.7). Then B_2^n is the unique maximal ellipsoid contained in K .

Proof. Let

$$\mathcal{E} = \left\{ x \in \mathbb{R}^n : \sum_{j=1}^n \frac{\langle x, e_j \rangle^2}{\alpha_j^2} \leq 1 \right\}$$

be an ellipsoid in K for some orthonormal basis (e_j) and positive (α_j) . We must show that

- $\prod_j \alpha_j \leq 1$ (this implies that B_2^n is a maximal ellipsoid) and
- if $\prod_j \alpha_j = 1$, then for every j , $\alpha_j = 1$ (this implies that B_2^n is *the* maximal ellipsoid).

Now, consider the *dual* of \mathcal{E} given by

$$\mathcal{E}^* = \left\{ y \in \mathbb{R}^n : \sum_{j=1}^n \alpha_j^2 \langle y, e_j \rangle^2 \leq 1 \right\}$$

Observe that we can more concisely describe \mathcal{E}^* as $\{y \in \mathbb{R}^n : \langle y, x \rangle \leq 1 \text{ for all } x \in \mathcal{E}\}$ (Why?).⁸

Now, note that since $\mathcal{E} \subseteq K$, for any $x \in \mathcal{E}$ and any i , $\langle x, u_i \rangle \leq 1$ (as proved in the first part of Theorem 1.5). This implies that for every i , $u_i \in \mathcal{E}^*$! We then have

$$\begin{aligned} \sum_j \alpha_j^2 &= \sum_j \alpha_j^2 \|e_j\|^2 \\ &= \sum_j \alpha_j^2 \sum_i c_i \langle u_i, e_j \rangle^2 \\ &= \sum_i \left(c_i \sum_j \alpha_j^2 \langle u_i, e_j \rangle^2 \right) \\ &\leq \sum_i c_i = n \end{aligned} \quad (\text{since } u_i \in \mathcal{E}^*)$$

Then, using the AM-GM inequality,

$$\prod_j \alpha_j \leq \left(\frac{1}{n} \sum_j \alpha_j^2 \right)^{n/2} \leq 1.$$

This proves the first part. The second part follows directly as well, since if equality holds in the above equation, then every α_i^2 must be the same (the condition for equality to hold in the AM-GM inequality). \blacksquare

This is the easier of the two directions in Fritz John's Theorem. We now prove the harder.

Lemma 1.7 (Separation Theorem). Let X and Y be two disjoint closed convex bodies in \mathbb{R}^n with at least one of them bounded. Then there exists some $v \in \mathbb{R}^n$ such that for all $x \in X$, $\langle x, v \rangle < b$ and for all $y \in Y$, $\langle y, v \rangle > b$.

We leave the proof of the above to the reader.

Lemma 1.8 (Fritz John's Theorem Pt. 2). Let K be a convex body such that B_2^n is a maximal ellipsoid contained in K . Then, for some integer m , there exist unit vectors $(u_i)_1^m$ in ∂K and positive reals $(c_i)_1^m$ satisfying Equation (1.6) and Equation (1.8).

Proof. We want to show that there exist unit vectors (u_i) in ∂K and positive constants (c_i) such that

$$\frac{1}{n} I_n = \sum_i \left(\frac{c_i}{n} \right) (u_i \otimes u_i)$$

Since $\sum_i c_i = n$, we essentially aim to show that $\frac{1}{n} I_n$ is in the convex hull of the $(u_i \otimes u_i)$ (in the space of matrices). To this end, define

$$T = \text{Conv}(\{u \otimes u : u \text{ is a unit vector in } \partial K\}).$$

⁸This becomes far easier to show when we apply a suitable linear transformation to reduce the problem to the case where $\mathcal{E} = B_2^n$.

We refer to such u as contact points. We want to show that $\frac{1}{n}I_n \in T$. Suppose that it is not (we shall finally show that this implies B_2^n is not a maximal ellipsoid). Then Lemma 1.7 implies that there exists a matrix $H = (h_{i,j})$ such that the linear map φ from the set of matrices to \mathbb{R} defined by

$$(a_{i,j}) \mapsto \sum_{i,j} h_{i,j} a_{i,j}$$

satisfies

$$\varphi\left(\frac{I_n}{n}\right) < \varphi(u \otimes u)$$

for all contact points u . Now, since the matrices on either side are symmetric, we may assume that H is symmetric as well (Why?). And since the matrices on either side have trace equal to 1, adding any constant to the diagonal elements of H leaves the inequality unchanged. Therefore, we may suppose that the trace of H is 0. But this just says that $\varphi(I_n) = 0$!

Therefore, we have essentially found a matrix H such that for any contact point u ,

$$u^\top H u > 0. \quad (\text{check that } \varphi(u \otimes u) = u^\top H u)$$

Now, for $\delta > 0$, consider the ellipsoid defined by

$$\mathcal{E}_\delta = \{x \in \mathbb{R}^n : x^\top (I_n + \delta H) x \leq 1\}.$$

We claim that \mathcal{E}_δ is strictly inside K for sufficiently small δ . Note that for each contact point u ,

$$u^\top (I_n + \delta H) u = 1 + \delta (u^\top H u) > 1$$

so no contact point (of B_2^n) is in \mathcal{E}_δ . For each contact point u , consider a neighbourhood n_u such that for all $x \in n_u$, $x^\top (I_n + \delta H) x > 0$ – we know that such a neighbourhood exists due to the continuity of $x \mapsto x^\top (I_n + \delta H) x$. Let N be the union of all these neighbourhoods.

We now want to show that for any $x \in \partial K \setminus N$, $x^\top (I_n + \delta H) x > 1$. To this end, let λ_{\min} be the minimum eigenvalue of H . For any $x \in \partial K \setminus N$, $x^\top H x \geq \lambda_{\min} \|x\|^2$. That is, for all such x ,

$$x^\top (I_n + \delta H) x \geq (1 + \delta \lambda_{\min}) \|x\|^2.$$

Observe that $\inf_{x \in \partial K \setminus N} \|x\|^2 > 1$.⁹ We may also assume that $\lambda_{\min} < 0$, since the claim holds trivially otherwise (we have $\|x\|^2 > 1$). Then, we may set δ as a positive real which is less than $\frac{1}{|\lambda_{\min}|} \left(1 - \frac{1}{\inf_{x \in \partial K \setminus N} \|x\|^2}\right)$. Then for all $x \in \partial K \setminus N$,

$$(1 + \delta \lambda_{\min}) \|x\|^2 > \|x\|^2 \left(1 - \left(1 - \frac{1}{\inf_{y \in \partial K \setminus N} \|y\|^2}\right)\right) \geq 1$$

Therefore, \mathcal{E}_δ does not intersect ∂K and is *strictly* inside K for sufficiently small δ !

Now, we claim that \mathcal{E}_δ has volume at least equal to that of B_2^n . Indeed, its volume is given by $v_n / \prod \lambda_i$, where (λ_i) are the eigenvalues of $(I_n + \delta H)$. Since the sum of the eigenvalues is equal to the trace of $I_n + \delta H$, which is n , we can use the AM-GM inequality to get

$$\prod_i \lambda_i \leq \left(\frac{1}{n} \sum_i \lambda_i\right)^n = 1,$$

which is exactly what we want, because equality holds iff the eigenvalues are all 1, that is, the ellipsoid is B_2^n (so this leads to a contradiction). ■

⁹if it was equal to 1, then for any $\varepsilon > 0$, we would be able to find an x such that $\|x\|^2 < 1 + \varepsilon$ (we trivially have that $\|x\|^2 \geq 1$). However, this is not possible because ∂K is compact, we have removed a neighbourhood around each contact point u , and contact points are the only points in ∂K which have norm 1.

Note that we can concatenate the proofs of Lemma 1.8 and Lemma 1.6 to show that *a* maximal ellipsoid is *the* maximal ellipsoid (contained in a convex body).

There is an analogue of Fritz John's Theorem that characterizes the minimal ellipsoid that contains a given body – this is near-direct from the notion of duality that we used in the proof of Lemma 1.6. So for example, it follows from this analogue that the minimal ellipsoid that contains $[-1, 1]^n$ is the ball of radius \sqrt{n} . This also enables us to say that $d([-1, 1]^n, B_2^n)$ is *exactly* equal to \sqrt{n} .

There are various extensions of this result. Recall how towards the beginning of these notes we had mentioned how a general convex body K is essentially a unit ball under some norm. Fritz John's Theorem essentially describes linear maps from the Euclidean space to a normed space (under which the unit ball is K) that have largest determinant under the constraint that the Euclidean ball is mapped into K . There is a more general theory that (attempts to) solve this problem under different constraints.

§2. Volume Inequalities

2.1. Spherical Sections of Symmetric Bodies

Consider the n -dimensional cross-polytope B_1^n . The maximal ellipsoid in B_1^n is the Euclidean ball of radius $1/\sqrt{n}$. If we take some orthogonal transformation U , then obviously, UB_1^n contains the ball as well, and so does $B_1^n \cap UB_1^n$. But what if we instead consider the minimal ball that contains $B_1^n \cap UB_1^n$? We have the following remarkable theorem, which we prove later.

Theorem 2.1 (Košin's Theorem). For each n , there is an orthogonal transformation U such that $B_1^n \cap UB_1^n$ is contained in the (Euclidean) ball of radius $32/\sqrt{n}$.

The important thing to note here is the fact that just by intersecting just two copies of the cross-polytope, we manage to reduce the radius of the minimal circumscribing ball by a factor of $\sqrt{n}!$. Indeed, this intersection is what we call “approximately spherical” since its distance from the Euclidean ball is then at most 32. The constant factor of 32 can be improved upon as well.

For the same orthogonal transformation U , $\text{Conv}(Q \cup UQ)$ is at distance at most 32 from the Euclidean ball as well (where Q is $[-1, 1]^n$).

How would one go about constructing such a transformation? The points of contact between the ball of radius $1/\sqrt{n}$ are those of the form $(\pm \frac{1}{n}, \dots, \pm \frac{1}{n})$.

The points furthest away are those near the corners of the cross-polytope. So we would want to take a transformation whose facets “chop off” these corners.

Recall that in the beginning, we had explained that the volume of the cross-polytope is $2^n/n!$, so if $r(\theta)$ is the radius of B_1^n in the direction θ , then

$$\int_{S^{n-1}} r(\theta)^n d\sigma = \frac{2^n}{n!v_n} \leq \left(\frac{2}{\sqrt{n}}\right)^n. \quad (2.1)$$

This feature wherein $r(\theta)$ is not expected to be much more than $2/\sqrt{n}$ is captured in the following definition.

Definition 2.1 (Volume Ratio). Let K be a convex body in \mathbb{R}^n . Then the *volume ratio* of K is defined as

$$\text{vr}(K) = \left(\frac{\text{vol}(K)}{\text{vol}(\mathcal{E})} \right)^{1/n}$$

where \mathcal{E} is the maximal ellipsoid contained in K .

Equation (2.1) then says that $\text{vr}(B_1^n) \leq 2$ for all n . Let us now prove (a slightly more general version of) Košin's Theorem, scaling everything up by n for the sake of convenience.

Theorem 2.2. Let K be a symmetric convex body in \mathbb{R}^n that contains B_2^n . Let

$$R = \left(\frac{\text{vol}(K)}{\text{vol}(B_2^n)} \right)^{1/n}.$$

Then there is an orthogonal transformation U of \mathbb{R}^n such that

$$K \cap UK \subseteq 8R^2 B_2^n.$$

Proof. Denote by $\|\cdot\|_K$ the norm under which K is the unit ball. Observe that since $B_2^n \subseteq K$, $\|x\|_K \leq \|x\|$ for all $x \in \mathbb{R}^n$. Note that if U is an orthogonal transformation, then the norm corresponding to $K \cap UK$ is the maximum of that corresponding to K and UK (at that point). Therefore, because the norm corresponding to $8R^2 B_2^n$ is $\frac{1}{8R^2}$ times the Euclidean norm, we just want to find an orthogonal transformation U such that for all $\theta \in S^{n-1}$,

$$\max(\|U\theta\|_K, \|\theta\|_K) \geq \frac{1}{8R^2}.$$

It suffices to show that for all $\theta \in S^{n-1}$,

$$\frac{\|U\theta\|_K + \|\theta\|_K}{2} \geq \frac{1}{8R^2}. \quad (2.2)$$

Now, note that the function N given by $x \mapsto \frac{\|Ux\|_K + \|x\|_K}{2}$ is a norm on \mathbb{R}^n . Also, it satisfies $N(x) \leq \|x\|$ for all x . We aim to show that N is “large” everywhere. Let ϕ be a point on the sphere such that $N(\phi) = t$. Then if $\|\theta - \phi\| \leq t$, then

$$N(\theta) \leq N(\phi) + N(\theta - \phi) \leq t + \|\theta - \phi\| \leq 2t.$$

That is, for θ in a spherical cap of radius t about ϕ , $N(\theta)$ is at most $2t$. Lemma 1.1 implies that such a cap has measure at least $\frac{1}{2} \left(\frac{t}{2}\right)^{n-1} \geq \left(\frac{t}{2}\right)^n$. Then, considering the integral over only the spherical cap, we have

$$\int_{S^{n-1}} \frac{1}{N(\theta)^{2n}} d\sigma \geq \frac{1}{(2t)^{2n}} \left(\frac{t}{2}\right)^n = \frac{1}{2^{3n} t^n}. \quad (2.3)$$

Now, we claim that there is an orthogonal transformation U such that

$$\int_{S^{n-1}} \frac{1}{N(\theta)^{2n}} d\sigma \leq R^{2n}. \quad (2.4)$$

Because $N(\theta)^2 \geq \|\theta\|_K \|U\theta\|_K$, it suffices to show the existence of an orthogonal transformation U such that

$$\int_{S^{n-1}} \frac{1}{\|\theta\|_K^n \|U\theta\|_K^n} d\sigma \leq R^{2n}.$$

We prove this probabilistically. Consider the average over all orthogonal transformations U of some function f on the sphere. This should just be the average of the value of f over the entire sphere. That is,

$$\text{avg}_U f(U\theta) = \int_{S^{n-1}} f(\phi) d\sigma(\phi).$$

Setting f as the function given by

$$\theta \mapsto \frac{1}{\|\theta\|_K^n},$$

we have the following:

$$\begin{aligned} \text{avg}_U \left(\int_{S^{n-1}} \frac{1}{\|U\theta\|_K^n \|\theta\|_K^n} d\sigma(\theta) \right) &= \int_{S^{n-1}} \left(\text{avg}_U \frac{1}{\|U\theta\|_K^n} \right) \frac{1}{\|\theta\|_K^n} d\sigma(\theta) \\ &= \int_{S^{n-1}} \left(\int_{S^{n-1}} \frac{1}{\|\phi\|_K^n} d\sigma(\phi) \right) \frac{1}{\|\theta\|_K^n} d\sigma(\theta) \\ &= \left(\int_{S^{n-1}} \frac{1}{\|\theta\|_K^n} d\sigma(\theta) \right)^2 = R^{2n}, \end{aligned}$$

where the last equality follows from Equation (1.4). Since the average of the integral over orthogonal transformations is at most R^{2n} , there must be some orthogonal transformation U such that the integral is at most R^{2n} and Equation (2.4) holds! Then, combining Equation (2.3) and Equation (2.4), we get

$$\frac{1}{2^{3n}t^n} \leq R^{2n} \implies t \geq \frac{1}{8R^2}.$$

That is, for any $\phi \in S^{n-1}$, $\|\phi\|_K \geq \frac{1}{8R^2}$, which is exactly what we set out to show in Equation (2.2)! ■

Due to the probabilistic nature of the above proof, we do not actually get an orthogonal transformation U . However, a question that might come to mind is - do there exist symmetric bodies for which we *can* explicitly construct U ? Consider the simple case of the cross-polytope. As mentioned towards the beginning of this section, we would like to “chop off” the corners. A relatively obvious method to do this that comes to mind is to construct a transformation such that the direction of each of the new corners coincides with the directions of the centers of the original facets. In 2 dimensions, such an orthogonal transformation just means we rotate B_1^2 by 45° .

However, does such an orthogonal transformation exist for the cross-polytope in any general dimension? Stating it more rigorously, we want to determine for each n if there is an orthogonal transformation U such that for each standard basis vector e_i of \mathbb{R}^n , Ue_i is \sqrt{n} times one of the vectors of the form $(\pm\frac{1}{n}, \dots, \pm\frac{1}{n})$.

That is, we are looking for an $n \times n$ orthogonal matrix with each entry as $\pm\frac{1}{\sqrt{n}}$. Such a matrix without the \sqrt{n} factor (it then merely requires that the rows are orthogonal) is known as a *Hadamard matrix*. For $n \leq 2$, there obviously exist Hadamard matrices

$$(1) \quad \text{and} \quad \begin{pmatrix} +1 & +1 \\ +1 & -1 \end{pmatrix}.$$

It may be shown that if a Hadamard matrix of dimension $n > 2$ exists, then n is a multiple of 4.¹⁰ However, it is unknown which multiples of 4 Hadamard matrices do indeed exist for. It is known that they do exist for n a power of 2, but even these (known as *Walsh matrices*) don't give good estimates. There are good reasons¹¹ for believing that we cannot explicitly find an orthogonal transformation that would give the right estimates.

Now, with the aid of Theorem 2.2, proving Theorem 2.1 is near-straightforward.

Recall how in the beginning of this section, we had stated that for the same orthogonal transformation U that is mentioned in Theorem 2.2, $\text{Conv}(Q \cup UQ)$ is at distance 32 from the Euclidean ball, where $Q = [-1, 1]^n$. However, we cannot get an approximately spherical body by taking the intersection as we have in Theorem 2.2.

Dually, we cannot get an approximately spherical body by taking the convex hull of a union for a cross-polytope. Both of these ideas (of taking the convex hull *and* the intersection) are combined in the following fascinating result of Milman's.

Theorem 2.3 (QS-Theorem). There is a constant M such that for all symmetric convex bodies K (of any dimension), there are linear maps Q and S and an ellipsoid \mathcal{E} such that if $\tilde{K} = \text{Conv}(K \cup QK)$, then

$$\mathcal{E} \subseteq \tilde{K} \cap S\tilde{K} \subseteq M\mathcal{E}.$$

Note that M is a universal constant independent of *everything*. Here the “QS” means “quotient of a subspace”.

¹⁰Let H be a Hadamard matrix. We may assume that all the elements in the first row are +1. Let a, b, c and d be the number of columns starting with $(+, +, +)$, $(+, +, -)$, $(+, -, +)$ and $(+, -, -)$ respectively. We trivially have $a + b + c + d = n$. Using the pairwise orthogonality of the first 3 rows, we get 3 other conditions which enable us to conclude that $n = 4a$.

¹¹see Ramsey Theory.

2.2. The Prékopa-Leindler Inequality

2.2.1. Brunn's Theorem

Consider some convex body K in \mathbb{R}^2 and the map $v : \mathbb{R} \rightarrow \mathbb{R}$ such that r maps to the length (the Lebesgue measure in \mathbb{R}) of the intersection of the line $x = r$ with the body K . We can think of this as “collapsing” the body onto the x -axis like a deck of cards. To understand this better, consider the following image which represents the graph of v for K .¹²



It may be shown that for any convex body K in \mathbb{R}^2 , the corresponding function v is concave on its support.

How would one go about generalizing this v to a higher dimensional K , say in 3 dimensions? As might be expected, the function $v : \mathbb{R} \rightarrow \mathbb{R}$ maps r to the Lebesgue measure (in \mathbb{R}^2) of the intersection of $x = r$ with the body K . Does this v need to be concave? No, it does not! Consider a cone - say the one given by

$$\{(x, y, z) \in \mathbb{R}^3 : y^2 + z^2 \leq x^2, x \geq 0\}.$$

Then since the area of the intersection grows as x^2 , the function is quite obviously not concave. However, the cone is a “maximal” convex body in some sense, it is just barely convex and the curved surface is composed of lines. One might now note that the function $r \mapsto \sqrt{v(r)}$ for the cone is indeed (barely) concave! Brunn perhaps noticed this pattern and proved an analogous result for higher dimensions.

Theorem 2.4 (Brunn's Theorem). Let K be a convex body in \mathbb{R}^n , u a unit vector in \mathbb{R}^n , and for each r , define

$$H_r = \{x \in \mathbb{R}^n : \langle x, u \rangle = r\}.$$

Then, the function

$$v : r \mapsto \text{vol}(H_r \cap K)^{1/(n-1)}$$

is concave on its support.

A consequence of this theorem is that given any centrally symmetric body in \mathbb{R}^n , the $(n-1)$ -dimensional slice with the largest area orthogonal to some fixed unit vector u is that through the origin!

2.2.2. The Brunn-Minkowski Inequality

Brunn's Theorem was turned from an idle observation to an extremely powerful tool by Minkowski in the form of the Brunn-Minkowski inequality. We omit the proof of Brunn's Theorem as it is obvious from this inequality, which

¹²Source: An Introduction to Modern Convex Geometry by Keith Ball.

we state shortly.

Before we do this, let us introduce some notation. If X and Y are sets in \mathbb{R}^n and $\alpha, \beta \in \mathbb{R}$, then we write

$$\alpha X + \beta Y = \{\alpha x + \beta y : x \in X, y \in Y\}.$$

This method of using addition in \mathbb{R}^n to define the addition of sets in \mathbb{R}^n is known as *Minkowski addition*.

In the context of Brunn's Theorem, consider three parallel slices A_r, A_s , and A_t of a body K in \mathbb{R}^n at positions r, s , and t . These slices can be thought of as subsets of \mathbb{R}^{n-1} . Further suppose that $r < s < t$ and we have $\lambda \in (0, 1)$ such that $s = \lambda r + (1 - \lambda)t$. Note that due to the convexity of K ,

$$A_s \supseteq \lambda A_r + (1 - \lambda)A_t.$$

All Brunn's Theorem says is that

$$\text{vol}(A_s)^{1/(n-1)} \geq \lambda \text{vol}(A_r)^{1/(n-1)} + (1 - \lambda) \text{vol}(A_t)^{1/(n-1)}.$$

This has reduced the original problem, which was in \mathbb{R}^n , to one in \mathbb{R}^{n-1} . More generally, we have the following.

Theorem 2.5 (Brunn-Minkowski Inequality). Let A and B be two non-empty compact subsets of \mathbb{R}^n . Then for any $\lambda \in [0, 1]$,

$$\text{vol}(\lambda A + (1 - \lambda)B)^{1/n} \geq \lambda \text{vol}(A)^{1/n} + (1 - \lambda) \text{vol}(B)^{1/n}. \quad (2.5)$$

It is quite obvious that given the above inequality, Brunn's Theorem is true. Here, the non-emptiness of A and B correspond to the fact that we restrict v to the support in Brunn's Theorem.

It is not too difficult to show that Equation (2.5) is equivalent to

$$\text{vol}(A + B)^{1/n} \geq \text{vol}(A)^{1/n} + \text{vol}(B)^{1/n} \quad (2.6)$$

We omit the proof of the Brunn-Minkowski inequality and instead show how it follows from the far more powerful, near-magical Prékopa-Leindler inequality.

Before we do this however, let us show how the popular isoperimetric inequality follows from the Brunn-Minkowski inequality.

Theorem 2.6 (Isoperimetric Inequality). Among bodies of a given volume, Euclidean balls have the least surface area.

Proof. Let C be a compact body of volume equal to that of B_2^n . The $((n - 1)$ -dimensional) “surface area” of C is equal to

$$\text{vol}(\partial C) = \lim_{\varepsilon \rightarrow 0} \frac{\text{vol}(C + \varepsilon B_2^n) - \text{vol}(C)}{\varepsilon}.$$

Equation (2.6) implies that

$$\begin{aligned} \text{vol}(C + \varepsilon B_2^n) &\geq \left(\text{vol}(C)^{1/n} + \varepsilon \text{vol}(B_2^n)^{1/n} \right)^n \\ &\geq \text{vol}(C) + n\varepsilon \text{vol}(B_2^n)^{1/n} \text{vol}(C)^{(n-1)/n}. \end{aligned}$$

Then,

$$\begin{aligned} \text{vol}(\partial C) &\geq \lim_{\varepsilon \rightarrow 0} \frac{n\varepsilon \text{vol}(B_2^n)^{1/n} \text{vol}(C)^{(n-1)/n}}{\varepsilon} \\ &= n \text{vol}(B_2^n) = \text{vol}(\partial B_2^n). \end{aligned}$$

■

It may also be shown using the **Brunn-Minkowski Inequality** and the weighted AM-GM inequality that for any compact subsets A, B of \mathbb{R}^n ,

$$\text{vol}(\lambda A + (1 - \lambda)B) \geq \text{vol}(A)^\lambda \text{vol}(B)^{1-\lambda} \quad (2.7)$$

The above equation is more commonly known as the *multiplicative Brunn-Minkowski inequality*, while Equation (2.5) is known as the *additive Brunn-Minkowski inequality*. It may also be shown that while this is weaker than the Brunn-Minkowski inequality for *particular* subsets A and B , the two are equivalent if we know Equation (2.7) for *all* A and B .

Multiplicative Brunn-Minkowski implies additive Brunn-Minkowski. Fix some $\lambda \in [0, 1]$ and let

$$\lambda' = \frac{\frac{\lambda}{\text{vol}(B)^{1/n}}}{\frac{\lambda}{\text{vol}(B)^{1/n}} + \frac{1-\lambda}{\text{vol}(A)^{1/n}}}.$$

Applying Equation (2.7), we get

$$\text{vol}\left(\lambda' \frac{A}{\text{vol}(A)^{1/n}} + (1 - \lambda') \frac{B}{\text{vol}(B)^{1/n}}\right) \geq 1.$$

Also,

$$\lambda' \frac{A}{\text{vol}(A)^{1/n}} + (1 - \lambda') \frac{B}{\text{vol}(B)^{1/n}} = \frac{\lambda A + (1 - \lambda)B}{\lambda \text{vol}(A)^{1/n} + (1 - \lambda) \text{vol}(B)^{1/n}}.$$

Therefore,

$$\text{vol}(\lambda A + (1 - \lambda)B) \geq \left(\lambda \text{vol}(A)^{1/n} + (1 - \lambda) \text{vol}(B)^{1/n}\right)^n,$$

which is just additive Brunn-Minkowski. ■

This form is slightly more advantageous because there is no mention of the dimension n or the non-emptiness of A and B .

2.2.3. The Prékopa-Leindler inequality

The Prékopa-Leindler inequality that we mentioned earlier is essentially a generalization of the Brunn-Minkowski inequality to a more functional form, similar to how the Cauchy-Bunyakovasky-Schwarz inequality is a functional analogue of the Cauchy-Schwarz inequality.

To get a little more intuition for how the Brunn-Minkowski inequality is connected to the Prékopa-Leindler inequality, define f as the indicator function on A , g as the indicator function on B , and m as the indicator function on $\lambda A + (1 - \lambda)B$.¹³ Then Equation (2.7) says

$$\int_{\mathbb{R}^n} m \geq \left(\int_{\mathbb{R}^n} f\right)^\lambda \left(\int_{\mathbb{R}^n} g\right)^{1-\lambda}.$$

What is the relation between m , f , and g that perhaps leads to this inequality being true? If for some x and y , $f(x) = 1$ and $g(y) = 1$, then we have $m(\lambda x + (1 - \lambda)y) = 1$ as well. Therefore, for any $x, y \in \mathbb{R}^n$

$$m(\lambda x + (1 - \lambda)y) \geq f(x)^\lambda g(y)^{1-\lambda}.$$

It turns out that this condition is enough to conclude Equation (2.7)!

¹³the indicator function on X for $X \subseteq \mathbb{R}^n$ is the map from \mathbb{R}^n to $\{0, 1\}$ such that $f(x) = 1$ if $x \in X$ and 0 otherwise.

Theorem 2.7 (Prékopa-Leindler inequality). Let f , g and m be non-negative measurable functions on \mathbb{R}^n and $\lambda \in (0, 1)$ such that for all $x, y \in \mathbb{R}^n$,

$$m(\lambda x + (1 - \lambda)y) \geq f(x)^\lambda g(y)^{1-\lambda}. \quad (2.8)$$

Then,

$$\int_{\mathbb{R}^n} m \geq \left(\int_{\mathbb{R}^n} f \right)^\lambda \left(\int_{\mathbb{R}^n} g \right)^{1-\lambda}.$$

The astute reader might notice that this is something of a reversed Hölder's inequality, which says that if we have non-negative functions f and g and define m by $m(z) = f(z)^\lambda g(z)^{1-\lambda}$ for each z , then

$$\int m \leq \left(\int f \right)^\lambda \left(\int g \right)^{1-\lambda}. \quad (2.9)$$

The difference is that in the Prékopa-Leindler inequality, we have

$$m(\lambda x + (1 - \lambda)y) \geq \sup_{x,y} f(x)^\lambda g(y)^{1-\lambda},$$

whereas in Hölder's, we only consider the pair $(x, y) = (z, z)$.

Proof of one-dimensional Brunn-Minkowski inequality. Suppose A and B are non-empty measurable subsets of \mathbb{R} . We use $\|\cdot\|$ to represent the Lebesgue measure on \mathbb{R} .

We can assume that A and B are compact¹⁴. We can now shift both sets and assume that $A \cap B = \{0\}$. However, in this case, we have $A \cup B \subseteq A + B$ and so, due to the almost-disjointedness of A and B ,

$$\|A + B\| \geq \|A \cup B\| = \|A\| + \|B\|.$$

This is just Equation (2.6). ■

Proof of one-dimensional Prékopa-Leindler inequality. We have non-negative measurable functions f , g , and m . We use $\|\cdot\|$ to represent the Lebesgue measure on \mathbb{R} . For any function $h : \mathbb{R} \rightarrow \mathbb{R}$ and $t \in \mathbb{R}$, define

$$L_h(t) = \{x \in \mathbb{R} : h(x) \geq t\}.$$

Then note that by Equation (2.8),

$$L_m(t) \supseteq \lambda L_f(t) + (1 - \lambda)L_g(t).$$

We can then apply the one-dimensional Brunn-Minkowski inequality to get

$$\|L_m(t)\| \geq \|\lambda L_f(t) + (1 - \lambda)L_g(t)\| \geq \lambda \|L_f(t)\| + (1 - \lambda) \|L_g(t)\|.$$

Finally, we can assume boundedness of all three functions and use Fubini's Theorem to say that

$$\begin{aligned} \int m &= \int \|L_m(t)\| dt \\ &\geq \lambda \int \|L_f(t)\| dt + (1 - \lambda) \int \|L_g(t)\| dt \\ &= \lambda \int f + (1 - \lambda) \int g \\ &\geq \left(\int f \right)^\lambda \left(\int g \right)^{1-\lambda}, \end{aligned}$$

where the last step follows from the weighted AM-GM inequality. ■

¹⁴due to the **inner regularity** of the Lebesgue measure.

Proof of Prékopa-Leindler inequality. We prove this inductively. Suppose we have m , f , and g from $\mathbb{R}^n \rightarrow \mathbb{R}$ ($n > 1$) satisfying Equation (2.8). For any $z \in \mathbb{R}$ and any function $h : \mathbb{R}^n \rightarrow \mathbb{R}$, we denote by $h_z : \mathbb{R}^{n-1} \rightarrow \mathbb{R}$ the function given by $h_z(x) = h(x, z)$ (for $z \in \mathbb{R}^{n-1}$) – we make the last coordinate constant and consider the resulting function on the remaining $n - 1$ coordinates. Now, let $\alpha, \beta \in \mathbb{R}$, $x, y \in \mathbb{R}^{n-1}$ and let $\gamma = \lambda\alpha + (1 - \lambda)\beta$. Then,

$$\begin{aligned} m_\gamma(\lambda x + (1 - \lambda)y) &= m(\lambda x + (1 - \lambda)y, \lambda\alpha + (1 - \lambda)\beta) \\ &\geq f(x, \alpha)^\lambda g(y, \beta)^{1-\lambda} \\ &= f_\alpha(x)^\lambda g_\beta(y)^{1-\lambda}. \end{aligned}$$

That is, m_γ , f_α , and g_β satisfy Equation (2.8) (on \mathbb{R}^{n-1}). We can then apply the inductive hypothesis on them to get

$$\int_{\mathbb{R}^{n-1}} m_\gamma \geq \left(\int_{\mathbb{R}^{n-1}} f_\alpha \right)^\lambda \left(\int_{\mathbb{R}^{n-1}} g_\beta \right)^{1-\lambda}.$$

Now, for any function $h : \mathbb{R}^n \rightarrow \mathbb{R}$, we denote by $\tilde{h} : \mathbb{R} \rightarrow \mathbb{R}$ the function given by

$$\gamma \mapsto \int_{\mathbb{R}^{n-1}} f_\gamma.$$

Note that the functions \tilde{m} , \tilde{f} , and \tilde{g} satisfy the condition for the one-dimensional Prékopa-Leindler inequality! Therefore, condensing the iterated integral to a joint integral, we get

$$\int_{\mathbb{R}^n} m \geq \left(\int_{\mathbb{R}^n} f \right)^\lambda \left(\int_{\mathbb{R}^n} g \right)^{1-\lambda},$$

which is exactly what we desire! ■

This proof is quite magical - we use the inequality on \mathbb{R}^{n-1} and \mathbb{R}^1 with barely any extra work to conclude that it holds for \mathbb{R}^n .

To conclude this section, we state another surprising result (from [Bus49]) in a similar vein to the nice observation that is Brunn's Theorem.

Theorem 2.8 (Busemann's Theorem). Let K be a symmetric convex body in \mathbb{R}^n and for each unit vector u , let $r(u)$ be the volume of the slice of K by the subspace orthogonal to u . Then the body whose radius in each direction u is $r(u)$ is convex as well.

2.3. The Reverse Isoperimetric Problem

The **Isoperimetric Inequality** solves the problem of finding the body with the largest volume among bodies with a given surface area. How would one go about solving the reversed problem – finding the body with the largest surface area among bodies with a given volume? We must phrase this more carefully such that it makes sense because as it stands, we could make the surface area arbitrarily large (consider a large thin disc). So the more common way of phrasing it is – given a convex body, how small can we make its surface area by applying an affine transformation that preserves volume?

Theorem 2.9. Let K be a convex body, T a regular solid simplex in \mathbb{R}^n , and Q a cube in \mathbb{R}^n . Then, there is an affine transformation \tilde{K} of K such that the volume of \tilde{K} is equal to that of T and whose surface area is at most that of T . If K is symmetric, then there is an affine transformation \tilde{K} of K such that the volume of \tilde{K} is equal to that of Q and whose surface area is at most that of Q .

The primary focus of this section is to find the bodies with the largest volume ratios – this is answered for symmetric bodies in Theorem 2.10, which we encourage the reader to look at now.

Given this, we can prove the second part of Theorem 2.9 as follows.

Choose \tilde{K} such that its maximal ellipsoid is B_2^n . Then \tilde{K} has volume at most 2^n (since this is the volume of the cube with maximal ellipsoid B_2^n). Note that

$$\text{vol}(\partial Q) = 2n \text{vol}(Q)^{(n-1)/n}.$$

Therefore, we shall show that

$$\text{vol}(\partial\tilde{K}) \leq 2n \text{vol}(\tilde{K})^{(n-1)/n}$$

Indeed, we have

$$\begin{aligned} \text{vol}(\partial\tilde{K}) &= \lim_{\varepsilon \rightarrow 0} \frac{\text{vol}(\tilde{K} + \varepsilon B_2^n) - \text{vol}(\tilde{K})}{\varepsilon} \\ &\leq \lim_{\varepsilon \rightarrow 0} \frac{\text{vol}(\tilde{K} + \varepsilon \tilde{K}) - \text{vol}(\tilde{K})}{\varepsilon} && (\text{because } B_2^n \subseteq \tilde{K}) \\ &= \text{vol}(\tilde{K}) \lim_{\varepsilon \rightarrow 0} \frac{(1 + \varepsilon)^n - 1}{\varepsilon} \\ &= n \text{vol}(\tilde{K}) \\ &= n \text{vol}(\tilde{K})^{1/n} \text{vol}(\tilde{K})^{(n-1)/n} \\ &\leq 2n \text{vol}(\tilde{K})^{(n-1)/n}. && (\text{by Theorem 2.10}) \end{aligned}$$

2.3.1. Volume Ratio Estimates and Young's Convolution Inequality

Theorem 2.10. Among symmetric convex bodies, the cube has the largest volume ratio.

The above is equivalent to saying that if K is a convex body whose maximal ellipsoid is B_2^n , then $\text{vol}(K) \leq 2^n$. By [Fritz John's Theorem](#), there exist unit vectors (u_i) and positive (c_i) ,

$$\sum_i c_i u_i \otimes u_i = I_n.$$

Consider the polytope

$$C = \{x \in \mathbb{R}^n : |\langle x, u_i \rangle| \leq 1 \text{ for } 1 \leq i \leq m\}. \quad (2.10)$$

We clearly have $K \subseteq C$, so it suffices to show that $\text{vol}(C) \leq 2^n$.

The most important tool we use for this is the following.

Theorem 2.11 (Young's Convolution Inequality). Suppose $f \in L^p(\mathbb{R})$, $g \in L^q(\mathbb{R})$, and $\frac{1}{p} + \frac{1}{q} = 1 + \frac{1}{s}$. Then,

$$\|f * g\|_s \leq \|f\|_p \|g\|_q, \quad (2.11)$$

In the above, $f * g$ represents the *convolution* of f and g and is the function given by

$$x \mapsto \int_{\mathbb{R}} f(x)g(x - y) dy.$$

In compact spaces, equality holds in Equation (2.11) when f and g are constant functions.

On \mathbb{R} however, we can add a multiplicative constant $c_{p,q} < 1$ on the right and improve the inequality. Here, equality holds when f and g are appropriate Gaussians $x \mapsto e^{-ax^2}$ and $x \mapsto e^{-bx^2}$, where a and b are some constants depending on p and q .¹⁵

Young's inequality is often written in an alternate form. Let r be equal to $1 - \frac{1}{s}$. We then have $\frac{1}{p} + \frac{1}{q} + \frac{1}{r} = 2$. Let h be a function such that $\|h\|_r = 1$ and

$$\|(f * g)(h)\|_1 = \|f * g\|_s \|h\|_r.$$

We know that such a h exists by choosing that which satisfies the equality condition in Hölder's inequality.

Therefore, rewriting the above in terms of h ,

¹⁵see [this paper](#) by Brascamp and Lieb.

$$\|(f * g)(h)\| \leq \|f\|_p \|g\|_q \|h\|_r.$$

More explicitly,

$$\int \int f(y)g(x-y)h(x) \, dy \, dx \leq \|f\|_p \|g\|_q \|h\|_r.$$

Equivalently,

$$\int \int f(y)g(x-y)h(-x) \, dy \, dx \leq \|f\|_p \|g\|_q \|h\|_r.$$

Note that $(y) + (x - y) + (-x) = 0$. Consider the map from $\mathbb{R}^2 \rightarrow \mathbb{R}^3$ given by

$$(x, y) \mapsto (y, x - y, -x).$$

The image of this transformation is equal to

$$H = \{(u, v, w) : u + v + w = 0\}.$$

Therefore, if $\frac{1}{p} + \frac{1}{q} + \frac{1}{r} = 2$,

$$\int_H f(u)g(v)h(w) \leq \|f\|_p \|g\|_q \|h\|_r.$$

We integrate over a two-dimensional measure on the subspace H .

2.3.2. A Generalization

So this is all well and good, but how is it related to volume ratios? The paper of Brascamp and Lieb mentioned in a footnote previously did more than just say that equality holds when the functions are appropriate Gaussians. It actually *generalized* Young's Convolution Inequality to higher-dimensional spaces and any number of functions. Note that the map from \mathbb{R}^2 to \mathbb{R}^3 that leads to H is given by

$$x \mapsto (\langle x, v_1 \rangle, \langle x, v_2 \rangle, \langle x, v_3 \rangle),$$

where $v_1 = (0, 1)$, $v_2 = (1, -1)$, and $v_3 = (-1, 0)$. The generalisation led to the following:

Theorem 2.12. If $(v_i)_1^m$ are vectors in \mathbb{R}^n and $(p_i)_1^m$ are positive numbers satisfying

$$\sum_i \frac{1}{p_i} = n$$

and $(f_i)_1^m$ are non-negative measurable functions on \mathbb{R} , then the expression

$$\frac{\int_{\mathbb{R}^n} \prod_{i=1}^m f_i(\langle x, v_i \rangle)}{\prod_{i=1}^m \|f_i\|_{p_i}}$$

is “maximized”¹⁶ when the (f_i) are appropriate Gaussian densities $f_i(x) = e^{-\alpha_i x^2}$, where each α_i depends on the (p_i) , (v_i) , m , and n .

However, this seems quite unwieldy. The constants α_i are quite difficult to compute since they result from non-linear equations of all the variables. When we talk about convex bodies however, this issue completely disappears and gives a surprising connection back to **Fritz John's Theorem**!

¹⁶there are degenerate cases for which the maximum is not attained

Theorem 2.13. If $(u_i)_1^m$ are unit vectors in \mathbb{R}^n , $(c_i)_1^m$ are positive reals, and $(f_i)_1^m$ are non-negative measurable functions such that

$$\sum_{i=1}^m c_i u_i \otimes u_i = I_n,$$

and

$$\int_{\mathbb{R}^n} \prod_{i=1}^m f_i(\langle x, u_i \rangle)^{c_i} \leq \prod_{i=1}^m \left(\int f_i \right)^{c_i}$$

A couple of things to note here are:

- The maximized value is 1 now! The inequality is sharp.
- The c_i play the role of the $\frac{1}{p_i}$. As observed earlier, the (c_i) sum up to 1 just like the $(\frac{1}{p_i})$ should.
- We replace each f_i with $f_i^{c_i}$ to make it easier to state the equality condition.

When each f_i is equal to $t \mapsto e^{-t^2}$,

$$\begin{aligned} \int_{\mathbb{R}^n} \prod_{i=1}^m f_i(\langle x, u_i \rangle)^{c_i} &= \int_{\mathbb{R}^n} \exp \left(- \sum_i c_i \langle x, u_i \rangle^2 \right) \\ &= \int_{\mathbb{R}^n} \exp(-\|x\|^2) \\ &= \int_{\mathbb{R}^n} \exp \left(- \sum_i x_i^2 \right) \\ &= \left(\int e^{-t^2} \right)^n \\ &= \left(\int e^{-t^2} \right)^{\sum_i c_i} \\ &= \prod_{i=1}^m \left(\int f_i \right)^{c_i} \end{aligned}$$

We now prove Theorem 2.10.

Proof. Let K be a convex body with maximal ellipsoid B_2^n , $(u_i)_1^m$ and $(c_i)_1^m$ be the points and constants as mentioned in [Fritz John's Theorem](#), and C be the polytope defined in Equation (2.10). For each $1 \leq i \leq m$, define $f_i : \mathbb{R} \rightarrow \mathbb{R}$ to be the indicator function on $[-1, 1]$. Observe that for $x \in \mathbb{R}^n$, $f_i(\langle x, u_i \rangle)$ is non-zero for every i if and only if $|\langle x, u_i \rangle| \leq 1$ for every i , that is, $x \in C$. Therefore,

$$\begin{aligned} \text{vol}(C) &= \int_{\mathbb{R}^n} \prod_{i=1}^m f_i(\langle x, u_i \rangle)^{c_i} \\ &\leq \prod_{i=1}^m \left(\int f_i \right)^{c_i} \\ &= \prod_{i=1}^m 2^{c_i} = 2^n, \end{aligned}$$

which proves our claim. ■

The analogous result of Theorem 2.10 for general convex bodies, as might be expected, says that among convex bodies, the regular solid simplex has the largest volume ratio.

§3. Concentration and Almost-Balls

Before we formally begin this section, we state without proof some results in probability that will be helpful later.

Unlike usual convention in probability, we take that a Bernoulli random variable takes -1 and $+1$ (instead of 0 and 1) with probability $\frac{1}{2}$ each.

Theorem 3.1 (Hoeffding's inequality). If $(\varepsilon_i)_1^n$ are independent Bernoulli random variables and $(a_i)_1^n$ are reals that satisfy $\sum_i a_i^2 = 1$, then for $t > 0$,

$$\Pr \left[\left| \sum_{i=1}^n a_i \varepsilon_i \right| > t \right] \leq 2e^{-t^2/2}.$$

We also have

Theorem 3.2. If $(X_i)_1^n$ are iid random variables, each of which is uniformly distributed on $[-\frac{1}{2}, \frac{1}{2}]$ and $(a_i)_1^n$ are reals that satisfy $\sum_i a_i^2 = 1$, then for $t > 0$,

$$\Pr \left[\left| \sum_{i=1}^n a_i X_i \right| > t \right] \leq 2e^{-6t^2}.$$

Given a point $x \in \mathbb{R}^n$, $\sum_i a_i x_i$ is the distance of x from the hyperplane orthogonal to $(a_1, \dots, a_n) \in \mathbb{R}^n$ that passes through the origin. So the above theorem essentially says that if we uniformly randomly pick a point from $[-\frac{1}{2}, \frac{1}{2}]^n$, then it is close to any $(n-1)$ -dimensional hyperplane passing through the origin. This might be reminiscent of how a majority of the volume in a ball is contained in (relatively) thin slabs.

We elaborate further on this phenomenon in the following section.

3.1. Concentration in Geometry

Given a compact set $A \subseteq \mathbb{R}^n$ and $x \in \mathbb{R}^n$, we write

$$d(x, A) = \inf\{d(x, y) : y \in A\}.$$

Note that for $\varepsilon > 0$,

$$A + \varepsilon B_2^n = \{x \in \mathbb{R}^n : d(x, A) \leq \varepsilon\}.$$

Denote such a neighbourhood $(A + \varepsilon B_2^n)$ of A by A_ε .

Then the proof of the **Isoperimetric Inequality** we gave using the Brunn-Minkowski inequality essentially says that if B is a Euclidean ball of the same volume as A , then

$$\text{vol}(A_\varepsilon) > \text{vol}(B_\varepsilon) \text{ for any } \varepsilon > 0.$$

Observe that we have removed Minkowski addition and reformulated everything in terms of only the measure and the metric. A more general question that one might ask is:

Given a metric space (Ω, d) equipped with a Borel measure μ and some $\alpha, \varepsilon > 0$, for which sets A of measure α do the “blow-ups” A_ε have the smallest measure?

3.1.1. The Chordal Metric

First, consider the example of $\Omega = S^{n-1}$ and d being the Euclidean metric inherited from \mathbb{R}^n (also known as the *chordal metric*). The measure is σ_{n-1} .

It was shown (with great difficulty) that the sets A are exactly spherical caps in \mathbb{R}^n , which are the balls in S^{n-1} .

This might not seem like a big deal, but it does lead to some very startling results. For example, consider some hemisphere H ($\alpha = \frac{1}{2}$). Then for any set A of measure $\frac{1}{2}$, $\sigma(A_\varepsilon) \geq \sigma(H_\varepsilon)$. Further, since the complement of A is a ε -cap, we can use Lemma 1.2 to write

$$\sigma(A_\varepsilon) \geq 1 - e^{-n\varepsilon^2/2}.$$

This means (for sufficiently large n), that nearly the entire sphere lies within distance ε of A , although there might be points that are far from A .

Similar to the observation made at the beginning where the majority of the mass was concentrated around any hyperplane through the origin, we see that the majority of the mass is concentrated around any set of measure $\frac{1}{2}$.

Let us now reformulate this same property in another way. Let $f : S^{n-1} \rightarrow \mathbb{R}$ be a 1-Lipschitz function:

$$|f(\theta) - f(\phi)| \leq \|\theta - \phi\| \text{ for any } \theta, \phi \in S^{n-1}$$

Let $M \in \mathbb{R}$ (a median of f), be such that $\sigma(\{f \geq M\}) = \sigma(\{f \leq M\}) = \frac{1}{2}$. Due to the Lipschitz nature of f , for any $\varepsilon > 0$, if x is at distance at most ε from $\{f \leq M\}$,

$$\sigma(\{f > M + \varepsilon\}) \leq e^{-n\varepsilon^2/2}.$$

Writing a similar expression for $\sigma(\{f < M - \varepsilon\})$ and combining the two, we get

$$\sigma(\{|f - M| \leq \varepsilon\}) \leq 2e^{-n\varepsilon^2/2}.$$

That is, any 1-Lipschitz function on S^{n-1} is practically constant!

For future reference, we also state two more results. Here, $\text{med}(\cdot)$ represents a *median* of the function, that is, a number M such that $\sigma(\{f \leq M\}) \geq \frac{1}{2}$ and $\sigma(\{f \geq M\}) \leq \frac{1}{2}$.

Lemma 3.3. Let $f : S^{n-1} \rightarrow \mathbb{R}$ be 1-Lipschitz. Then

$$|\text{med}(f) - \mathbf{E}(f)| \leq 12n^{-1/2}.$$

Proof. We have

$$\begin{aligned} |\text{med}(f) - \mathbf{E}(f)| &\leq \mathbf{E}(|f - \text{med}(f)|) \\ &\leq \sum_{k=0}^{\infty} \frac{k+1}{\sqrt{n}} \Pr \left[|f - \text{med}(f)| \geq \frac{k}{\sqrt{n}} \right] \\ &\leq n^{-1/2} \sum_{k=0}^{\infty} (k+1) 2e^{-k^2/2} \\ &\leq 12n^{-1/2}. \end{aligned}$$

■

3.1.2. The Gaussian Metric

Second, let us consider the example of \mathbb{R}^n equipped with the standard Gaussian probability measure μ that has density

$$\gamma(x) = (2\pi)^{-n/2} e^{-|x|^2/2}.$$

The solutions to the problem for $\alpha = \frac{1}{2}$ were found to be *half-spaces*. That is, if $A \subseteq \mathbb{R}^n$ and $\mu(A) = \frac{1}{2}$, then for any $\varepsilon > 0$, $\mu(A_\varepsilon) \geq \mu(H_\varepsilon)$, where $H = \{x \in \mathbb{R}^n : x_1 \leq 0\}$ and so, $H_\varepsilon = \{x \in \mathbb{R}^n : x_1 \leq \varepsilon\}$. We have

$$\mu(\overline{H_\varepsilon}) = \frac{1}{\sqrt{2\pi}} \int_\varepsilon^\infty e^{-x^2/2} dx \leq e^{-\varepsilon^2/2}$$

and therefore,

$$\mu(A_\varepsilon) \geq 1 - e^{-\varepsilon^2/2}.$$

A more general result about the Gaussian metric states that

Theorem 3.4. Let $A \subseteq \mathbb{R}^n$ be measurable and μ the standard Gaussian probability measure on \mathbb{R} . Then

$$\int e^{d(x,A)^2/4} d\mu \leq \frac{1}{\mu(A)}.$$

In particular, if $\mu(A) = \frac{1}{2}$,

$$\mu(A_\varepsilon) \geq 1 - 2e^{-\varepsilon^2/4}.$$

Proof. Define the functions

$$\begin{aligned} f &: x \mapsto e^{d(x,A)^2/4} \gamma(x), \\ g &: x \mapsto \mathbb{1}_A \gamma(x), \text{ and} \\ m &: x \mapsto \gamma(x), \end{aligned}$$

where $\mathbb{1}_A$ represents the indicator function on A . Then, for any $x \notin A$ and $y \in A$,

$$\begin{aligned} f(x)g(y) &= e^{d(x,A)^2/4} \cdot (2\pi)^{-n} e^{-(|x|^2+|y|^2)/2} \\ &\leq (2\pi)^{-n} e^{\|x-y\|^2/4} e^{-(\|x\|^2+\|y\|^2)/2} \\ &= (2\pi)^{-n} e^{-\|x+y\|^2/4} \\ &= m\left(\frac{x+y}{2}\right)^2. \end{aligned}$$

Using the above, it is obvious that for any $x, y \in \mathbb{R}^n$,

$$f(x)g(y) \leq m\left(\frac{x+y}{2}\right)^2.$$

We can then use the **Prékopa-Leindler inequality** to conclude that

$$\left(\int_{\mathbb{R}^n} f\right) \left(\int_{\mathbb{R}^n} g\right) \leq \left(\int_{\mathbb{R}^n} m\right)^2.$$

That is,

$$\mu(A) \int e^{d(x,A)^2/4} d\mu \leq 1,$$

which is exactly what we want to show.

For the second part, we have

$$e^{d(x,A)^2/4} \leq 2.$$

For any $\varepsilon > 0$, the integral on the left is at least $e^{\varepsilon^2/4} \mu(\{d(x,A) \geq \varepsilon\})$. We then have

$$\mu(\{d(x,A) \geq \varepsilon\}) \leq 2e^{-\varepsilon^2/4},$$

which directly results in our claim. ■

The reader might have noticed that we have proved slightly different bounds from what we claimed at the beginning of this subsection ($\varepsilon^2/4$ instead of $\varepsilon^2/2$), we can get arbitrarily close to the given bound by changing f , g and λ (which we chose to be $\frac{1}{2}$) slightly. Henceforth, we use the $\varepsilon^2/2$ bound itself.

3.2. Dvoretzky's Theorem

Theorem 3.5 (Dvoretzky's Theorem). There is a positive number c such that for every $\varepsilon > 0$ and natural n , every symmetric body of dimension n has a slice of dimension

$$k \geq \frac{c\varepsilon^2}{\log(1 + \varepsilon^{-1})} \log n$$

that is within distance $1 + \varepsilon$ of the Euclidean ball.

The above theorem essentially says that any symmetric convex body possesses almost spherical slices. While the original proof was by Dvoretzky, Milman found a different proof of the above theorem which is based on concentration of measure. A few years later, Gordon removed the $\log(1 + \varepsilon^{-1})$ factor from the denominator. We describe Milman's approach without making explicit the dependence on n (for the sake of simplicity).

Loosely, the proof goes as follows:

- Section 3.2.3 - Using Theorem 3.7, restrict to a “good” subspace that is not too much smaller than \mathbb{R}^n .
- Section 3.2.4 - Bound the expectation, and thus the median, of the norm corresponding to the body by some constant multiple of $\sqrt{\frac{\log n}{n}}$.
- Section 3.2.1 - Find a general bound on a valid k in terms of the median and use the bound from the previous step.

3.2.1. Expressing the Result in Terms of the Median

Let K be a symmetric convex body such that the maximal ellipsoid in it is the Euclidean ball. Let $\|\cdot\|_K$ be the metric under which K is the unit ball.

We then want to find a k -dimensional subspace H of \mathbb{R}^n such that the function $f : \theta \mapsto \|\theta\|_K$ is almost constant on the k -dimensional ball $H \cap S^{n-1}$. Now, for any $x \in \mathbb{R}^n$, we have $\|x\| \geq \|x\|_K$. This implies that

$$|\|\theta\|_K - \|\phi\|_K| \leq \|\theta - \phi\|_K \leq \|\theta - \phi\|$$

so f is 1-Lipschitz on S^{n-1} . From the discussion in Section 3.1.1, we know that on a large part of S^{n-1} , f is approximately equal to

$$M = \int_{S^{n-1}} f \, d\sigma.$$

We can view any such subspace H as an embedding $T : \mathbb{R}^k \rightarrow \mathbb{R}^n$. For any unit vector $\psi \in \mathbb{R}^k$, $\|T\psi\|_K$ is close to M with high probability. Then for any unit vectors $(\psi_i)_{i=1}^m$, $\|T\psi\|_K$ is close to M with high probability for some choice of T . What we would like to show is that if we pin down $\|T\psi_i\|_K$ at sufficiently many points that are “well-distributed” around the ball (in \mathbb{R}^k), then the radius will be almost constant on the sphere as well.

To make this more concrete, we bring back some terminology that we used in the proof of Theorem 1.3. Define a set $\{\psi_1, \dots, \psi_m\}$ to be a δ -set in S^{k-1} if for any $x \in S^{k-1}$, $d(x, \psi_i) \leq \delta$ for some i .

Lemma 3.6. Let $\|\cdot\|_K$ be a norm on \mathbb{R}^k . Suppose that for some $\gamma > 0$, each point ψ of some δ -net on S^{k-1} satisfies

$$M(1 - \gamma) \leq \|\psi\|_K \leq M(1 + \gamma).$$

Then for every $\theta \in S^{k-1}$,

$$\frac{M(1 - \gamma - 2\delta)}{1 - \delta} \leq \|\theta\|_K \leq \frac{M(1 + \gamma)}{1 - \delta}.$$

Proof. We may assume without loss of generality that $M = 1$. Let

$$C = \sup_{\theta \in S^{n-1}} \|\theta\|_K = \sup_{\theta \in S^{n-1}} \frac{\|\theta\|_K}{\|\theta\|}$$

and θ_0 be the point on S^{n-1} for which this is attained. Let ψ_0 be a point of the δ -net such that $\|\theta_0 - \psi\| \leq \delta$. Then,

$$\begin{aligned} C &= \|\theta_0\|_K \\ &\leq \|\psi_0 - \theta_0\|_K + \|\psi_0\|_K \\ &\leq C\delta + (1 + \gamma). \end{aligned}$$

Therefore,

$$C \leq \frac{1 + \gamma}{1 - \delta}.$$

Now, for any $\theta \in S^{n-1}$, if ψ is a point of the δ -net such that $\|\theta - \psi\| \leq \delta$, then

$$\begin{aligned} 1 - \gamma &\leq \|\psi\|_K \\ &\leq \|\theta\|_K + \|\psi - \theta\|_K \\ &\leq \|\theta\|_K + \left(\frac{1 + \gamma}{1 - \delta}\right) \delta. \end{aligned}$$

This directly gives the other side of the inequality. ■

Now, let us bring the problem to the above form.

From the discussion in Section 3.1.1, we know that for any $\gamma > 0$,

$$M(1 - \gamma) \leq \|\theta\|_K \leq M(1 + \gamma)$$

on all but a set of measure (at most) $2e^{-nM^2\gamma^2/2}$.

We can find a δ -net \mathcal{A} (of the sphere in \mathbb{R}^{k-1} that has at most $\frac{1}{2} \cdot \left(\frac{\delta}{2}\right)^{k-1}$ points.

Now, rather than considering every k -dimensional subspace of \mathbb{R}^n , we can instead fix a particular embedding of \mathbb{R}^k in \mathbb{R}^n and subsequently consider every orthogonal transformation U of this space.

Rephrasing it in these terms, we want to determine if there is an orthogonal transformation U such that every $\psi \in \mathcal{A}$,

$$M(1 - \gamma) \leq \|U\psi\|_K \leq M(1 + \gamma).$$

For a particular ψ , the set of “bad” transformations is of measure at most $2e^{-nM^2\gamma^2/2}$. Further, a necessary (and sufficient) condition for there to be a valid U is that the total set of bad transformations is of measure less than 1. This yields

$$\left(\frac{4}{\delta}\right)^{k-1} \cdot e^{-nM^2\gamma^2/2} < 1$$

which gives a k in the order of

$$\frac{nM^2\gamma^2}{2\log(4/\delta)}.$$

Both the γ and the δ contribute to the ε as mentioned in **Dvoretzky’s Theorem**, so we should aim to bound M by a reasonably quantity to get the $\log(n)$ estimate we gave in the beginning. In particular, we should show that

$$M = \int_{S^{n-1}} \|\theta\|_K d\sigma \text{ is of the order of } \sqrt{\frac{\log n}{n}}.$$

To show this, we must use the fact that B_2^n is the maximal ellipsoid in K . Before we prove the general case, we examine a specific case.

3.2.2. Dvoretzky's Theorem for a Cross-Polytope under the Gaussian Measure

Consider the case where the measure is the Gaussian measure on \mathbb{R}^n . Then,

$$\begin{aligned} M &= \int_{S^{n-1}} \|\theta\|_K d\sigma \\ &= \frac{\Gamma\left(\frac{n}{2}\right)}{\sqrt{2}\Gamma\left(\frac{n+1}{2}\right)} \int_{\mathbb{R}^n} \|x\|_K d\mu(x) \quad (\text{converting from polar coordinates using Equation (1.1)}) \\ &> \frac{1}{\sqrt{n}} \int_{\mathbb{R}^n} \|x\|_K d\mu(x) \end{aligned}$$

and the body K under consideration is the cross-polytope. The corresponding norm is $x \mapsto \frac{1}{\sqrt{n}} \sum_i |x_i|$. We can split this integral to n separate integrals (in terms of each coordinate) to get

$$M > \frac{1}{\sqrt{n}} \int_{\mathbb{R}^n} \|x\|_K d\mu(x) = \int_{-\infty}^{\infty} |x| \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx = \sqrt{\frac{2}{\pi}}$$

This proves that for this example, there are in fact almost-spherical sections of dimension of the order of n .¹⁷

3.2.3. A Weaker Version of the Dvoretzky-Rogers Lemma

To aid us in our goal, we give the following lemma.

Theorem 3.7 (Dvoretzky-Rogers Lemma). Let $K \subseteq \mathbb{R}^n$ be a symmetric body with maximal ellipsoid B_2^n . Then, there exists some subspace $Z \subseteq \mathbb{R}^n$ of dimension $k = \left\lfloor \frac{n}{\log_2 n} \right\rfloor$ and an orthonormal basis $(u_i)_1^k$ of Z such that $\|u_i\|_K \geq \frac{1}{2}$ for all i .

The above is quite similar in spirit to Theorem 1.5. Instead of bounding the body between B_2^n and $\sqrt{n}B_2^n$, we bound the restriction of the body to a subspace between a ball and a parallelotope.¹⁸

The basic idea of the proof is as follows. Either the body K touches the inner ball at a “large number” of places, in which case we can construct the (u_i) , or it stays away from the ball in some “large” subspace. In this case, we restrict to this subspace, inflate the inner ball, and repeat the process. Since we cannot inflate the inner ball forever (it must be contained within $\sqrt{n}B_2^n$), this will end at some point.

Proof. Consider two cases.

- If every subspace $Y \subseteq \mathbb{R}^n$ of dimension $> n - k$ contains a vector u with $\|u\| = 1$ and $\|u\|_K \geq \frac{1}{2}$, then choose one such vector from each of k orthogonal subspaces of dimension $n - k + 1$ to construct the required.
- Otherwise, there exists some subspace Y of dimension greater than $n - k$ such that for every unit vector $u \in Y$, $\|u\|_K \leq \frac{1}{2}$. Let \tilde{K} and \tilde{B}_2^n be the restriction of K and B_2^n to this subspace respectively. Observe that $2\tilde{B}_2^n \subseteq \tilde{K}$. We can then recurse on the subspace Y scaled down by a factor of $\frac{1}{2}$.

Since K is contained in $\sqrt{n}B_2^n$, this process must terminate in at most $i_0 := \log_2(n) - 1$ steps. Because $n - ki_0 \geq k$, the result holds. ■

Note that we could have repeated the above proof to get a similar result that is off by a constant factor if in Theorem 1.5, we had the weaker bound of something like n or n^{43} instead of \sqrt{n} .

While we have found a subspace of dimension $\frac{n}{\log_2 n}$, there are alternate proofs that give much better results. One in particular gives $\dim(Z) = \frac{n}{2}$.

¹⁷exclamation mark, not factorial!

¹⁸the parallelotope is defined by the separating hyperplanes between each $(2u_i)$ and K .

3.2.4. Bounding the Expectation

Henceforth, we restrict ourselves to the subspace Z as defined in Theorem 3.7. We can do so because the reduction in dimension from n to $\frac{n}{\log n}$ makes barely any difference.¹⁹ Assume that $Z = \mathbb{R}^n$.

We now want to get a lower bound on the median of $x \mapsto \|x\|_K$ (restricted to S^{n-1}). Instead of doing this, we shall bound the *expectation*. This is justified because as seen in Lemma 3.3, the difference between them is $\mathcal{O}(n^{-1/2})$ which is irrelevant compared to the quantity we aim to bound it by.

Let $\|\cdot\|_P$ be the norm that defines the corresponding parallelotope.

We clearly have $\|\theta\|_K \geq \|\theta\|_P$. Therefore, it suffices to instead bound the expectation of $\|\cdot\|_P$.

Now, we show that it in fact suffices to consider the cube $[-2, 2]^n$ instead of the parallelotope! The norm corresponding to the cube is $\frac{1}{2} \|\cdot\|_\infty$.

Lemma 3.8. Let v_1, \dots, v_n be vectors in a normed space with norm $\|\cdot\|$. Then

$$\sum_{\sigma \in \{-1, 1\}^n} \left\| \sum_{i=1}^n \sigma_i v_i \right\| \geq 2^n \max_i \|v_i\|$$

Proof. Assume without loss of generality that v_1 has the largest norm. Then,

$$\begin{aligned} \sum_{\sigma \in \{-1, 1\}^n} \left\| \sum_{i=1}^n \sigma_i v_i \right\| &= 2 \sum_{\sigma \in \{-1, 1\}^{n-1}} \left\| v_1 + \sum_{i=1}^n \sigma_{i-1} v_i \right\| \\ &= 2 \sum_{\sigma \in \{-1, 1\}^{n-2}} \left\| v_1 + \left(v_2 + \sum_{i=2}^n \sigma_{i-2} v_i \right) \right\| + \left\| v_1 - \left(v_2 + \sum_{i=2}^n \sigma_{i-2} v_i \right) \right\| \\ &\geq 2 \sum_{\sigma \in \{-1, 1\}^{n-2}} 2 \|v_1\| \\ &= 2^n \|v_1\|. \end{aligned}$$

■

For the sake of simplicity, denote the function $x \mapsto \|x\|_P$ by f_P and $x \mapsto \frac{1}{2} \|x\|_\infty$ by f_C . We want to show that $\mathbf{E}[f_P] \geq \mathbf{E}[f_C]$. We use an averaging argument as follows, writing each $x \in S^{n-1}$ as $\sum_i \alpha_i u_i$ for some (α_i) . We then have

$$\begin{aligned} 2^n \mathbf{E}[f_P] &= 2^n \int_{S^{n-1}} f_P(x) d\sigma(x) \\ &= \sum_{\sigma \in \{-1, 1\}^n} \int_{S^{n-1}} f_P \left(\sum_{i=1}^n \sigma_i \alpha_i u_i \right) d\sigma(x) \\ &= \int_{S^{n-1}} \sum_{\sigma \in \{-1, 1\}^n} f_P \left(\sum_{i=1}^n \sigma_i \alpha_i u_i \right) d\sigma(x) \\ &\geq \int_{S^{n-1}} 2^n \max_i |\alpha_i| d\sigma(x) \\ &\geq \int_{S^{n-1}} 2^n \cdot \frac{1}{2} \max_i |\alpha_i| d\sigma(x) \\ &= 2^n \int_{S^{n-1}} f_C(x) d\sigma(x) = 2^n \mathbf{E}[f_C]. \end{aligned}$$

¹⁹For a more convincing argument, one could just work in the subspace of dimension $\frac{n}{2}$.

Finally, we shall show that for some constant c ,

$$\mathbf{E}[f_C] = \frac{1}{2} \int_{S^{n-1}} \|x\|_\infty d\sigma(x) \geq c \sqrt{\frac{\log n}{n}}$$

To show this, we give an elegant probabilistic method that uses the fact that the n -dimensional Gaussian is symmetric about the origin. Let $Z = (Z_1, \dots, Z_n)$ be the standard normal. We can draw a point uniformly randomly from S^{n-1} using $\frac{Z}{\|Z\|}$. Clearly,

$$\mathbf{E}[f_C] = \mathbf{E} \left[\frac{\|Z\|_\infty}{\|Z\|} \right].$$

Now, note that

$$\Pr[\|Z\| \geq \sqrt{3n}] = \Pr[\|Z\|^2 \geq 3\mathbf{E}[\|Z\|^2]] \leq \frac{1}{3}.$$

That is, $\|Z\|$ is less than some constant multiple of \sqrt{n} with probability at least $\frac{2}{3}$. On the other hand, for any constant z ,

$$\begin{aligned} \Pr[\|Z\|_\infty \leq z] &= (\Pr[|Z_1| \leq z])^n \\ &= \left(1 - \int_z^\infty \frac{2}{\sqrt{2\pi}} e^{-t^2/2} dt \right)^n \\ &\leq \left(1 - \frac{2}{\sqrt{2\pi}} e^{-(z+1)^2/2} \right)^n \end{aligned}$$

Setting z to $\sqrt{\log n} - 1$, we get

$$\Pr[\|Z\|_\infty \leq z] \leq \left(1 - \frac{2}{\sqrt{2\pi}} n^{-1/2} \right)^n,$$

which is less than $\frac{1}{3}$ for all n . Therefore, $\|Z\|_\infty \leq c_2 \sqrt{n}$ with probability at least $\frac{2}{3}$ and $\|Z\| \geq c_1 \sqrt{\log n}$ with probability at least $\frac{2}{3}$ for some constants c_1, c_2 . This implies that $\frac{\|Z\|_\infty}{\|Z\|} \geq c \sqrt{\frac{\log n}{n}}$ for some suitable c ,²⁰ which is exactly what we want.

²⁰since we know that it occurs with probability at least $\frac{1}{3}$.

§4. Computing Volume in High Dimensions

A very popular problem in high-dimensional convex geometry is that of determining the volume of an arbitrary body.

For a fixed dimension n , this problem isn't too difficult if we want to measure it up to some precision ε . We could assume that the body K is enclosed in a box $B = \times_{i \leq n} [a_i, b_i]$, subdivide this box up to precision ε , and count how many subdivided boxes have non-empty intersection with K . This (after normalizing appropriately) can be considered efficient in a fixed dimension, where polynomiality is measure in $\frac{1}{\varepsilon}$. If we measure it in n on the other hand, this method is useless.

We are looking for algorithms that are efficient (polynomial) in the *dimension* n .

There are a few issues that arise when we even want to formulate this problem.

- What does it mean when we say that a convex body K is “given”? In what form is it given?
- What does “efficient” exactly mean?

We have already answered the second question above – we are looking for algorithms that are *polynomial* in the dimension n . We either want the exact volume or an approximation up to some small *relative error* $\varepsilon > 0$. If it is the latter, we would also like the algorithm to be polynomial in $\frac{1}{\varepsilon}$.²¹

4.1. Sandwiching and Deterministic Algorithms

Let us answer the first question that we mentioned – how is an arbitrary body K represented? What information do we have access to?

4.1.1. Oracles

We represent the body using an *oracle*. We explain the different types of oracles one may consider over the course of this section.

Definition 4.1. A body K is said to be *well-guaranteed* if it contains rB_2^n and is contained in RB_2^n for some $r, R > 0$.

We restrict ourselves to well-guaranteed bodies since otherwise, we may ask any (finite) number of questions about the body (say of the form “is $x \in K$ ”) and receive a **no** every time. This doesn't allow us to make any useful inferences about $\text{vol}(K)$. The fact that K contains rB_2^n ensures that it isn't too small and the containment in RB_2^n ensures that it isn't “at infinity”.

A body K is given by an *oracle* K if we know nothing about it other than the fact that it is well-guaranteed with r and R and we may ask questions about K , and receive answers to said questions. Depending on the questions and answers, we get different types of oracles.

We primarily use *weak separation oracles* and *strong membership oracles*.

Definition 4.2 (Strong Membership Oracle). For a fixed convex body K , the *strong membership oracle* (correctly) answers questions of the form “Is $x \in K$?”.

Now, for $x \notin K$, we know that there is a hyperplane separating them by Lemma 1.7. This gives rise to the strong separation oracle.

Definition 4.3 (Strong Separation Oracle). For a fixed convex body K , the *strong separation oracle* (correctly) answers questions of the form “Is $x \in K$?”. If the answer is **no**, it also returns a hyperplane S separating x from K .

This hyperplane is returned as a vector $s \in \mathbb{R}^n$ with $\|s\|_\infty = 1$ such that $\langle s, x \rangle > 1$ and $\langle s, y \rangle \leq 1$ for any $y \in K$. This leads to the weak separation oracle.

²¹Note that ε takes only $\log(1/\varepsilon)$ bits, so this is a relaxation in some sense.

Definition 4.4 (Weak Separation Oracle). For a fixed convex body K , we can fix an $\varepsilon > 0$ and ask the *weak separation oracle* questions of the form “Is $x \in K$ for the positive number ε ?”. However, in this case, the precision of the answer is ε in the sense that

- (i) If $d(x, \partial K) < \varepsilon$, we can get any answer.
- (ii) If $B(x, \varepsilon) \subseteq K$, we get the correct answer (**yes**).
- (iii) If $d(x, K) \geq \varepsilon$, we get the correct answer (**no**) and a vector s normalized by $\|s\|_\infty = 1$ for which $\langle s, y \rangle < \langle s, x \rangle + \varepsilon$ for every $y \in K$.

A *weak membership oracle* is similar, where if it is within ε of ∂K , it may return either answer and if it is farther than ε , it returns the correct answer.

The complexity of the algorithm is measured in the number of calls to the oracle, since this is usually the most expensive step.

4.1.2. Sandwiching

We earlier mentioned that we only consider well-guaranteed bodies. As might be expected, the ratio R/r is quite important. Defining it slightly more concretely,

Definition 4.5. Given a convex body K , let \mathcal{E} an ellipsoid centered at 0 such that $\mathcal{E} \subseteq K \subseteq d\mathcal{E}$ for some $d \geq 1$. We are then said to have a *sandwiching* of K with *sandwiching ratio* d .

We are given a sandwiching of sandwiching ratio R/r initially. It is natural to want to obtain a sandwiching that has a lower ratio to make whatever algorithm we use more efficient.

Further, note that by Theorem 1.5, the minimum possible sandwiching ratio of (an affine transformation of) a body is at most n .

The information given to us initially (r and R) are not even necessarily useful all the time. For example, one could have a very “pencil-like” body in \mathbb{R}^n such that the inscribed ball is far far smaller than the circumscribed one. Thus, before we even begin our algorithm, we would want to do some preliminary sandwiching – perform an affine transformation to get a sandwiching with a more manageable sandwiching ratio.

Lovász showed in [Lov86] that it is possible to compute an affine transformation \tilde{K} of K in polynomial time such that

$$B_2^n \subseteq \tilde{K} \subseteq (n+1)\sqrt{n}B_2^n. \quad (4.1)$$

We first introduce the following common tool.

Lemma 4.1 (Basic ellipsoid method). For a convex body $K \subseteq \mathbb{R}^n$ along with some $R > 0$ such that $K \subseteq RB_2^n$ and a weak separation oracle, it is possible to find a point in K in polynomial time.

We prove it for the case where we have a *strong* separation oracle. The algorithm basically works by cutting down our search space until we find a point.

Proof. We construct a sequence $\mathcal{E}_0, \dots, \mathcal{E}_k$ of ellipsoids with $\mathcal{E}_0 = RB_2^n$. Given \mathcal{E}_r , check if its center x_r is contained in K . Otherwise, we have a half-space H_r such that $K \subseteq H_r$. We set \mathcal{E}_{r+1} to be the ellipsoid of minimal volume that contains $K \cap H_r$. The sequence terminates when the center of an ellipsoid is contained in K .

It may be shown that

$$\text{vol}(\mathcal{E}_{r+1}) = \left(\frac{n}{n+1} \right)^{(n+1)/2} \left(\frac{n}{n-1} \right)^{(n-1)/2} \text{vol}(\mathcal{E}_r).$$

Rewriting it more suggestively,

$$\begin{aligned} \text{vol}(\mathcal{E}_{r+1}) &= \left(\frac{n^2}{n^2-1} \right)^{(n-1)/2} \frac{n}{n+1} \text{vol}(\mathcal{E}_r) \\ &< \left(1 + \frac{1}{n^2} \right)^{(n-1)/2} \text{vol}(\mathcal{E}_r) < e^{-1/2n} \text{vol}(\mathcal{E}_r). \end{aligned}$$

The thing to note here is that $e^{-1/2n}$ is independent of the ellipsoids involved. Since we have $K \subseteq \mathcal{E}_k$,

$$\text{vol}(K) \leq \text{vol}(\mathcal{E}_k) \leq e^{-k/2n} (2R)^n.$$

That is,

$$k \leq 2n^2 \log(2R) - 2n \log(\text{vol}(K))$$

so there is a polynomial upper bound on the number of steps. ■

If each ellipsoid is given by

$$\mathcal{E}_r = \{x \in \mathbb{R}^n : (x - x_k)^\top A_k^{-1} (x - x_k) \leq 1\},$$

c_k is the vector returned by the separation oracle and $g_k = \frac{1}{\sqrt{c_k^\top A_k c_k}} c_k$, then

$$\begin{aligned} x_{k+1} &= x_k - \frac{1}{n+1} A_k g_k \text{ and} \\ A_{k+1} &= \frac{n^2}{n^2 - 1} \left(A_k - \frac{2}{n+1} A_k g_k g_k^\top A_k \right) \end{aligned}$$

Since there is rounding anyway (irrationals might become involved due to the $\sqrt{\cdot}$), it turns out that it suffices to have a weak separation oracle.

A pair of ellipsoids like that in Equation (4.1) is often known as a *weak Löwner-John pair* for K (the sandwiching ratio must be $(n+1)\sqrt{n}$).

Theorem 4.2. Let $K \subseteq \mathbb{R}^n$ be a convex body given by a weak separation oracle. Then a weak Löwner-John pair for K can be computed in polynomial time.

Again, we prove it for the case where we have a strong separation oracle instead. This algorithm is nearly identical to that of basic ellipsoid method, but at each step we perform a little extra computation to check if the corresponding ellipsoid scaled down by a factor of $(n+1)\sqrt{n}$ is contained in K .

Proof. We construct a sequence $\mathcal{E}_0, \dots, \mathcal{E}_k$ of ellipsoids with $\mathcal{E}_0 = RB_2^n$. Given \mathcal{E}_r , first check if its center x_r is contained in K . if it is not, then use the basic ellipsoid method to get an ellipsoid that does; we abuse notation and refer to this as \mathcal{E}_r as well.

Next, let the endpoints of the axes of the ellipsoid be given by $x_r \pm a_i$ (for $1 \leq i \leq n$). Check if the $2n$ points $x_r \pm \frac{1}{n+1} a_i$ are in K for each i . If they all are, then we are done, since this implies that the convex hull of these points is contained in K as well, and the maximal ellipsoid contained in the convex hull is just \mathcal{E}_r scaled down by a factor of $(n+1)\sqrt{n}$.

Otherwise, suppose that $x_r + \frac{1}{n+1} a_1$ is not in K and H_r is the half-space returned by the oracle that contains K . Similar to the basic ellipsoid method, find the minimal ellipsoid \mathcal{E}_{r+1} that contains $\mathcal{E}_r \cap H_r$.

It may be shown that in this case,

$$\text{vol}(\mathcal{E}_{r+1}) < e^{-3/2(n+1)(2n+1)^2} \text{vol}(\mathcal{E}_r).$$

The sequence terminates when we have found a weak Löwner-John pair. ■

It is also notable that for certain types of special convex bodies, we can improve the bound beyond $(n+1)\sqrt{n}$.

In particular, if K is symmetric, we can attain a factor of n , if K is a polytope given as the convex hull of a set of vectors, we can attain $n+1$, and if K is a symmetric polytope given as above, we can attain $\sqrt{n+1}$.

Typically, we assume that after performing sandwiching, we perform a linear transformation such that B_2^n becomes the maximal ellipsoid of the transformed body. That is, the problem boils down computing the volume of a body K with

$$B_2^n \subseteq K \subseteq (n+1)\sqrt{n} B_2^n.$$

Readers interested in oracles and sandwiching are highly recommended to take a look at [GLS93].

4.1.3. The Problem and Deterministic Attempts

Our problem is to find for some given convex body K , some quantities $\underline{\text{vol}}(K)$ and $\overline{\text{vol}}(K)$ such that

$$\underline{\text{vol}}(K) \leq \text{vol}(K) \leq \overline{\text{vol}}(K)$$

while minimizing $\frac{\overline{\text{vol}}(K)}{\underline{\text{vol}}(K)}$.

Theorem 4.2 produces estimates (equal to the volumes of the ellipsoids) with $\frac{\overline{\text{vol}}(K)}{\underline{\text{vol}}(K)} = n^n(n+1)^{n/2}$. This may seem ludicrously bad, but as it turns out, any deterministic attempts in general are destined to fail. Indeed, Elekes proved in [Ele86] that for any positive $\varepsilon < 2$, there exists no deterministic polynomial time algorithm that returns

$$\frac{\overline{\text{vol}}(K)}{\underline{\text{vol}}(K)} \leq (2 - \varepsilon)^n \quad (4.2)$$

for every convex body K . The reason for this is that the convex hull of polynomially many points in B_2^n is always bound to be far smaller than B_2^n itself – we’ve already seen this all the way back in Theorem 1.3. Let us now prove Equation (4.2).

Lemma 4.3 (Elekes’ Theorem). Every deterministic algorithm to estimate the volume of an arbitrary convex body $K \subseteq \mathbb{R}^n$ that uses q oracle queries has $\frac{\overline{\text{vol}}(K)}{\underline{\text{vol}}(K)} \geq \frac{2^n}{q}$ for some K given by a well-guaranteed weak separation oracle.

What exactly do we mean by a deterministic algorithm? Roughly, it means that if we pass the same body into the algorithm twice, we will get the exact same result. More specifically, if we pass two bodies K_1 and K_2 such that (x_i) and (y_i) are the queried points respectively, the first point where they differ, say $x_i \neq y_i$, must be such that $x_{i-1} = y_{i-1}$ is in $K_1 \triangle K_2$. We abuse this fact.

Proof. Let \mathcal{A} be some deterministic algorithm to estimate the volume of a convex body. Fix $\varepsilon = 2^n$ for the separation oracle. When we run \mathcal{A} on B_2^n , suppose that the points queried are x_1, \dots, x_q . Let C be the convex hull of these q points. Now, note that if we run \mathcal{A} on C , the same points (x_i) will be queried and as a result, the volume estimates $\underline{\text{vol}}$ and $\overline{\text{vol}}$ that are returned are the same as well!

To conclude the argument, note that

$$C \subseteq \bigcup_{i=1}^q B\left(\frac{x_i}{2}, \frac{1}{2}\right).$$

Therefore,

$$\frac{\text{vol}(C)}{\text{vol}(B_2^n)} \leq \frac{q}{2^n}.$$

We then have

$$\frac{\overline{\text{vol}}}{\underline{\text{vol}}} \geq \frac{\text{vol}(B_2^n)}{\text{vol}(C)} \geq \frac{2^n}{q}.$$

■

4.1.4. The Bárány-Füredi Theorem

We now give a stronger result known as the Bárány-Füredi Theorem (given in [BF87]), which shows that deterministic algorithms in general aren’t much better than even the estimate with an n^n error returned by basic sandwiching.

Theorem 4.4 (Bárány-Füredi Theorem). There is no deterministic polynomial time algorithm that computes a lower bound $\underline{\text{vol}}(K)$ and an upper bound $\overline{\text{vol}}(K)$ for the volume of every convex body $K \subseteq \mathbb{R}^n$ given by some oracle such that for every convex body,

$$\frac{\overline{\text{vol}}(K)}{\underline{\text{vol}}(K)} \leq \left(c \frac{n}{\log n}\right)^n$$

The basic outline of the proof is as follows.

Proof. Rather than considering a simple separation oracle, we consider an even stronger oracle. First of all, we know beforehand that the convex body K is such that $B_1^n \subseteq K \subseteq B_\infty^n$.

For $x \in \mathbb{R}^n$, denote $x^\circ = x / \|x\|$, $H^+(x^\circ) = \{z \in \mathbb{R}^d : \langle z, x^\circ \rangle \leq 1\}$ and $H^-(x^\circ) = \{z \in \mathbb{R}^d : \langle z, x^\circ \rangle \geq 1\}$.

When we query $x \in \mathbb{R}^n$, in addition to the information given by the separation oracle, we also receive “ $x^\circ \in K$ and $-x^\circ \in K$ and $K \subseteq H^-(x^\circ)$ and $K \subseteq H^+(x^\circ)$ ”. That is, if $x \notin K$, in addition to a separating hyperplane, we also receive information as to whether the hyperplanes at $\pm x^\circ$ that are orthogonal to x are tangential to K .

Now, for the main part of the proof, suppose we have some deterministic polynomial time algorithm \mathcal{A} that returns a lower and upper bound $\underline{\text{vol}}(K)$ and $\overline{\text{vol}}(K)$ for any body K . The basic idea is roughly similar to that of Elekes’ Theorem. Suppose we run \mathcal{A} on B_2^n until $m \leq n^a - n$ questions have been asked for some $a \geq 2$ (due to the polynomial nature of the algorithm) and x_1, \dots, x_m are the points queried. Define

$$C = \text{Conv}(\pm e_1, \pm e_2, \dots, \pm e_n, x_1^\circ, \dots, x_m^\circ).$$

Now, consider the dual C^* of C (recall what a dual is from the proof of Lemma 1.6). Observe that for any of the x_i , the output of the oracle on passing x_i (or $\pm e_i$) must be the same whether we pass it with regards to C , C^* , or B_2^n .²² Indeed, each $H^+(x_i^\circ)$ and $H^-(x_i^\circ)$ is a supporting hyperplane of all three bodies. This implies that the estimates returned by \mathcal{A} are the same for all three bodies!

We then have

$$\overline{\text{vol}}(B_2^n) \geq \text{vol}(C^*) \text{ and } \underline{\text{vol}}(B_2^n) \leq \text{vol}(C).$$

Therefore,

$$\frac{\overline{\text{vol}}(C)}{\underline{\text{vol}}(C)} = \frac{\overline{\text{vol}}(C^*)}{\underline{\text{vol}}(C^*)} = \frac{\overline{\text{vol}}(B_2^n)}{\underline{\text{vol}}(B_2^n)} \geq \frac{\text{vol}(C^*)}{\text{vol}(C)}.$$

■

Over the rest of this section, we show that there is some constant c such that

$$\frac{\text{vol}(C^*)}{\text{vol}(C)} \geq \left(c \frac{n}{\log n} \right)^n.$$

To do this, we introduce some more notation. Let

$$V(n, m) = \sup\{\text{vol}(K) : K = \text{Conv}(\{v_1, \dots, v_m\}) \subseteq B_2^n\}$$

and

$$S(n, m) = \inf\{\text{vol}(\{x : |\langle x, v_i \rangle| \leq 1 \text{ for each } i\}) : (v_i)_1^m \in \mathbb{R}^n \text{ such that for each } i, \|v_i\| \leq 1\}$$

Clearly, it suffices to show that

$$\frac{S(n, n^a)}{V(n, n^a)} \geq \left(c \frac{n}{\log n} \right)^n \quad (4.3)$$

since C^* and C are of the above considered forms.

4.1.5. Bounding $V(n, m)$ and $S(n, m)$

For $1 \leq k \leq n$, define

$$\rho(n, k) = \begin{cases} 1, & \text{if } k = 0 \\ \sqrt{(n-k)/nk}, & \text{if } 1 \leq k \leq n-2 \\ 1/n, & \text{if } k = n-1. \end{cases}$$

²²if $x_i \in B_2^n$, we receive a **yes**. Otherwise, we receive a **no** along with the information that the hyperplanes at the x_i° are tangential.

Lemma 4.5. Let $S = \text{Conv}(\{v_0, v_1, \dots, v_n\}) \subseteq B_2^n$ be an n -dimensional simplex and $x \in S$. Then for every k such that $0 \leq k \leq n-1$, S has a k -dimensional face $S_k = \text{Conv}(\{v_{i_0}, v_{i_1}, \dots, v_{i_k}\})$ and a point x_k in the interior²³ of S_k such that $(x - x_k) \perp \text{span}(S_k)$ and $\|x - x_k\| \leq \rho(n, k)$.

Proof. The result for $k = n-1$ follows directly from the fact that the maximal ellipsoid in S is at most $\frac{1}{n}B_2^n$.

For $1 \leq k \leq n-2$, we use strong (backward) induction on k .

Let $x_n = x$ and for each $r : n > k > r$, let x_r be such that $(x_{r+1} - x_r) \perp \text{span}(S_r)$ and $\|x_{r+1} - x_r\| \leq \rho(n, r)$.

Note that $x_n - x_{n-1}, x_{n-1} - x_{n-2}, \dots, x_{k+1} - x_k$ are all orthogonal and $\|x_{r+1} - x_r\| \leq \frac{1}{r}$ for each r . We then have

$$\begin{aligned} \|x_n - x_k\|^2 &= \sum_{r=k}^{n-1} \|x_{r+1} - x_r\|^2 \\ &\leq \sum_{r=k+1}^n \frac{1}{r^2} \\ &\leq \sum_{r=k+1}^n \frac{1}{r(r-1)} \\ &= \frac{1}{k} - \frac{1}{n}. \end{aligned}$$

Finally, the result for $k = 0$ follows from the fact that the (v_i) are contained in B_2^n . ■

Observe that this bound is only tight when k is 1 or n . Putting this in a slightly more compact form, let $S \subseteq \mathbb{R}^n$ and $U = \text{span}(S)$. If we define

$$S^\rho = S + (U^\perp + \rho B_2^n),$$

Lemma 4.5 just says that for some $S_k, x \in S_k^{\rho(n,k)}$.

It is also worth noting that if S is convex and $\dim U = k$,

$$\text{vol}(S^\rho) = \text{vol}_k(S) v_{n-k} \rho^{n-k} \quad (4.4)$$

Theorem 4.6. There is a constant $c > 0$ such that

$$\frac{V(n, m)}{v_n} \leq \left(c \frac{1 + \log(m/n)}{n} \right)^{n/2}$$

and so,

$$V(n, m) \leq \left(\gamma \frac{\sqrt{1 + \log(m/n)}}{n} \right)^n$$

where $\gamma = \sqrt{2\pi e c}$.

If $m/n \rightarrow \infty$ and $n/\log(m/n) \rightarrow \infty$, then there is a constant c' such that

$$\frac{V(n, m)}{v_n} \leq \left(c' \frac{\log(m/n)}{n} \right)^{n/2}$$

Proof. It may be shown that if $K = \text{Conv}(\{v_1, \dots, v_m\}) \subseteq \mathbb{R}^n$, then K is the union of its n -dimensional simplices. That is,

$$K = \bigcup_{i_0 < \dots < i_n} \text{Conv}(\{v_{i_0}, \dots, v_{i_n}\}).$$

²³it is a convex combination of the (v_{i_j})

This allows us to bound the volume of K . For any $1 \leq k \leq n-1$, we can write

$$K \subseteq \bigcup_{i_0 < \dots < i_k} \left\{ S^{\rho(n,k)} : S = \text{Conv}(\{v_{i_0}, \dots, v_{i_k}\}) \right\}.$$

Bounding the volume,

$$\text{vol}(K) \leq \binom{m}{k+1} \max \left\{ \text{vol} \left(S^{\rho(n,k)} : S = \text{Conv}(\{x_0, \dots, x_k\}) \subseteq B_2^n \right) \right\}.$$

Using Equation (4.4),

$$\text{vol}(K) \leq \binom{m}{k+1} \cdot v_{n-k} \rho(n, k)^{n-k} \cdot \max \{ \text{vol}_k(S) : S = \text{Conv}(\{x_0, \dots, x_k\}) \subseteq B_2^n \}.$$

The right-most quantity is maximum when the body is the k -dimensional regular solid simplex, whose volume is $(n+1)^{(n+1)/2}/n^{n/2}n!$. This is easily computed by using induction on dimension and the maximality was briefly mentioned at the end of Section 2.3. So,

$$\begin{aligned} \text{vol}(K) &\leq \binom{m}{k+1} \cdot \frac{\pi^{(n-k)/2}}{\Gamma\left(\frac{n-k}{2} + 1\right)} \left(\frac{n-k}{nk}\right)^{(n-k)/2} \frac{(k+1)^{(k+1)/2}}{k^{k/2}k!} \\ &\leq \binom{m}{k+1} \cdot \left(\frac{2\pi e}{n-k}\right)^{(n-k)/2} \left(\frac{n-k}{nk}\right)^{(n-k)/2} \frac{(k+1)^{(k+1)/2}}{k^{k/2}k!} \\ &= \binom{m}{k+1} \cdot \left(\frac{2\pi e}{nk}\right)^{(n-k)/2} \frac{(k+1)^{(k+1)/2}}{k^{k/2}k!} \\ &\leq \frac{m^{k+1}}{(k+1)!} \cdot \left(\frac{2\pi e}{nk}\right)^{(n-k)/2} \frac{(k+1)^{(k+1)/2}}{k^{k/2}k!} \\ &\leq \left(\frac{em}{k+1}\right)^{k+1} \cdot \left(\frac{2\pi e}{nk}\right)^{(n-k)/2} \left(\frac{e}{k}\right)^k. \end{aligned}$$

And therefore,

$$\frac{\text{vol}(K)}{v_n} \leq \left(\frac{em}{k+1}\right)^{k+1} n^{k/2} k^{-(n+k)/2}.$$

It remains to choose a suitable value of k . For the case when $m/n \rightarrow \infty$ and $n/\log(m/n) \rightarrow \infty$, we can let $k = \left\lceil \frac{n}{2\log(m/n)} \right\rceil$ to obtain

$$\frac{\text{vol}(K)}{v_n} \leq e^{o(n)} \left(\frac{2e \log(m/n)}{n} \right)^{n/2}.$$

■

Note that the above again leads to an inference similar to that we made in Theorem 1.3 – the volume is comparable only when m is exponentially large.

It remains to bound $S(n, m)$.

To do this, we use the second of the following beautiful results (we state the first for the sake of completeness).

Theorem 4.7 (Blaschke-Santaló Inequality). Let K be a convex body in \mathbb{R}^n with dual K^* . Then

$$\text{vol}(K) \text{vol}(K^*) \leq \text{vol}(B_2^n)^2$$

with equality when K is an ellipsoid.

Theorem 4.8 (Inverse Santaló Inequality). Let K be a convex body in \mathbb{R}^n with dual K^* . Then

$$\text{vol}(K) \text{vol}(K^*) \geq \frac{4^n}{n!}$$

with equality when K is the regular solid simplex.

For our purposes, it suffices to know that there is some constant c_2 such that

$$\text{vol}(K) \text{vol}(K^*) \geq \left(\frac{c_2}{n}\right)^n.$$

If we let $K = \{x \in \mathbb{R}^n : |\langle x, v_i \rangle| \leq 1 \text{ for each } i\}$ for some $(v_i)_{i=1}^m \in \mathbb{R}^n$ such that $\|v_i\| \leq 1$ for each i , then note that $K^* = \text{Conv}(\{v_1, \dots, v_m\})$.

An upper bound then directly follows from Theorem 4.8 and Theorem 4.6. We get for some constants c_2 and γ ,

$$S(n, m) \geq \left(\frac{c_2}{n}\right)^n \left(\frac{n}{\gamma \sqrt{\log(m/n) + 1}}\right)^n = \left(\frac{c'}{\sqrt{\log(m/n) + 1}}\right)^n \quad (4.5)$$

for some constant c' .

Finally, to show the bound mentioned in Equation (4.3), use Theorem 4.6 and Equation (4.5) to get

$$\frac{\overline{\text{vol}}(C)}{\underline{\text{vol}}(C)} \geq \frac{S(n, n^a)}{V(n, n^a)} \geq \left(\frac{c_1}{\gamma a} \frac{n}{\log n}\right)^n$$

which is exactly what we want.

4.2. Rapidly Mixing Random Walks

It has now clearly been established beyond doubt that deterministic algorithms will get us nowhere. What if instead, we consider randomized algorithms? That is, we are fine with some small probability, say η , of getting the incorrect answer? We can do far *far* better in this case.

4.2.1. An Issue with High Dimensions and the Solution

Reformulating the problem in this context, we pass some $0 < \eta < 1$, some $\varepsilon > 0$, and a well-guaranteed strong membership oracle²⁴ of a body K , and ask for an estimate $\widetilde{\text{vol}}(K)$ such that with probability at least $1 - \eta$,

$$(1 - \varepsilon)\widetilde{\text{vol}}(K) \leq \text{vol}(K) \leq (1 + \varepsilon)\widetilde{\text{vol}}(K).$$

Henceforth, we assume that the reader has a basic understanding of Markov chains and stationary distributions thereof, at least in the discrete case. In case the reader does not, they can skip ahead to Section 4.4.

A simple method that might come to mind is a Monte Carlo algorithm. Find some box Q in which K is contained, uniformly randomly generate a large number of points in Q , and find the fraction of points generated that are in K – this is a good estimate of $\frac{\text{vol}(K)}{\text{vol}(Q)}$.

However, the issue is one that we emphasised very heavily on in the very first (and quantified to some extent in the previous) section: if we take $K = B_2^n$ and $Q = B_\infty^n$, then $\text{vol}(K)/\text{vol}(Q)$ is extremely (exponentially) small, so it will not work (in polynomial time) at all.

²⁴it is in general not too important which oracle we are given.

That is, the issue is that $\text{vol}(K)$ is extremely small compared to a box it is contained in. To get around this, there is a surprisingly simple solution.

Rather than considering just K , consider some $m + 1$ bodies $K_0 \subseteq K_1 \subseteq \dots \subseteq K_m = K$ (for appropriately large m) and for each i , estimate $\Lambda_i := \text{vol}(K_i) / \text{vol}(K_{i-1})$ (we can then estimate $\text{vol}(K)$ as $\text{vol}(K_0) \prod_i \Lambda_i$). Usually, we take $K_i = K \cap 2^{i/n} B_2^n$. Note that because $K_i \subseteq 2^{i/n} K_{i-1}$ in this case,

$$\Lambda_i = \frac{\text{vol}(K_i)}{\text{vol}(K_{i-1})} \leq 2$$

is not large at all.

The value of $\text{vol}(K_0)$ is already known. But how do we estimate Λ_i ?

As observed earlier, since $1/\Lambda_i$ is not small, we can just stick with Monte Carlo methods, the basic idea being to somehow generate a uniform random distribution on K_i and find the fraction of points generated that are within K_{i-1} . Here on out, our main interest is just to figure out a way of efficiently uniformly randomly generating points from K_i .

To do this, we synthesize a Markov chain whose stationary distribution is the uniform distribution on K_i . We run the chain for polynomially many steps, and take the resultant state as a point uniformly randomly generated from K_i .

Obviously, we want Markov chains that converge to the stationary distribution very rapidly (in polynomial time) since that is the main part of the algorithm that must be made efficient. To restrict ourselves to finding the uniform distribution *within* K_i , we skip any move where the random walk attempts to leave K_i .²⁵ At the same time, we count how often we are in $K_{i-1} \subseteq K_i$. In the two algorithms we discuss, we modify this to a Metropolis chain, the idea of which is discussed at the end of Section 4.2.4

Succinctly, we use “Multiphase Monte Carlo Markov Chain methods” for volume computation. We call the random walk “rapidly mixing” if it gets sufficiently close to the stationary distribution in polynomially many steps.

Another small change is that we make the random walk *lazy*. That is, if we are at $a \in K$, we stay at a with probability $\frac{1}{2}$, and with probability $\frac{1}{2}$ we choose a random direction $a + v$. If $a + v \in K$, we move there. Otherwise, we stay put. There are two reasons for doing this. The first is that sometimes parity issues arise due to which the stationary distribution might not be the uniform one. The second is that it turns the matrix describing the random walk into a positive semidefinite matrix, which is much easier to analyze.

4.2.2. Random Walks on Graphs

Before we move onto the general case, let us define random walks in graphs and study them for a bit. Let $G = (V, E)$ be a connected d -regular simple graph with $V = \{1, \dots, n\}$. A *simple random walk on G with initial state X_0* is given by

$$\Pr[X_{t+1} = j \mid X_t = i] = \begin{cases} \frac{1}{2}, & i = j, \\ \frac{1}{2d}, & ij \in E, \\ 0, & \text{otherwise.} \end{cases}$$

It may be shown that irrespective of X_0 , $\lim_{t \rightarrow \infty} \Pr[X_t = i] = \frac{1}{n}$ for any i . But to see whether the walk is rapidly mixing, we need to know how fast it converges. Let

$$e_{i,t} = \Pr[X_t = i] - \frac{1}{n}$$

be the “excess” probability at time t on vertex i . Also, denote $\Pr[X_t = i]$ as $p_i^{(t)}$ for the sake of brevity. Denoting

²⁵For the hit-and-run strategy we describe later, this is unimportant since it never even tries to leave the body.

the neighbourhood of i by $\Gamma(i)$,

$$\begin{aligned}
 e_{i,t+1} &= p_i^{(t+1)} - \frac{1}{n} \\
 &= \left(\frac{1}{2} p_i^{(t)} + \frac{1}{2d} \sum_{j \in \Gamma(i)} p_j^{(t)} \right) - \frac{1}{n} \\
 &= \frac{1}{2} e_{i,t} + \frac{1}{2d} \sum_{j \in \Gamma(i)} e_{j,t} \\
 &= \frac{1}{2d} \sum_{j \in \Gamma(i)} (e_{i,t} + e_{j,t})
 \end{aligned} \tag{4.6}$$

To be able to quantify our closeness to the stationary distribution, define

$$d_1(t) = d_1(\tilde{X}, t) = \sum_i |e_{i,t}|$$

and

$$d_2(t) = d_2(\tilde{X}, t) = \sum_i e_{i,t}^2.$$

We call a walk \tilde{X} on G *rapidly mixing* if there exists a polynomial f such that for any $0 < \varepsilon < \frac{1}{3}$ and $t \geq f(\log n) \log(1/\varepsilon)$, $d_1(t) \leq \varepsilon$. However, this doesn't completely make sense right now since if we only have a single graph, n is constant.

Definition 4.6 (Rapidly Mixing Random Walks). Let $(G_i)_{i \in \mathbb{N}}$ be a sequence of graphs where G_i has n_i vertices and $n_i \rightarrow \infty$. We say that the simple random walks on G_1, G_2, \dots are *randomly mixing* if there is a polynomial f (depending only on the sequence (G_i)) such that if $0 < \varepsilon < \frac{1}{3}$ and $t \geq f(\log n_i) \log(1/\varepsilon)$, then $d(\tilde{X}_i, t) \leq \varepsilon$ whenever \tilde{X}_i is a simple random walk on G_i .

There are some issues that arise when we want to synthesize a rapidly mixing walk. For example, suppose we have a random walk on $[-1, 1]^n$ and we somehow find ourselves near one of the corners. Then the probability of leaving the corner is extremely low (of the order of 2^{-n}) at each step, which would greatly hinder the speed of convergence.

4.2.3. Conductance and Bounding the Speed of Convergence

In a graph, the analogous event is that we get stuck within some subset of vertices that is highly connected within itself, but not very well-connected to its complement. With this in mind, let us define the conductance of a graph. Let $G = (V, E)$ be a graph and $U \subseteq V$ be non-empty. Then define

$$\Phi_G(U) = \frac{e(U, V \setminus U)}{d|U|}$$

where $e(U, V \setminus U)$ is the number of edges between U and V .

$\Phi_G(U)$ gives a measure of the “difficulty” we mentioned earlier. The lower it is, the more difficult it is to leave U . We might as well consider only sets U with $|U| \leq \frac{n}{2}$. Thus, we define the *conductance* of G by

$$\Phi_G = \min_{1 \leq |U| \leq n/2} \Phi_G(U).$$

In graph theoretic contexts, this quantity is more often known as the *Cheeger's constant* of a graph or its *isoperimetric number*.

For graphs in general, denote $\text{vol}(U) = \sum_{u \in U} d(u)$. Then its conductance is

$$\Phi_G = \min_{\substack{U \subseteq V \\ U \neq \emptyset}} \frac{e(U, V \setminus U)}{\min(\text{vol}(U), \text{vol}(V \setminus U))}.$$

Obviously, $0 \leq \Phi_G \leq 1$ for any graph G . The upper bound is only attained when G is the graph containing a single vertex, a single edge, or a triangle. The lower bound is attained only when G is disconnected. If G is large, then the best we can hope for is that Φ_G is not too much lower than $\frac{1}{2}$.

It is intuitively clear that if a graph has high conductance, then any simple walk will converge quite rapidly. This is stated quantitatively in the following.

Theorem 4.9. Every simple random walk on a connected d -regular graph G satisfies

$$d_2(t+1) \leq \left(1 - \frac{1}{4}\Phi_G^2\right) d_2(t).$$

In particular,

$$d_2(t) \leq \left(1 - \frac{1}{4}\Phi_G^2\right)^t d_2(0) \leq 2 \left(1 - \frac{1}{4}\Phi_G^2\right)^t.$$

We prove this using two other lemmas.

Lemma 4.10. For any simple random walk on a connected d -regular simple graph on G ,

$$d_2(t+1) \leq d_2(t) - \frac{1}{2d} \sum_{ij \in E} (e_{i,t} - e_{j,t})^2.$$

Proof. Using Equation (4.6) along with the Cauchy-Schwarz inequality,

$$\begin{aligned} d_2(t+1) &= \frac{1}{4d^2} \sum_{i=1}^n \left(\sum_{j \in \Gamma(i)} e_{i,t} + e_{j,t} \right)^2 \\ &\leq \frac{1}{4d} \sum_{i=1}^n \sum_{j \in \Gamma(i)} (e_{i,t} + e_{j,t})^2 \\ &= \frac{1}{2d} \sum_{ij \in E} (e_{i,t} + e_{j,t})^2 \\ &= \frac{1}{d} \sum_{ij \in E} (e_{i,t}^2 + e_{j,t}^2) - \frac{1}{2d} \sum_{ij \in E} (e_{i,t} - e_{j,t})^2 \\ &= d_2(t) - \frac{1}{2d} \sum_{ij \in E} (e_{i,t} - e_{j,t})^2 \end{aligned}$$

■

Lemma 4.11. Suppose weights x_i are assigned to the elements of the vertex set $V = [n]$ satisfying $\sum_i x_i = 0$. Then

$$\sum_{ij \in E} (x_i - x_j)^2 \geq \frac{d}{2} \Phi_G^2 \sum_{i=1}^n x_i^2.$$

Observe that setting $x_i = e_{i,t}$ for each i and substituting the above in Lemma 4.10 directly gives Theorem 4.9.

Proof. We may assume without loss of generality that $x_1 \geq x_2 \geq \dots \geq x_n$. Fix $m = \lceil n/2 \rceil$ and for each i , let $y_i = x_i - x_m$. Note that it suffices (and is in fact stronger) to prove the inequality for the (y_i) instead of the (x_i) since

$$\frac{d}{2} \Phi_G^2 \sum_{i=1}^n (x_i - x_m)^2 = \frac{d}{2} \Phi_G^2 \sum_{i=1}^n x_i^2 + \frac{nd}{2} \Phi_G^2 x_m^2.$$

Also, let

$$u_i = \begin{cases} y_i, & i \leq m, \\ 0, & \text{otherwise,} \end{cases} \quad v_i = \begin{cases} 0, & i \leq m, \\ y_i, & \text{otherwise.} \end{cases}$$

Obviously, it suffices to prove the inequality for the (u_i) and (v_i) since

$$(y_i - y_j)^2 = (u_i - u_j + v_i - v_j)^2 \geq (u_i - u_j)^2 + (v_i - v_j)^2$$

and $\sum_i x_i^2 = \sum_i u_i^2 + \sum_i v_i^2$.

We prove it only for the (u_i) . Using the Cauchy-Schwarz inequality,

$$\begin{aligned} 2d \sum_{i=1}^n u_i^2 \sum_{ij \in E} (u_i - u_j)^2 &= \sum_{ij \in E} 2(u_i^2 + u_j^2) \sum_{ij \in E} (u_i - u_j)^2 \\ &\geq \sum_{ij \in E} (u_i + u_j)^2 \sum_{ij \in E} (u_i - u_j)^2 \\ &\geq \left(\sum_{ij \in E} (u_i^2 - u_j^2) \right)^2 \end{aligned} \tag{4.7}$$

We aim now to bound the term within the square in the final expression.

Suppose that in every edge $ij \in E$, $i < j$. We can then rewrite the expression as

$$\sum_{ij \in E} (u_i^2 - u_j^2) = \sum_{ij \in E} \sum_{l=i}^{j-1} (u_l^2 - u_{l+1}^2) = \sum_{l=1}^n (u_l^2 - u_{l+1}^2) e([l], [n] \setminus [l]).$$

It is very clear now how the conductance enters the picture. Since we can disregard the terms of the summation after $l = m$, the expression on the right is bounded below by $dl\Phi_G$. That is,

$$\begin{aligned} \sum_{ij \in E} (u_i^2 - u_j^2) &\geq \sum_{l=1}^m (u_l^2 - u_{l+1}^2) dl\Phi_G \\ &= d\Phi_G \sum_{l=1}^m u_l^2. \end{aligned}$$

Substituting the above in Equation (4.7),

$$\sum_{ij \in E} (u_i - u_j)^2 \geq \frac{d}{2} \Phi_G^2 \sum_{l=1}^m u_l^2,$$

which is exactly what we want to show. ■

Since $d_1(t)^2 \leq nd_2(t)$, we have the following corollary of Theorem 4.9.

Corollary 4.12. Every simple random walk on a connected d -regular graph G satisfies

$$d_1(t) \leq (2n)^{1/2} \left(1 - \frac{1}{4} \Phi_G^2 \right)^{t/2}$$

Note that if G is connected (so $\Phi_G \neq 0$), then for

$$t > 8\Phi_G^{-2} (\log(2n) + \log(1/\varepsilon)) > \frac{2}{-\log(1 - \frac{1}{4}\Phi_G^2)} (\log(2n) + \log(1/\varepsilon)), \quad (4.8)$$

$d_1(t) < \varepsilon$. Thus, we have the following sufficient condition for rapid mixing.

Lemma 4.13. Let $(G_i)_{i \in \mathbb{N}}$ be a sequence of regular graphs with $|G_i| = n_i \rightarrow \infty$. If there exists $k \in \mathbb{N}$ such that

$$\Phi_{G_i} \geq (\log n_i)^{-k}$$

for sufficiently large i , then the simple random walks on (G_i) are rapidly mixing.

The entirety of the discussion thus far has been regarding simple random walks. How would one go about generalizing this to aperiodic reversible random walks on finite sets in general?

Definition 4.7. Let V be a finite set and X a random walk on V with transition probabilities $p(u, v)$ such that for each u , $p(u, u) \geq \frac{1}{2}$. Let λ be the (reversible) stationary distribution that satisfies $\lambda(u)p(u, v) = \lambda(v)p(v, u)$. Also, for $U \subseteq V$, write $\lambda(U) = \sum_{u \in U} \lambda(u)$. The *conductance* of X is then

$$\tilde{\Phi}_X = \min_{\lambda(U) \leq \frac{1}{2}} \frac{\sum_{u \in U} \sum_{v \in V \setminus U} \lambda(u)p(u, v)}{\lambda(U)}.$$

Similar to earlier, the lower the conductance, the higher the probability of getting “stuck” somewhere. Note that the conductance here is half as large as the definition we gave for regular graphs (since in this case, $p(u, v) = 1/2d$ replaces the $1/d$ earlier). That is, if X is a simple random walk on a regular graph,

$$\tilde{\Phi}_X = \frac{1}{2}\Phi_G.$$

As earlier, we can measure the distance from λ by

$$d_2(t) = \sum_{v \in V} \left(p_v^{(t)} - \lambda(v) \right)^2.$$

We can then prove the following analogue of Theorem 4.9 (in exactly the same way).

Theorem 4.14. Let X be a reversible random walk. Then with the notation above,

$$d_2(t+1) \leq (1 - \tilde{\Phi}_X^2) d_2(t).$$

In particular,

$$d_2(t) \leq 2(1 - \tilde{\Phi}_X^2)^t.$$

4.2.4. An Overview of Random Walks for Uniform Distributions

The basic algorithm used in most algorithms that attempt to solve this problem, which we mentioned at the beginning of this section, was proposed by Dyer, Frieze, and Kannan in [DFK91] and has remained largely unchanged. This algorithm is $\mathcal{O}(n^{23}(\log n)^5 \varepsilon^{-2} \log(1/\varepsilon) \log(1/\eta))$. Henceforth, to make things relatively simple, we use the \mathcal{O}^* notation that suppresses any powers of $\log n$ and polynomials of $(1/\varepsilon)$ and $\log(1/\eta)$. With this notation, the algorithm is $\mathcal{O}^*(n^{23})$.

We use a multiphase Monte Carlo algorithm while using random walks to sample. The improvements on this algorithm since its proposal have primarily involved changing the random walk used, using the conductance to bound the mixing time when we are likely to be close to the stationary distribution, and bounding the conductance using isoperimetric inequalities.

There are mainly three different types of random walks used.

Walking on the Grid. This is probably the simplest graph. It defines a sufficiently fine grid \mathbb{L}_δ where each step is of size δ . Suppose we are at x_t . At each step, we stay put at x_t with probability $\frac{1}{2}$. Otherwise, we choose a random vector v of the $2n$ possible directions. If $x_t + v \notin K$, we remain at x_t and otherwise, we move to $x_{t+1} = x_t + v$. [DFK91] uses this walk with a value of δ around $n^{-5/2}$. In [LS90], this was improved to a δ around $n^{-3/2}$.

Ball-Steps. In this random walk, we choose some small step-size δ . We use a lazy random walk but when we try to move, we choose a random $v \in \delta B_2^n$. Similar to the grid, if $x_j + v \notin K$, we remain at x_j and otherwise, we move to $x_{j+1} = x_j + v$. In [KLS97], the value of δ was around $n^{-1/2}$.

Hit-and-Run. Unlike the previous two walks where we had to choose a step-size δ , this walk doesn't need anything of the sort. We choose a random unit vector v from B_2^n . We then find the length of the intersection of $\{x + tv : t \in \mathbb{R}\}$ with K and pick a uniformly distributed x' from this segment. It is believed that this walk converges very rapidly.

An issue (in any of the walks) that we must figure out how to rectify is that of getting stuck in some corner (we had given this as motivation for defining the conductance of a random walk).

For example, in the ball-step walk, we can consider the *local conductance*

$$\ell_\delta(x) := \frac{\text{vol}(K \cap (x + \delta B_2^n))}{\text{vol}(\delta B_2^n)}$$

and the overall conductance

$$\lambda := \frac{1}{\text{vol}(K)} \int_K \ell_\delta(x) \, dx.$$

In recent times, it has also been a common theme to use *Metropolis chains*, which are defined as follows.

Metropolis Chain. Suppose we have a function f on K and a random walk (of any of the above types). We can modify our walk using the same laziness as above, but when we wish to move, we check if $f(x) \geq f(x+v)$ (where x is the original position and $x+v$ is the new proposed position) and

- if **yes**, move to $x+v$.
- if **no**, move to $x+v$ with probability $\frac{f(x)}{f(x+v)}$ (and stay at x otherwise).

If $\int f < \infty$, this produces a random walk with stationary distribution that is proportional to $f(x)$.

So far, we have only tried finding uniform distributions within the body K (and never return a point outside the body K). Often, however, we sacrifice this in favour of a distribution that can return a point outside of K with not too high probability (say less than $\frac{1}{2}$) that mixes more rapidly. We detail one such algorithm, similar to that in [DF98], in the following section.

4.3. A Modified Grid Walk that Runs in $\mathcal{O}^*(n^8)$

4.3.1. A Description of the Walk

The algorithm we describe here uses the “Walking on the Grid” mentioned in the previous section. This involves splitting the body into cubes. To this end, it was observed that if want to sandwich a body between two concentric cubes instead of balls, then a ratio of $\mathcal{O}(n)$ can be obtained (instead of the ball-sandwiching ratio of $\mathcal{O}(n^{3/2})$). In particular, [AK91] shows that we can find an affine transformation \tilde{K} of K such that

$$B_\infty^n \subseteq \tilde{K} \subseteq 2(n+1)B_\infty^n.$$

Henceforth, we refer to this \tilde{K} as K . So in this case, it is more convenient to consider $K_i = 2^{i/n}$, $0 \leq i \leq m := \lceil n \log_2(2(n+1)) \rceil$ instead of the intersections with the balls we used earlier. That is, at each phase we have two bodies K and L such that

$$K_0 = B_\infty^n \subseteq L \subseteq K \subseteq 2(n+1)B_\infty^n = K_m$$

and

$$L \subseteq K \subseteq 2^{1/n}L.$$

The grid graph over which we design our random walk has vertex set

$$V = \frac{1}{2n} \mathbb{Z}^n \cap K_m.$$

That is, V is the vertex set of the grid graph P_l^n with $l = 8n(n+1) + 1$ (having l^n vertices). Denote this graph by G (there is an edge between points whose distance under the ℓ_∞ norm is $\frac{1}{2n}$).

We wish to create a rapidly mixing random walk that converges to the stationary distribution on K (or something that could serve the same purpose). Let us now define a distribution on V that is the stationary distribution of a specific random walk.

Consider the function φ_0 on \mathbb{R}^n defined by

$$\varphi_0(x) = \min \left\{ s \geq 0 : x \in \left(1 + \frac{s}{2n} \right) K \right\}$$

and φ defined by $\varphi(x) = \lceil \varphi_0(x) \rceil$. Finally, define $f(x) = 2^{-\varphi(x)}$.

There are a few things to observe that make it apparent why this f is a good choice for our purposes:

- For $x \in K$, $f(x) = 1$.
- If x, y are such that $\|x - y\|_\infty \leq \frac{1}{2n}$, then $|\varphi_0(x) - \varphi_0(y)| \leq 1$. Indeed,

$$x = y + (x - y) \in \left(1 + \frac{\varphi_0(y)}{2n} \right) K + \frac{1}{2n} K = \left(1 + \frac{\varphi_0(y) + 1}{2n} \right) K$$

so $\varphi_0(x) \leq \varphi_0(y) + 1$.

- How many $x \in V$ are there such that $\varphi(x) = s > 0$ (so $f(x) = 2^{-s}$)? We must have

$$x \in \left(1 + \frac{s}{2n} \right) K \setminus \left(1 + \frac{s-1}{2n} \right) K.$$

The volume of the body on the right is about

$$\left(\left(1 + \frac{s}{2n} \right)^n - \left(1 + \frac{s-1}{2n} \right)^n \right) \text{vol}(K) < (e^{s/2} - 1) \text{vol}(K).$$

Multiplying by an appropriate factor on either side, the number of points in V in this body is at most $(e^{s/2} - 1)f(K)$. Therefore, for $n > 3$,

$$f(V) = f(K) + \sum_{s=1}^{\infty} 2^{-s} (e^{s/2} - 1) f(K) < 5f(K).$$

The above suggests that a Metropolis chain under this function might be exactly what we want – the first point ensures that the resulting distribution is constant on K .

What is the Metropolis chain corresponding to f for G ? It is easily checked that its transition matrix is given by

$$p(x, y) = \begin{cases} \frac{1}{4n}, & xy \in E \text{ and } \varphi(y) \leq \varphi(x), \\ \frac{1}{8n}, & xy \in E \text{ and } \varphi(y) = \varphi(x) + 1, \\ 1 - \sum_{z \in \Gamma(x)} p(x, z), & x = y, \\ 0, & \text{otherwise.} \end{cases}$$

It can also easily be checked that this walk is reversible.

Now, let the stationary distribution of this walk be λ , given by $\lambda(x) = cf(x)$ for a suitable normalizing constant c . The third point above ensures that $\lambda(K) > 1/5$ and we don't get points outside of K too often.

There is another issue that we haven't mentioned so far that this walk takes care of. When we have such a walk (in general), we would want to be able to compute the transition probabilities efficiently only at the points where we need it – it would be absurd to store the entire transition matrix all the time. In this example, all we have to do is “carry” the current value of φ with us. At most $4n$ appeals to the oracle will give us the values of φ at all the neighbours! We can start at a point that we know the value of φ of, such as $0 \in B_\infty^n \subseteq K$.

4.3.2. Showing Rapid Mixing by Bounding Conductance

The only thing that remains to show now is that it suffices to run the above random walk for a polynomial amount of time to get sufficiently close to the stationary distribution, that is, that the walk is rapidly mixing.

By Theorem 4.14, it suffices to show that this walk has large conductance. To do this, we use the following isoperimetric inequality given in [LS90].

Theorem 4.15. Let $M \subseteq \mathbb{R}^n$ and $\mathcal{B}(M)$ be the σ -field of Borel subsets of M . Let $F : \text{Int } M \rightarrow \mathbb{R}^+$ be a log-concave function and let μ be the measure on $\mathcal{B}(M)$ with density F

$$\mu_F(A) = \int_A F$$

for $A \in \mathcal{B}(M)$. Then for $A_1, A_2 \in \mathcal{B}(M)$,

$$\mu_F(M \setminus (A_1 \cup A_2)) \geq \frac{d(A_1, A_2)}{\text{diam } M} \min(\mu_F(A_1), \mu_F(A_2)),$$

where $\text{diam } M = \sup\{\|x - y\| : x, y \in M\}$.

This inequality is slightly loose. The best possible constant on the right has an extra multiplicative factor of 2 and was proved in [DF98]. We omit the proof of the above for now and later prove a better bound in Theorem 4.34 (and in the process, prove Theorem 4.15 as a simple consequence of Theorem 4.31). We shall now use this to show that the conductance of our random walk is large.

Let us have $U \subseteq V$ with $0 < \lambda(U) < \frac{1}{2}$ and let $\bar{U} = V \setminus U$. Also, let ∂U be the set of vertices in \bar{U} with at least one neighbour in U .

Let M be the union of the cubes of side length $1/2n$ centered at vertices of V (M is a solid cube) and A_1 be the union of cubes of side length $1/2n$ centered at vertices of U . Let B be the union of cubes of volume $2/(2n)^n$ centered at vertices of ∂U and $A_2 = M \setminus (A_1 \cup B)$. Obviously,

$$\text{diam}(M) = \mathcal{O}(n^{3/2}). \quad (4.9)$$

Then, observe that

$$d(A_1, A_2) \geq \frac{1}{2n} \frac{\sqrt{n}}{2} (2^{1/n} - 1) = \Omega(n^{-3/2}). \quad (4.10)$$

for some suitable positive constant c_1 . Also, for some positive constant c_2 ,

$$\begin{aligned} \sum_{\substack{u \in U \\ v \in \bar{U}}} \lambda(u)p(u, v) &= \sum_{\substack{u \in U \\ v \in B}} \lambda(v)p(v, u) \\ &\geq \sum_{v \in B} \frac{1}{8n} \lambda(v) = c_2 \frac{\lambda(B)}{n}. \end{aligned}$$

We may assume that $\lambda(B)$ is small. Now, define a measure μ on $\mathcal{B}(M)$ as in Theorem 4.15 with $F = 2^{-\varphi_1}$, where φ_1 is the maximal convex function on M bounded above by φ . Observe that $\lambda(u)$ is always within a constant factor of the μ -measure of the unit cube centered at u . Thus, we have

$$\begin{aligned} \frac{\sum_{u \in U} \sum_{v \in \bar{U}} \lambda(u) p(u, v)}{\lambda(U)} &\geq \frac{c_3}{n} \frac{\mu(B)}{\min\{\lambda(U), \lambda(\bar{U} \setminus \partial U)\}} \\ &= \frac{c_3}{n} \frac{\mu(M \setminus (A_1 \cup A_2))}{\min\{\mu(A_1), \mu(A_2)\}} \\ &\geq \frac{c_3}{n} \frac{d(A_1, A_2)}{\text{diam } M} \\ &= \Omega(n^{-4}) \end{aligned} \tag{4.11}$$

So what is the total time complexity of the algorithm? Combining Equation (4.11) and Equation (4.8) (or rather, the corresponding result for $d_2(t)$ that does not have the $\log n$ factor), the number of steps in the random walk of each phase of the multiphase Metropolis walk is $\mathcal{O}^*(n^8)$. At each step of the walk, we perform $\mathcal{O}(n)$ oracle queries. Finally, there are $\mathcal{O}^*(n)$ phases. All together, the algorithm is $\mathcal{O}^*(n^{10})$.

In [DF98], a more careful analysis is done to show that this algorithm is in fact $\mathcal{O}^*(n^8)$.²⁶ More precisely, it is

$$\mathcal{O} \left(n^8 \varepsilon^{-2} \log \left(\frac{n}{\varepsilon} \right) \log \left(\frac{1}{\eta} \right) \right).$$

Over the course of the next few sections, we describe a $\mathcal{O}^*(n^7)$ volume estimation algorithm given in [LS93].

4.4. Measure-Theoretic Markov Chains and Conductance

4.4.1. Some Basic Definitions

Definition 4.8. Let Ω be a non-empty set and \mathcal{A} a σ -algebra on Ω . For every $u \in \Omega$, let P_u be a probability measure on Ω . Also assume that as a function of u , $P_u(A)$ is measurable for any $A \in \mathcal{A}$. We call the triple $(\Omega, \mathcal{A}, \{P_u : u \in \Omega\})$ a *Markov scheme*. Together with an initial distribution Q_0 on Ω , this defines a *Markov chain*.

A Markov chain is essentially just a sequence of random variables w_0, w_1, \dots such that w_0 is drawn from Q_0 and w_{i+1} is drawn from P_{w_i} (independently of the values of w_0, \dots, w_{i-1}). Therefore,

$$\Pr[w_{i+1} \in A \mid w_1 = u_1, \dots, w_i = u_i] = \Pr[w_{i+1} \in A \mid w_i = u_i] = P_{u_i}(A).$$

Let $f : \Omega \times \Omega \rightarrow \mathbb{R}$ be an integrable function (with respect to the product measure $\mu \times \mu$) such that $\int_{\Omega} f(u, v) d\mu(v) = 1$ for all $u \in \Omega$. f then defines a Markov scheme as

$$P_u(A) = \int_A f(u, v) d\mu(v).$$

In this case, f is known as the *transition function* of the Markov scheme. The transition function is said to be *symmetric* if for all x, y , $f(x, y) = f(y, x)$.

A probability measure Q on Ω is said to be the *stationary distribution* of a Markov scheme if for all $A \in \mathcal{A}$,

$$\int_{\Omega} P_u(A) dQ(u) = Q(A).$$

²⁶The conductance is actually $\Omega(n^{-3})$.

This just means that every w_i has the same distribution as Q .

Now, consider the inner product space $L^2 = L^2(\Omega, \mathcal{A}, Q)$ with inner product

$$\langle f, g \rangle = \int_{\Omega} f g \, dQ.$$

Suppose we have some function $g \in L^2$. Then note that the expectation of $g(w_{i+1})$ (as a function of $w_i = u$) defines a positive linear operator²⁷ $M : L^2 \rightarrow L^2$ by

$$(Mg)(u) = \int_{\Omega} g(v) \, dP_u(v).$$

Further note that $(M^k g)(u)$ represents the expectation of $g(w_{i+k})$ given that $w_i = u$.

Now, consider a Markov chain where the first element is drawn from the stationary distribution. Then for any function $g \in L^2$,

$$\begin{aligned} \mathbf{E}[g(w_i)] &= \mathbf{E}[g(w_0)] = \langle g, 1 \rangle \\ \mathbf{E}[g(w_i)^2] &= \mathbf{E}[g(w_0)^2] = \langle g, g \rangle \\ \mathbf{E}[g(w_i)g(w_{i+k})] &= \mathbf{E}[g(w_0)g(w_k)] = \langle g, M^k g \rangle \end{aligned}$$

A Markov chain is said to be *time-reversible* if for any $A, B \in \mathcal{A}$, the probability of going from B to A is the same as that of going from A to B . That is,

$$\int_B P_u(A) \, dQ(u) = \int_A P_u(B) \, dQ(u).$$

It is easy to see that it suffices to have the above for all disjoint sets A and B . The above can be rewritten in a more symmetric fashion as

$$\int_B \int_A 1 \, dP_u(v) \, dQ(u) = \int_A \int_B 1 \, dP_u(v) \, dQ(u). \quad (4.12)$$

This is equivalent to saying that for any function $g : \Omega \times \Omega \rightarrow \mathbb{R}$ (assuming both sides are well-defined),

$$\int_{\Omega} \int_{\Omega} g(u, v) \, dP_u(v) \, dQ(u) = \int_{\Omega} \int_{\Omega} g(v, u) \, dP_u(v) \, dQ(u). \quad (4.13)$$

It is also equivalent to say that the operator M is self-adjoint.²⁸ If the Markov scheme can be described by a transition function f (with respect to Q), then time-reversibility is equivalent to the symmetry of f (this isn't too difficult to prove using Equation (4.12) and Fubini's Theorem).

If the Markov scheme is time-reversible, then for any $g \in L^2$,

$$\begin{aligned} \langle g, g \rangle - \langle g, Mg \rangle &= \int_{\Omega} g^2 \, dQ - \int_{\Omega} \int_{\Omega} g(u)g(v) \, dP_u(v) \, dQ(u) \\ &= \int_{\Omega} \int_{\Omega} g^2(u) \, dP_u(v) \, dQ(u) - \int_{\Omega} \int_{\Omega} g(u)g(v) \, dP_u(v) \, dQ(u) \\ &= \frac{1}{2} \left(\int_{\Omega} \int_{\Omega} (g^2(u) + g^2(v)) \, dP_u(v) \, dQ(u) - \int_{\Omega} \int_{\Omega} 2g(u)g(v) \, dP_u(v) \, dQ(u) \right) \quad (\text{by Equation (4.13)}) \\ &= \frac{1}{2} \int_{\Omega} \int_{\Omega} (g(u) - g(v))^2 \, dP_u(v) \, dQ(u) \geq 0. \end{aligned} \quad (4.14)$$

Therefore, the spectral radius²⁹ of M is exactly 1.

²⁷a linear operator A such that $\langle Ax, x \rangle \geq 0$ for any x .

²⁸an operator A such that $\langle Ax, y \rangle = \langle x, Ay \rangle$ for any x, y .

²⁹the largest absolute value of its eigenvalues.

Definition 4.9 (Laziness). A Markov chain is said to be *lazy* if for each u ,

$$P_u(\{u\}) \geq \frac{1}{2}.$$

There are two main, albeit minor and technical, reasons for desiring laziness:

- Sometimes, a lack of laziness can cause parity issues which result in the limit distribution of a chain not converging to the stationary distribution.
- In the time-reversible case, it makes the operator M positive semidefinite, thus making it far easier to analyze.

To see why the latter occurs, observe that if M is self-adjoint, then so is $2M - I$ (and is thus associated with a Markov scheme) and thus,

$$\langle f, Mf \rangle \geq \frac{1}{2} \langle f, f \rangle - \frac{1}{2} \langle f, (2M - I)f \rangle \geq 0.$$

Any Markov scheme can be made lazy easily by flipping a (fair) coin at each step and making a move only if it lands on tails.

Lemma 4.16. Let w_1, w_2, \dots be a time-reversible Markov chain generated by a lazy Markov scheme \mathcal{M} with w_0 drawn from the stationary distribution Q of \mathcal{M} . Then for any function $g \in L^2$,

$$\mathbf{E}[g(w_i)g(w_j)] \geq \mathbf{E}[g(w_i)]\mathbf{E}[g(w_j)] = \mathbf{E}[g(w_0)]^2.$$

Proof. Assume without loss of generality that $j > i$ and $j - i = k$. Then for any function h , the positive semidefiniteness of M implies that

$$\mathbf{E}[h(w_i)h(w_j)] = \langle h, M^k h \rangle \geq 0.$$

Applying this to $(g - \mathbf{E}[g(w_0)])$ yields the result. ■

4.4.2. Conductance

Definition 4.10 (Ergodic Flow). Define the *ergodic flow* $\Phi : \mathcal{A} \rightarrow [0, 1]$ of a Markov scheme by

$$\Phi(A) = \int_A P_u(\Omega \setminus A) dQ(u).$$

This just measures how likely the Markov chain is to leave A if it is initially in A (and drawn from Q). Since Q is stationary,

$$\begin{aligned} \Phi(A) - \Phi(\Omega \setminus A) &= \int_A P_u(\Omega \setminus A) dQ(u) - \int_{\Omega \setminus A} P_u(A) dQ(u) \\ &= Q(A) - \int_A P_u(A) dQ(u) - \int_{\Omega \setminus A} P_u(A) dQ(u) \quad (\text{since } P_u(\Omega \setminus A) = 1 - P_u(A)) \\ &= Q(A) - \int_{\Omega} P_u(A) dQ(u) = 0. \end{aligned}$$

Even conversely, if for some probability distribution Q' , the function $\Phi' : \mathcal{A} \rightarrow [0, 1]$ defined by

$$A \mapsto \int_A P_u(\Omega \setminus A) dQ'(u)$$

is invariant under complementation, then Q' is stationary.

Definition 4.11. The *conductance* of the Markov scheme is then defined as

$$\Phi = \inf_{0 < Q(A) < 1/2} \frac{\Phi(A)}{Q(A)}.$$

For $0 \leq s \leq 1$, the *s-conductance* is defined as

$$\Phi_s = \inf_{s < Q(A) \leq 1/2} \frac{\Phi(A)}{Q(A) - s}.$$

The lower the conductance is, the more likely the Markov chain is to “get stuck” somewhere. Loosely, $Q(A)$ represents the probability of entering a “bad region” whereas $\Phi(A)$ represents the probability of leaving it.

For any u , $1 - P_u(\{u\})$ is called the *local conductance* of the Markov chain at u . If $Q(u) > 0$, then the local conductance is an upper bound on the conductance.

More generally, let

$$H_t = \{u \in \Omega : P_u(\{u\}) > 1 - t\}$$

and $s = Q(H_t)$. Then

$$\Phi(H_t) = \int_{H_t} P_u(\Omega \setminus H_t) dQ(u) \leq tQ(H_t).$$

Therefore, the $(s/2)$ -conductance is at most $2t$.

The main use of defining conductance is that it is closely related to how fast Markov chains converge to their stationary distribution.

Suppose that Q_k is the distribution in the k th step of the chain ($Q_k(A) = \Pr[w_k \in A]$). It turns out that if for all $A \in \mathcal{A}$ such that $Q(A) > 0$, $\Phi(A) > 0$, then $Q_k \rightarrow Q$ (in the ℓ_1 distance³⁰). This manifests as an associated bound in the speed of convergence.

To make concrete this notion of “speed of convergence”, let us define the following specific distance function.

4.4.3. A Distance Function

Definition 4.12. For $x \in [0, 1]$, consider all measurable functions $g : \Omega \rightarrow [0, 1]$ such that

$$\int_{\Omega} g dQ = x.$$

We then define the *distance function* of Q and Q_k by

$$h_k(x) = \sup_g \int_{\Omega} g(dQ_k - dQ) = \sup_g \int_{\Omega} g dQ_k - x.$$

For example, it is easily shown that for a finite Markov chain with N states and uniform stationary distribution, $h_k(j/N)$ is the sum of the j largest $(Q_k(\omega) - \frac{1}{n})$.

There are a few things to note.

- For any x , $0 \leq h_k \leq 1 - x$. The lower bound is because one can consider the constant function x on Ω . The upper bound is because $\int_{\Omega} g dQ_k$ is bounded above by 1. In particular, $h_k(1) = 0$.

³⁰given by $\|f\|_1 = \int_{\Omega} |f| dQ$

- h_k is a concave function of x . We shall see below in Lemma 4.18 that the supremum in the definition of h_k is attained. Then, for any $a, b, \lambda \in [0, 1]$, set $x = \lambda a + (1 - \lambda)b$ and let g_1, g_2 be the functions that attain the supremums for $h_k(a)$ and $h_k(b)$. Then,

$$\sup_g \int_{\Omega} g dQ_k - x \geq \int_{\Omega} (\lambda g_1 + (1 - \lambda)g_2) dQ_k = \lambda h_k(a) + (1 - \lambda)h_k(b).$$

The definition of h_k is similar to a continuous analogue of the fractional knapsack problem wherein the sum of the weights corresponds to integration with respect to Q , the sum of values corresponds to integration with respect to Q_k , and the weight capacity is x . This analogy also lends itself very naturally in the proof of Lemma 4.18, where we “assign g ” to the points which have a high value-weight ratio – this corresponds to the Radon-Nikodym derivative in the continuous case.

This definition might still seem slightly artificial at the moment, but we hope to give more context to it with the following few lemmas.

Lemma 4.17. For every set $A \in \mathcal{A}$ with $Q(A) = x$,

$$-h_k(1 - x) \leq Q_k(A) - Q(A) \leq h_k(x).$$

Proof. The upper bound is immediate from the definition of the distance function by taking $g = \mathbb{1}_A$ (the indicator function on A). The similar upper bound for $\Omega \setminus A$ gives the result. ■

Lemma 4.18. For every $0 < x < 1$, there exists a function G that is 0-1 valued except possibly on a Q -atom³¹ that attains the supremum in the definition of $h_k(x)$.

Proof. Let $U \in \mathcal{A}$ such that $Q(U) = 0$ and $Q_k(U)$ is maximum. Let Q' and Q'_k be the restrictions of Q and Q_k to $\Omega \setminus U$ respectively. Clearly, the way we have defined U implies that Q'_k is absolutely continuous with respect to Q' . Thus, let ϕ be the Radon-Nikodym derivative of Q'_k with respect to Q' .

Now, let $x \in [0, 1]$ and $g : \Omega \rightarrow [0, 1]$ such that $\int_{\Omega} g dQ = x$.

For $t \geq 0$, define

$$A_t = U \cup \{u \in \Omega \setminus U : \phi(u) \geq t\} \text{ and } s = \inf\{t \geq 0 : Q(A_t) \leq x\}.$$

Observe that since $A_s = \bigcap_{t < s} A_t$, upper semicontinuity implies that $Q(A_s) \geq x$. Also define

$$A' = \bigcup_{t > s} A_t = U \cup \{u \in \Omega \setminus U : \phi(u) > s\}.$$

Lower semicontinuity implies that $Q(A') \leq x$. We also have that $A' \subseteq A_s$ and for every $u \in A_s \setminus A'$, $\phi(u) = s$.

Now, choose a $B \in \mathcal{A}$ such that $A' \subseteq B \subseteq A_s$, $Q(B) \leq x$, and $Q(B)$ is maximum.

We first show that if $Q(B) = x$, then the indicator function on B suffices. Indeed, in this case,

$$\begin{aligned} \int_{\Omega} g dQ_k &= \int_U g dQ_k + \int_{B \setminus U} g \phi dQ + \int_{\Omega \setminus B} g \phi dQ \\ &= \int_U g dQ_k + \int_{B \setminus U} (g - 1) \phi dQ + \int_{B \setminus U} dQ_k + \int_{\Omega \setminus B} g \phi dQ \\ &\leq \int_U dQ_k + s \int_{B \setminus U} (g - 1) dQ + \int_{B \setminus U} dQ_k + s \int_{\Omega \setminus B} g dQ \quad (0 \leq g \leq 1 \text{ and } \phi \leq s \text{ } Q\text{-almost everywhere on } \Omega \setminus B) \\ &= Q_k(B) + s \int_{\Omega \setminus U} g dQ - s \int_{B \setminus U} dQ \\ &= Q_k(B) + s(x - Q(B)) = Q_k(B). \end{aligned}$$

We also see that the supremum is attained when $g = \mathbb{1}_B$.

Next, assume that $Q(B) < x$. Then for every $W \subseteq A_s \setminus B$, either $Q(W) = 0$ or $Q(W) > x - Q(B)$. That is, the measure on $A' \setminus B$ is concentrated on atoms. Let V be one such atom. As shown above,

$$\int_{\Omega} g dQ_k \leq Q_k(B) + s(x - Q(B)).$$

³¹a Q -atom is a set $V \in \mathcal{A}$ such that $Q(V) > 0$ and for any $V' \subseteq V$, either $Q(V') = Q(V)$ or $Q(V') = 0$.

To show that this bound is attained, let $g = \mathbb{1}_B + \lambda \mathbb{1}_V$ where $\lambda = (x - Q(B))/Q(V)$. Clearly, $0 \leq g \leq 1$. Further,

$$\int_{\Omega} g \, dQ = Q(B) + \lambda Q(V) = x$$

and

$$\int_{\Omega} g \, dQ_k = Q_k(B) + \lambda Q_k(V) = Q_k(B) + s(x - Q(B))$$

where the last step follows since $\phi(u) = s$ for all $u \in V \subseteq A_s \setminus A'$. ■

Lemma 4.19. If Q is atom-free, then

$$h_k(x) = \sup_{\substack{A \in \mathcal{A} \\ Q(A)=x}} (Q_k(A) - Q(A)).$$

This follows directly from the previous lemma.

If Q is atom-free, note that

$$\sup_x h_k(x) = \sup_{A \in \mathcal{A}} |Q_k(A) - Q(A)| = \frac{1}{2} \|Q_k - Q\|_1. \quad (4.15)$$

Although we did say what a rapidly mixing random walk is earlier in Definition 4.6, we now define it more generally.

4.4.4. Rapidly Mixing Markov Chains

Definition 4.13 (Rapidly Mixing Markov Chain). A Markov chain is said to be *rapidly mixing* if for some $\theta < 1$, $\sup_x h_k(x)$ is $\mathcal{O}(\theta^k)$.

For our needs, the stationary distribution Q is usually atom-free. Unless mentioned otherwise, we assume henceforth that this is the case. We also assume that the chains are lazy.

Let us now get on to the main subject of this section, namely that of bounding the speed of convergence of rapidly mixing Markov chains.

Theorem 4.20. For $k \geq 1$, if $s \leq x \leq 1/2$, then

$$h_k(x) \leq \frac{1}{2} (h_{k-1}(x - 2\Phi_s(x - s)) + h_{k-1}(x + 2\Phi_s(x - s)))$$

and if $1/2 \leq x \leq 1 - s$, then

$$h_k(x) \leq \frac{1}{2} (h_{k-1}(x - 2\Phi_s(1 - x - s)) + h_{k-1}(x + 2\Phi_s(1 - x - s))).$$

Proof. We prove the first inequality alone.

By Lemma 4.18, let A be a set such that $Q(A) = x$ and $h_k(x) = Q_k(A) - Q(A)$. Define $g_1, g_2 : \Omega \rightarrow [0, 1]$ by

$$g_1(u) = \begin{cases} 2P_u(A) - 1, & u \in A, \\ 0, & \text{otherwise,} \end{cases} \quad g_2(u) = \begin{cases} 1, & u \in A, \\ 2P_u(A), & \text{otherwise.} \end{cases}$$

The functions map into $[0, 1]$ because the chain is lazy.

Also, let $x_1 = \int_{\Omega} g_1 \, dQ$ and $x_2 = \int_{\Omega} g_2 \, dQ$. Observe that $x_1 + x_2 = \int_{\Omega} 2P_u(A) \, dQ(u) = 2x$. We have

$$\begin{aligned} h_k(x) &= Q_k(A) - Q(A) \\ &= \frac{1}{2} \left(\left(\int_{\Omega} g_1 \, dQ_{k-1} - x_1 \right) + \left(\int_{\Omega} g_2 \, dQ_{k-1} - x_2 \right) \right) \\ &\leq \frac{1}{2} (h_{k-1}(x_1) + h_{k-1}(x_2)). \end{aligned}$$

We also have

$$x_2 - x = x - x_1 = \int_A (2 - 2P_u(A)) dQ(u) = 2\Phi(A) \geq 2\Phi_s(x - s).$$

Then with the above, the concavity of h_{k-1} then implies that

$$h_{k-1}(x_1) + h_{k-1}(x_2) \leq h_{k-1}(x - \Phi_s(x - s)) + h_{k-1}(x + \Phi_s(x - s)),$$

completing the proof. ■

The next result is analogous to Theorem 4.14 and is our main tool in bounding the speed of convergence using the conductance.

Theorem 4.21. Let $0 \leq s \leq 1/2$ and suppose we have c_1, c_2 such that for $s \leq x \leq 1 - s$,

$$h_0(x) \leq c_1 + c_2 \min\{\sqrt{x - s}, \sqrt{1 - s - x}\}.$$

Then for every $k \geq 0$ and $s \leq x \leq 1 - s$,

$$h_k(x) \leq c_1 + c_2 \min\{\sqrt{x - s}, \sqrt{1 - s - x}\} \left(1 - \frac{\Phi_s^2}{2}\right)^k.$$

Proof. We prove this via induction. It clearly holds for $k = 0$. Suppose that $k \leq 1$ and $s \leq x \leq 1/2$. Using induction,

$$\begin{aligned} h_k(x) &\leq \frac{1}{2} (h_{k-1}(x - 2\Phi_s(x - s)) + h_{k-1}(x + 2\Phi_s(x - s))) \\ &\leq c_1 + \frac{c_2}{2} \left(1 - \frac{\Phi_s^2}{2}\right)^{k-1} \left(\sqrt{x - 2\Phi_s(x - s) - s} + \sqrt{x + 2\Phi_s(x - s) - s}\right) \\ &= c_1 + \frac{c_2}{2} \sqrt{x - s} \left(1 - \frac{\Phi_s^2}{2}\right)^{k-1} \left(\sqrt{1 - 2\Phi_s} + \sqrt{1 + 2\Phi_s}\right) \\ &\leq c_1 + \frac{c_2}{2} \sqrt{x - s} \left(1 - \frac{\Phi_s^2}{2}\right)^{k-1} \left(1 - \frac{2\Phi_s}{2} - \frac{4\Phi_s^2}{8} + 1 + \frac{2\Phi_s}{2} - \frac{4\Phi_s^2}{8}\right) \\ &= c_1 + c_2 \sqrt{x - s} \left(1 - \frac{\Phi_s^2}{2}\right)^k \end{aligned}$$
■

Writing the above in a slightly more useful form,

Corollary 4.22. Let $M = \sup_A Q_0(A)/Q(A)$. Then for every $A \in \mathcal{A}$,

$$|Q_k(A) - Q(A)| \leq \sqrt{M} \left(1 - \frac{\Phi_s^2}{2}\right)^k.$$

Proof. Clearly, for any x , $h_0(x) \leq Mx$. We also have $h_0(x) \leq 1 - x$. Therefore,

$$h_0(x) \leq \sqrt{Mx(1 - x)} \leq \sqrt{M} \min\{\sqrt{x}, \sqrt{1 - x}\}.$$

Theorem 4.21 then implies the required. ■

4.4.5. An Important Inequality involving the operator M

A little bit of thought makes it quite clear that to analyze the speed of mixing of Markov chains, the spectrum of the operator M is an important parameter.

Theorem 4.23. Let \mathcal{M} be a time-reversible Markov scheme with conductance Φ . Then for every $g \in L^2$ with $\mathbf{E}[g] = 0$,

$$\langle g, Mg \rangle \leq \left(1 - \frac{\Phi^2}{2}\right) \|g\|^2.$$

Proof. As might be expected, we use Equation (4.14) in this proof. It suffices to show that if $\mathbf{E}[g] = 0$,

$$\int_{\Omega} \int_{\Omega} (g(u) - g(v))^2 dP_u(v) dQ(u) \geq \Phi^2 \|g\|^2.$$

Choose a median r of g , that is, a real number such that $Q(\{x : g(x) > r\}) \leq 1/2$ and $Q(\{x : g(x) < r\}) \leq 1/2$. Let $h(x) = \max\{g(x) - r, 0\}$. Observe that

$$\int_{\Omega} \int_{\Omega} (g(u) - g(v))^2 dP_u(v) dQ(u) \geq \int_{\Omega} \int_{\Omega} (h(u) - h(v))^2 dP_u(v) dQ(u)$$

Therefore, it suffices to bound the quantity on the right suitably. To do this, use the Cauchy-Schwarz inequality to get

$$\int_{\Omega} \int_{\Omega} (h(u) - h(v))^2 dP_u(v) dQ(u) \geq \frac{(\int_{\Omega} \int_{\Omega} |h^2(u) - h^2(v)| dP_u(v) dQ(u))^2}{\int_{\Omega} \int_{\Omega} (h(u) + h(v))^2 dP_u(v) dQ(u)}$$

Now, by definition, $Q(\{h \geq 0\}) \geq 1/2$. Therefore,

$$\int_{\Omega} h^2 dQ \geq \frac{1}{2} \int_{\Omega} (g(x) - r)^2 = \frac{\|g\|^2 + r^2}{2} \geq \frac{\|g\|^2}{2}.$$

To bound the denominator,

$$\int_{\Omega} \int_{\Omega} (h(u) + h(v))^2 dP_u(v) dQ(u) \leq 2 \int_{\Omega} \int_{\Omega} (h^2(u) + h^2(v)) dP_u(v) dQ(u) = 2 \|h\|$$

For each t , define $A_t = \{x \in \Omega : h(x)^2 \geq t\}$. Then

$$\begin{aligned} \int_{\Omega} \int_{\Omega} |h^2(u) - h^2(v)| dP_u(v) dQ(u) &= 2 \int_{\Omega} \int_{A(h^2(u))} (h^2(v) - h^2(u)) dP_u(v) dQ(u) \\ &= 2 \int_{\Omega} \int_{h^2(u)}^{\infty} P_u(A(t)) dt dQ(u) && \text{(by Fubini's Theorem)} \\ &= 2 \int_0^{\infty} \int_{\Omega \setminus A(t)} P_u(A(t)) dQ(u) dt \\ &\geq 2\Phi \int_0^{\infty} Q(A(t)) dt = 2\Phi \int_{\Omega} h^2 dQ = 2\Phi \|h\|^2. \end{aligned}$$

The result follows directly, since we now have

$$\int_{\Omega} \int_{\Omega} (h(u) - h(v))^2 dP_u(v) dQ(u) \geq \frac{4\Phi^2 \|h\|^4}{4 \|h\|^2} = 2\Phi^2 \|h\|^2 \geq \Phi^2 \|g\|^2,$$

which is exactly what we set out to show. ■

Corollary 4.24. Let \mathcal{M} be a time-reversible Markov scheme with conductance Φ . Then for every $f \in L^2$ with $\mathbf{E}[f] = 0$,

$$\langle f, M^k f \rangle \leq \left(1 - \frac{\Phi^2}{2}\right)^k \|f\|^2.$$

We omit the proof of the above.³² This quite neatly captures the fact that rapid mixing depends heavily on conductance. Indeed, it implies that $\|M^k f\| \leq (1 - \Phi^2/2)^k \|f\|$, so as time progresses, f “flattens out” and goes closer to 0.

The next inequality can be thought of a central limit theorem style inequality.

Theorem 4.25. Let \mathcal{M} be a time-reversible Markov scheme with stationary distribution Q and let w_1, w_2, \dots be a Markov chain generated by \mathcal{M} with initial distribution Q . Let $F \in L^2$ and $\xi = \sum_{i=0}^{T-1} F(w_i)$ for some T . Then,

$$\mathbf{Var}[\xi] \leq \frac{4T}{\Phi^2} \|F\|^2$$

Proof. We may assume that $\mathbf{E}[\xi] = 0$. Then Theorem 4.23 implies that

$$\begin{aligned} \mathbf{Var}[\xi] &= \mathbf{E}[\xi^2] = \sum_{0 \leq i, j \leq T-1} \mathbf{E}[F(w_i)F(w_j)] \\ &= T \|F\|^2 + 2 \sum_{0 \leq i < j \leq T-1} \mathbf{E}[F(w_0)F(w_{|i-j|})] \\ &= T \|F\|^2 + 2 \sum_{k=1}^{T-1} (T-k) \langle F, M^k F \rangle \\ &\leq \|F\|^2 \left(T + 2 \sum_{k=1}^{T-1} (T-k) \left(1 - \frac{\Phi^2}{2} \right)^k \right) \\ &< 2T \|F\|^2 \sum_{k=0}^{T-1} \left(1 - \frac{\Phi^2}{2} \right)^k \leq \frac{4T}{\Phi^2} \|F\|^2. \end{aligned}$$

■

4.4.6. Metropolis Chains

While we have used Metropolis chains previously, let us define them more formally for the sake of completeness.

Definition 4.14 (Metropolis Chain). Let \mathcal{M} be a time-reversible Markov chain on (Ω, \mathcal{A}) and let $F : \Omega \rightarrow \mathbb{R}$ be a non-negative measurable function. Suppose that $\bar{F} = \int_{\Omega} F dQ$ is finite. Denote by μ_F the measure with density F . We then define the *filtering* of \mathcal{M} by F , denoted \mathcal{M}/F , as the Markov scheme with transition probabilities

$$P_u^F(A) = \begin{cases} \int_A \min \left\{ 1, \frac{F(v)}{F(u)} \right\} dP_u(v), & u \notin A, \\ \int_A \min \left\{ 1, \frac{F(v)}{F(u)} \right\} dP_u(v) + \int_{\Omega} \max \left\{ 0, 1 - \frac{F(v)}{F(u)} \right\} dP_u(v), & u \in A. \end{cases}$$

And as mentioned, this modified chain converges to a distribution proportional to F .

Theorem 4.26. If \mathcal{M} is time-reversible, then \mathcal{M}/F is also time-reversible and has stationary distribution $Q_F = (1/\bar{F})\mu_F$.

Proof. From the remark after Definition 4.10, it suffices to show that for any disjoint measurable sets A and B ($B = \Omega \setminus A$ in particular),

$$\int_B P_u^F(A) dQ_F(u) = \int_A P_u^F(B) dQ_F(u),$$

³²It may be shown by considering \tilde{M} , the restriction of M to the invariant subspace $\mathbf{E}[f] = 0$. By the above lemma, $\|\tilde{M}\| \leq 1 - \Phi^2/2$. Then $\|\tilde{M}^k\| \leq \|\tilde{M}\|^k$, which immediately gives the result.

that is,

$$\int_B \int_A \min \left\{ 1, \frac{F(v)}{F(u)} \right\} \frac{F(u)}{\bar{F}} dP_u(v) dQ(u) = \int_A \int_B \min \left\{ 1, \frac{F(v)}{F(u)} \right\} \frac{F(u)}{\bar{F}} dP_u(v) dQ(u).$$

Rewriting, we want to show that

$$\int_B \int_A \min \{F(u), F(v)\} dP_u(v) dQ(u) = \int_A \int_B \min \{F(u), F(v)\} dP_u(v) dQ(u),$$

but this follows from the time-reversibility of \mathcal{M} . ■

Before we move on to the main algorithm, we set up some prerequisite results to make the discussion in the subsequent section more natural.

4.5. An Isoperimetric Inequality

4.5.1. Log-Concave Functions

A function $f : \mathbb{R}^n \rightarrow \mathbb{R}^{\geq 0}$ is said to be *log-concave* if for any $x, y \in \mathbb{R}^n$ and $0 < \lambda < 1$,

$$f(\lambda x + (1 - \lambda)y) \leq f(x)^\lambda f(y)^{1-\lambda}.$$

If f is positive, this just means that $\log f$ is concave. While we did not mention this by name, we discussed similar ideas back in the (multiplicative) Brunn-Minkowski inequality (2.7).

It is quite obvious that if f and g are log-concave functions, then so are fg and $\min\{f, g\}$. The following is far less obvious however.

Lemma 4.27. Let f and g be two log-concave functions. If their convolution h defined by $h(x) = \int_{\mathbb{R}^n} g(u)f(x-u) du$ is well-defined, it is log-concave.

Let F be a non-negative integrable function on \mathbb{R}^n . As in Theorem 4.15, denote by μ_F the measure with density F . We then get the following corollary.

Corollary 4.28. Let $K \subseteq \mathbb{R}^n$ be a convex body and $F : \mathbb{R}^n \rightarrow \mathbb{R}$ a log-concave function. Then $\mu_F(x + K)$ is a log-concave function of x .

This is quite easily proved by setting $f = F$ and $g = \mathbb{1}_K$ in Lemma 4.27.

Setting K to be a rectangle aligned with the axes having edges of length ε in k directions and $1/\varepsilon$ in the remaining directions and then taking $\varepsilon \rightarrow 0$ gives

Corollary 4.29. Let $F : \mathbb{R}^n \rightarrow \mathbb{R}^+$ be a log-concave function with finite integral. Then for any subset $\{x_1, \dots, x_k\}$ of variables, the function

$$\int_{\mathbb{R}} \int_{\mathbb{R}} \dots \int_{\mathbb{R}} F dx_1 \dots dx_k$$

in the remaining variables is log-concave.

Slightly more generally, setting $f = \mathbb{1}_{K'}$ and $g = \mathbb{1}_K$, we get that the function $x \mapsto \text{vol}((x + K') \cap K)$ is log-concave.

Corollary 4.30. Let K and K' be two convex bodies and $t > 0$. If $\{x \in \mathbb{R}^n : \text{vol}((x + K') \cap K) > t\}$ has an interior point, then it is convex. In particular, for any $0 < s < 1$,

$$K_s = \{x \in K : \text{vol}((x + K) \cap K) \geq s \text{vol}(K)\}$$

is a convex body.

4.5.2. An Improvement of a Past Result

The main result of this section is Theorem 4.34, which is an improvement of Theorem 4.15.

Theorem 4.31 (Localization Lemma). Let g and h be lower semicontinuous Lebesgue integrable functions on \mathbb{R}^n such that their integrals on \mathbb{R}^n are positive. Then there exist points $a, b \in \mathbb{R}^n$ and a linear function $\ell : [0, 1] \rightarrow \mathbb{R}^{\geq 0}$ such that

$$\int_0^1 \ell(t)^{n-1} g((1-t)a + tb) dt > 0 \text{ and } \int_0^1 \ell(t)^{n-1} h((1-t)a + tb) dt > 0$$

The above result is quite useful and reduces integrals in n -dimensions to a single dimension. We shall solidify this relationship further and give a few related results in Sections 5.1.2 and 5.1.3.

It suffices to consider the case where g and h are continuous. If not, we can find some monotone (strictly) increasing sequence of continuous integrable functions (g_k) and (h_k) that converge to g and h . We then have

$$\lim_{k \rightarrow \infty} \int_{\mathbb{R}^n} g_k = \int_{\mathbb{R}^n} g > 0$$

so for sufficiently large k , $\int_{\mathbb{R}^n} g_k > 0$ and likewise, $\int_{\mathbb{R}^n} h_k > 0$. It then suffices to show it for the g_k and h_k for sufficiently large k , so we may assume continuity.

Further, note that it suffices to show the inequality with ≥ 0 instead of > 0 . Indeed, if we prove it for the weak inequality, we can apply it to $(g - a)$ and $(h - a)$ for some function a that is everywhere positive and continuous with a sufficiently small integral to get the strict inequality.

We continue the proof over two lemmas. In Lemma 4.33, we in fact obtain the exact required result with a concave function instead of a linear one. Over the remainder, we refine it to obtain linearity.

Lemma 4.32. There exists a sequence $K_0 \supseteq K_1 \supseteq \dots$ of convex bodies such that for each i ,

$$\int_{K_i} g(x) dx > 0 \text{ and } \int_{K_i} h(x) dx > 0$$

and $K = \bigcap_i K_i$ is a point or a segment.

Proof. We may choose K_0 to be a sufficiently large ball. To find K_{i+1} given K_i , we use a bisection argument. We choose a half-space H such that

$$\int_{K_i \cap H} g(x) dx = \frac{1}{2} \int_{K_i} g(x) dx.$$

The hyperplane supporting the half-space is referred to as a *bisecting hyperplane*. It remains to show that it is possible to choose a H at each step such that the K_i shrink to a 0 or 1-dimensional body.

Claim. Given any $(n-2)$ -dimensional affine subspace A , there is a bisecting hyperplane containing it.

This is easily shown by taking any hyperplane containing A , rotating it about A , and using the continuity of the resulting map that maps a hyperplane to the integral over the half-space on a particular side. This reduces to showing that for a continuous map g from the unit circle S^1 in \mathbb{R}^2 to \mathbb{R} , there exists x on the unit circle such that $f(x) = f(-x)$. This is not difficult to show, and is left as an exercise.

Now, choose A_0, A_1, \dots to be the sequence of $(n-2)$ -dimensional affine subspaces defined by $x_i = r_1$ and $x_j = r_2$ for $1 \leq i < j \leq n$, where r_1 and r_2 are rational. For each i , let P_i be the bisecting hyperplane of K_i that passes through A_i and define $K_{i+1} = A_i \cap H_i$, where H_i is a half-space with supporting hyperplane P_i .

We wish to show that $\bigcap_i K_i$ is at most 1-dimensional. Suppose instead that it is (at least) 2-dimensional. Then the projection of K onto one of the planes spanned by two coordinates axes (say x_1 and x_2) must be two-dimensional, and therefore has a rational interior point (r_1, r_2) . However, the hyperplane defined by $x_1 = r_1$, $x_2 = r_2$ is one of the A_i , and in this case, P_i bisects K , and therefore also K_{i+1} , which is a contradiction. ■

In the case where the resulting K is a point a , it follows that $g(a) \geq 0$ and $h(a) \geq 0$, so Theorem 4.31 follows for $b = a$ and $\ell \equiv 1$.

Therefore, we assume that K is a segment. Let a and b be the endpoints of this segment.

Lemma 4.33. There exists a concave function $\psi : [0, 1] \rightarrow \mathbb{R}^+$, not identically zero, such that

$$\int_0^1 \psi(t)^{n-1} g((1-t)a + tb) dt \geq 0 \text{ and } \int_0^1 \psi(t)^{n-1} h((1-t)a + tb) dt \geq 0.$$

Proof. Assume without loss of generality that $a = 0$ and $b = e_1$. For $t \in \mathbb{R}$, set $Z_t = \{x \in \mathbb{R}^n : x_1 = t\}$ and for each $i \in \mathbb{N}$,

$$\psi_i(t) = \left(\frac{\text{vol}_{n-1}(K_i \cap Z_t)}{\text{vol}(K_i)} \right)^{1/(n-1)}.$$

Denote by α_i and β_i the maximum and minimum of x_1 over K_i . Since $K \subseteq K_i$, $\alpha_i \geq 1$ and $\beta_i \leq 0$ for each i and moreover, $\alpha_i \rightarrow 1$ and $\beta_i \rightarrow 0$. By **Brunn's Theorem**, each ψ_i is concave on $[\beta_i, \alpha_i]$.

Note that on any closed subinterval $[s, t] \subseteq (0, 1) \subseteq [\beta_i, \alpha_i]$, the (ψ_i) are Lipschitz (due to concavity).³³ In particular, if $\delta \leq s \leq t \leq 1 - \delta$, for any $s \leq x \leq y \leq t$,

$$|\psi_i(y) - \psi_i(x)| \leq \frac{\sup_{x \in (0,1)} \psi_i(x)}{\delta} |y - x|.$$

The above implies that if we show uniform boundedness of the (ψ_i) on $[s, t]$, then (uniform) equicontinuity follows as well. And indeed, since the (ψ_i) are concave, then letting ψ_i attain its supremum in $[s, t]$ at x_i , we have

$$1 \geq \int_s^t \psi_i(t)^{n-1} dt \geq \int_{(s+x_i)/2}^{(x_i+t)/2} \left(\frac{\sup_{x \in [s,t]} \psi_i(x)}{2} \right)^{n-1} dt,$$

which, after a straightforward simplification, implies uniform boundedness.

Therefore, by the Arzelà-Ascoli Theorem, the (ψ_i) have a uniformly convergent subsequence on any $[s, t]$; let ψ be the resulting limit function. Extending this appropriately to a function on $[0, 1]$, we clearly have that ψ is non-negative, concave, and

$$\int_0^1 \psi(t)^{n-1} dt = 1.$$

Now, setting $x = (t, y)$ for $t \in \mathbb{R}$ and $y \in \mathbb{R}^{n-1}$,

$$\begin{aligned} \int_{K_i} g(x) dx &= \int_{\beta_i}^{\alpha_i} \int_{K_i \cap Z_t} g(t, y) dy dt \\ &= \int_{\beta_i}^{\alpha_i} \left(\frac{1}{\text{vol}_{n-1}(K_i \cap Z_t)} \int_{K_i \cap Z_t} g(t, y) dy \right) \text{vol}(K_i) \psi_i(t)^{n-1} dt. \\ \frac{1}{\text{vol}(K_i)} \int_{K_i} g(x) dx &= \int_{\beta_i}^{\alpha_i} \left(\frac{1}{\text{vol}_{n-1}(K_i \cap Z_t)} \int_{K_i \cap Z_t} g(t, y) dy \right) \psi_i(t)^{n-1} dt. \end{aligned}$$

By definition, the left hand side is non-negative and

$$\int_{\beta_i}^{\alpha_i} \left(\frac{1}{\text{vol}_{n-1}(K_i \cap Z_t)} \int_{K_i \cap Z_t} g(t, y) dy \right) \psi_i(t)^{n-1} dt \rightarrow \int_0^1 g(t, 0) \psi(t)^{n-1} dt.$$

Therefore, this integral is non-negative and the claim is proved (the expression for h is non-negative by an identical argument). ■

Let us now get back to the main proof equipped with the above two intermediate steps.

We need to somehow get from the above concave function ψ to a linear function.

Continued Proof. Define ψ , a , and b as in the previous lemma but further, make two assumptions:

- Choose $a, b \in K$ such that $\|a - b\|$ is minimum. When we say “minimum”, we mean that one of the two integrals involved is equal to 0, so we cannot make the segment any shorter. Without loss of generality, assume $a = 0$ and $b = e_1$.

³³See [this StackExchange answer](#) if you are unfamiliar with the result.

- Let $[\alpha, \beta] \subseteq [0, 1]$ be the largest interval that ψ is linear on. That is, ψ is linear on $[\alpha, \beta]$ and $|\beta - \alpha|$ is maximum – in the case where ψ is nowhere linear, $\beta - \alpha = 0$ (How can we assume that such an interval exists?).

For the sake of simplicity, define π_1 to be the projection of $x \in \mathbb{R}^n$ onto the first axis ($\pi_1(x) = x_1$). Define the functions $\hat{g}, \hat{h} : \mathbb{R}^n \rightarrow \mathbb{R}$ by

$$\hat{g}(x) = g(\pi_1(x)e_1) \text{ and } \hat{h}(x) = h(\pi_1(x)e_1).$$

Also, consider the convex body

$$K' = \{x \in \mathbb{R}^n : 0 \leq x_1 \leq 1, x_2, \dots, x_n \geq 0, \text{ and } x_2 + \dots + x_n \leq \psi(x_1)\}.$$

The body K' can be visualized more naturally as taking the union of the $(n-1)$ -dimensional simplices spanned by $te_1, te_1 + \psi(t)e_2, \dots, te_1 + \psi(t)e_n$ over all $0 \leq t \leq 1$. As a result,

$$\text{vol}_{n-1}(K' \cap Z_t) = \frac{\psi(t)^{n-1}}{n!},$$

where $Z_t = \pi_1^{-1}(t)$ is defined as in the previous lemma.

Then,

$$\int_{K'} \hat{g}(x) dx = \int_0^1 \text{vol}(K' \cap Z_t) g(te_1) dt = \frac{1}{(n-1)!} \int_0^1 \psi(t)^{n-1} g(te_1) dt \geq 0,$$

where the last inequality follows from the definition of ψ in the previous lemma. We have a similar inequality for the integral of \hat{h} as well.

Since we have taken $\|a - b\|$ to be minimal, we may assume without loss of generality that $\int_{K'} \hat{g}(x) dx = 0$.

Consider the $(n-2)$ -dimensional affine space A defined by $x_1 = \sigma$ and $x_2 + \dots + x_n = \tau$ for some $0 < \sigma < 1$ and $\tau > 1$ (which we shall fix later). Suppose that A intersects the interior of K' . Then by Lemma 4.32, there exists a hyperplane H through A that splits K' into convex bodies L_A and L'_A such that

$$\int_{L_A} \hat{g}(x) dx = \int_{L'_A} \hat{g}(x) dx = 0 \text{ and } \int_{L_A} \hat{h}(x) dx \geq 0.$$

Note that

$$L'_A \cap (Z_0 \cap K') \neq \emptyset \text{ and } L'_A \cap (Z_1 \cap K') \neq \emptyset \quad (*)$$

since otherwise, the minimality of $\|a - b\|$ is contradicted.³⁴ As a consequence, H cannot be orthogonal to the x_1 -axis and so, it can be described as $x_2 + \dots + x_n = \ell(x_1)$ for some linear function ℓ (due to the structure of the $(n-2)$ -dimensional affine space A it contains). Due to $(*)$, this ℓ must also satisfy $\ell(0) \geq 0$ and $\ell(1) \geq 0$. Further, observe that we can succinctly describe $L_A \cap K'$ as

$$\{x \in \mathbb{R}^n : 0 \leq x_1 \leq 1, x_2, \dots, x_n \geq 0, \text{ and } x_2 + \dots + x_n \leq \psi'(t)\},$$

where

$$\psi'(t) = \min\{\psi(t), \ell(t)\}$$

is concave as well.

Now, since ψ is concave on $[0, 1]$, it is continuous on $(0, 1)$. Therefore, if there is a discontinuity, it must be at either 0 or 1. Based on this, we take 3 cases and in each, construct an A that yields the desired linear function.

- **Case 1.** $\psi(0) = \psi(1) = 0$. Consider the affine space A for $\sigma = 1/2$. Due to $(*)$, $(1/2)e_1 \in L_A$ (Why?). Since $\ell(0), \ell(1) \geq 0$ and $\ell(1/2) = \tau$, as we take $\tau \rightarrow 0$, ℓ tends to 0 *uniformly* on $[0, 1]$. Making τ sufficiently small, we see that ψ' satisfies the required condition and becomes linear on a length tending to 1 (it becomes equal to ℓ for a larger portion as τ becomes smaller and smaller).
- **Case 2.** $\psi(0) = 0$ and $\psi(1) > 0$ (the reversed case is nearly identical). Consider the affine space A for $\tau = \psi(1)\sigma$. $(*)$ implies that $0 \leq \ell(1) \leq \psi(1)$. However, in this case, ψ' must be linear on $[\sigma, 1]$, so we can obtain linearity on a length tending to 1.

³⁴we can then restrict ourselves to L_A instead of K' while maintaining non-negativity of the two integrals.

- **Case 3.** $\psi(0), \psi(1) > 0$. Consider a convex(!) function $\eta : [0, 1] \rightarrow \mathbb{R}^{\geq 0}$ such that
 - $0 \leq \eta(0) \leq \psi(0)$ and $0 \leq \eta(1) \leq \psi(1)$,
 - the convex body K_η defined by

$$K_\eta = \{x \in \mathbb{R}^n : 0 \leq x_1 \leq 1, x_2, \dots, x_n \geq 0, \text{ and } \eta(x_1) \leq x_2 + \dots + x_n \leq \psi(x_1)\}$$

satisfies

$$\int_{K_\eta} \hat{g}(x) dx = 0 \text{ and } \int_{K_\eta} \hat{h}(x) dx \geq 0, \text{ and}$$

$$- \int_0^1 \eta(x) dx \text{ is maximal.}$$

Such an η must exist since the zero function satisfies the first two conditions.

If $\psi(0) = \eta(0)$ or $\psi(1) = \eta(1)$, then we are done, since $\psi - \eta$ satisfies the original conditions (non-negative integrals), and it is already covered in the first two cases.

Otherwise, we have $\eta(0) < \psi(0)$ and $\eta(1) < \psi(1)$. Let (σ, τ) be the intersection point of the segments joining $(0, \eta(0))$, $(1, \psi(1))$ and $(0, \psi(0))$, $(1, \eta(1))$ and A be the corresponding affine space. Let H be a hyperplane containing A dividing space into two half-spaces M and M' such that

$$\int_{K_\eta \cap M} \hat{g}(x) dx = \int_{K_\eta \cap M'} \hat{g}(x) dx = 0.$$

Also, choose M to be the half-space that contains $(1/2)e_1$ (the one that “faces down”).

It is clear from construction that any $(n-1)$ -dimensional hyperplane containing A , H in particular, either intersects both $Z_0 \cap K_\eta$ and $Z_1 \cap K_\eta$ or neither. The latter cannot happen due to $(*)$ (or rather, the corresponding expression for K_η rather than K').

Now,

$$\int_{M'} \hat{h}(x) dx < 0.$$

Indeed, otherwise, the linear function ℓ corresponding to H contradicts the maximality of η . However, this implies that

$$\int_{M \cap K'} \hat{g}(x) dx = \int_{K'} \hat{g}(x) dx - \int_{M'} \hat{g}(x) dx = 0$$

and

$$\int_{M \cap K'} \hat{h}(x) dx = \int_{K'} \hat{h}(x) dx - \int_{M'} \hat{h}(x) dx > 0.$$

Finally, $M \cap K'$ is a truncated cone, thus completing the proof. ■

The above result has some interesting corollaries, namely Theorems 4.34 and 4.36, which are of interest to us. The following is an improvement of Theorem 4.15.

Theorem 4.34. Let $K \subseteq \mathbb{R}^n$ be a convex body, $0 < t < 1$, and K_1, K_2 be two measurable sets in K such that for any $a, b \in K$, the distance between $K_1 \cap [a, b]$ and $K_2 \cap [a, b]$ is at least $t \|a - b\|$. Then for any log-concave function F with support K ,

$$\mu_F(M \setminus (K_1 \cup K_2)) \geq \frac{2t}{1-t} \min\{\mu_F(K_1), \mu_F(K_2)\}.$$

The above bound is tight when K is a cylinder and F is identically 1. Note that $t \geq d(K_1, K_2)/\text{diam}(K)$ (which explains why this is an improvement of Theorem 4.15).

Proof. Suppose otherwise. Assume that K_1 and K_2 are open (otherwise, we can delete the boundary and enlarge them slightly to open sets while preserving both the assumptions and the inequality). Denote $K_3 = M \setminus (K_1 \cup K_2)$. Define

$$g(x) = \begin{cases} F(x), & x \in K_1, \\ -\frac{1-t}{2t}F(x), & x \in K_3, \\ 0, & \text{otherwise,} \end{cases} \quad \text{and} \quad h(x) = \begin{cases} F(x), & x \in K_2, \\ -\frac{1-t}{2t}F(x), & x \in K_3, \\ 0, & \text{otherwise.} \end{cases}$$

By our assumption, the integrals of g and h over \mathbb{R}^n are positive. We can then apply Theorem 4.31 to get a linear functional ℓ and $a, b \in \mathbb{R}^n$ such that

$$\int_0^1 \ell(u)^{n-1} g(ua + (1-u)b) du > 0 \quad \text{and} \quad \int_0^1 \ell(u)^{n-1} h(ua + (1-u)b) du > 0.$$

For each $1 \leq i \leq 3$, define

$$H_i = \{u \in [0, 1] : ua + (1-u)b \in K_i\} \quad \text{and} \quad G(u) = \ell(u)^{n-1} F(ua + (1-u)b).$$

Substituting g and h in the above equation, we get

$$\int_{H_3} G(u) du < \frac{2t}{1-t} \min \left\{ \int_{H_1} G(u) du, \int_{H_2} G(u) du \right\}. \quad (4.16)$$

Intuitively, the worst case to prove appears to be when H_3 is a single interval – as we shall see later in the proof, we can reduce it to this case even in general. We show the following claim, which just asserts that Equation (4.16) is incorrect (for the single-interval case). Define μ_G to be measure on $[0, 1]$ with density G .

Claim. For $0 \leq s < s+t \leq 1$,

$$\mu_G([s, s+t]) \geq \frac{2t}{1-t} \min\{\mu_G([0, s]), \mu_G([s+t, 1])\}. \quad (4.17)$$

Before we move to the proof, note that Theorem 4.15, which has a t in place of $2t/(1-t)$ above, is trivial now. Indeed, since G is unimodal³⁵,

$$\mu_G([s, s+t]) \geq t \inf_{x \in [s, s+t]} G(x) \geq t \max\{s, 1-s-t\} \inf_{x \in [s, s+t]} G(x) \geq t \min\{\mu_G([0, s]), \mu_G([s+t, 1])\}.$$

First, note that since G is the product of two log-concave functions, it is log-concave as well. Choose constants c, c_0 such that $G(s) = c_0 e^{cs}$ and $G(s+t) = c_0 e^{c(s+t)}$. By the log-concavity of G , $G(u) \geq c_0 e^{cu}$ for $s \leq u \leq s+t$ and $G(u) \leq c_0 e^{cu}$ elsewhere. As a consequence, it suffices to show Equation (4.17) for the case where $G(u) = c_0 e^{cu}$. Further, we may assume that $c_0 = 1$. We wish to show that

$$e^{c(s+t)} - e^{cs} \geq \frac{2t}{1-t} \min \left\{ e^{cs} - 1, e^c - e^{c(s+t)} \right\}.$$

The worst case is when $e^{cs} - 1 = e^c - e^{c(s+t)}$ (Why?). That is,

$$e^{cs} = \frac{1 + e^c}{1 + e^{ct}}.$$

We then aim to show that

$$(e^{ct} - 1) \frac{1 + e^c}{1 + e^{ct}} \geq \frac{2t}{1-t} \left(\frac{1 + e^c}{1 + e^{ct}} - 1 \right).$$

Let $x = e^{ct} > 1$ and $\lambda = 1/t > 1$. The equation then becomes

$$(x-1)(1+x^\lambda) \geq \frac{2}{\lambda-1}(x^\lambda - x),$$

³⁵there is some $m \in [0, 1]$ such that G is monotonically increasing for $x \leq m$ and monotonically decreasing for $x \geq m$.

that is,

$$(\lambda + 1)(x - x^\lambda) + (\lambda - 1)(x^{\lambda+1} - 1) \geq 0.$$

Letting the expression on the left be $h(x)$, we get $h(1) = h'(1) = 0$ and $h''(x) = (\lambda^2 - 1)\lambda(x^{\lambda-1} - x^{\lambda-2}) \geq 0$, thus proving the claim for all $x \geq 1$.

Now, how do we reduce the general case problem to this? For each maximal interval $I = (a, b)$ contained in H_3 of length at least t , colour $[0, a]$ red if $\mu_G([0, a]) < \mu_G([b, 1])$ and $[b, 1]$ red otherwise. The above claim implies that each interval introduces a red set of μ_G -measure at most $\frac{1-t}{2t}\mu_G((a, b))$. The entirety of the red set then has measure at most $\frac{1-t}{2t}\mu_G(H_3)$. It then suffices to show that either H_1 or H_2 is completely red.

Suppose otherwise. Denote by U the region that is uncoloured. We then have that U intersects both H_1 and H_2 . By construction, U is an open interval. Since the distance between H_1 and H_2 is at least t , $U \cap H_3$ must contain a subinterval (of length at least t). This is a contradiction because there is an adjacent red interval (that intersects U). \blacksquare

Setting F to be identically 1 on K in the above result, we get the following.

Corollary 4.35. Let $K \subseteq \mathbb{R}^n$ be a convex body, $0 < t < 1$, and K_1, K_2 be two measurable sets in K such that for any $a, b \in K$, the distance between $K_1 \cap [a, b]$ and $K_2 \cap [a, b]$ is at least $t \|a - b\|$. Then

$$\text{vol}(M \setminus (K_1 \cup K_2)) \geq \frac{2t}{1-t} \min\{\text{vol}(K_1), \text{vol}(K_2)\}.$$

In particular, if K has diameter d and the distance between K_1 and K_2 is at least 1,

$$\text{vol}(M \setminus (K_1 \cup K_2)) \geq \frac{2}{d-1} \min\{\text{vol}(K_1), \text{vol}(K_2)\}.$$

Theorem 4.36. Let F be a log-concave function on \mathbb{R}^n and $\theta \leq 1$ such that

$$\int_{\mathbb{R}^n \setminus B_2^n} F(x) dx = \theta \int_{\mathbb{R}^n} F(x) dx.$$

Then for every $u \geq 1$,

$$\int_{\mathbb{R}^n \setminus uB_2^n} F(x) dx \leq \theta^{(u+1)/2} \int_{\mathbb{R}^n} F(x) dx.$$

Proof. Suppose otherwise. Then exactly as we did in the proof of Theorem 4.34, there exist $a, b \in \mathbb{R}^n$ and a linear function $\ell : [0, 1] \rightarrow \mathbb{R}^+$ such that on setting

$$\begin{aligned} G(t) &= \ell(t)^{n-1} F((1-t)a + tb), \\ H_1 &= \{t \in [0, 1] : (1-t)a + tb \in B_2^n\}, \\ H_2 &= \{t \in [0, 1] : (1-t)a + tb \in uB_2^n \setminus B_2^n\}, \text{ and} \\ H_3 &= [0, 1] \setminus (H_1 \cup H_2), \end{aligned}$$

we have

$$\int_{H_2 \cup H_3} G(t) dt \leq \theta \int_0^1 G(t) dt \tag{4.18}$$

and

$$\int_{H_3} G(t) dt > \theta^{(u+1)/2} \int_0^1 G(t) dt \tag{4.19}$$

As seen before, G is log-concave. Further, note that H_1 is an interval and H_2, H_3 consist of 1 or 2 intervals.

If $0 \notin H_1$, we can choose a point $s \in H_1$ such that

$$\frac{\int_{[0,s] \cap H_1} G(t) dt}{\int_{[s,1] \cap H_1} G(t) dt} = \frac{\int_{[0,s]} G(t) dt}{\int_{[s,1]} G(t) dt}.$$

We can then replace $[a, b]$ with one of $[a, (1-s)a + sb]$ and $[(1-s)a + sb, b]$ (that is, replace $[0, 1]$ with $[0, s]$ or $[s, 1]$).³⁶ Therefore, we may assume wlog that $0 \in H_1$, that is, $a \in B_2^n$. Let $H_1 = [0, \alpha]$, $H_2 = (\alpha, \beta]$, and $H_3 = (\beta, 1]$. It is easily shown that $\beta \geq (\frac{u+1}{2})\alpha$.

Now, choose constants c and c_0 such that

$$\int_0^\alpha G(t) dt = \int_0^\alpha c_0 e^{-ct} dt \text{ and } \int_\beta^1 G(t) dt = \int_\alpha^\infty c_0 e^{-ct} dt.$$

Note that the log-concavity (unimodality in particular) of G implies that for all $\alpha \leq t \leq \beta$, $G(t) \geq c_0 e^{-ct}$. Therefore,

$$\int_0^1 G(t) dt \geq \int_0^\infty c_0 e^{-ct} dt.$$

However, Equation (4.18) then implies that

$$\begin{aligned} \theta &\geq \frac{\int_\alpha^1 G(t) dt}{\int_0^1 G(t) dt} \\ &= 1 - \frac{\int_0^\alpha G(t) dt}{\int_0^1 G(t) dt} \\ &\geq 1 - \frac{\int_0^\alpha c_0 e^{-ct} dt}{\int_0^\infty c_0 e^{-ct} dt} \\ &= \frac{\int_\alpha^\infty c_0 e^{-ct} dt}{\int_0^\infty c_0 e^{-ct} dt} = e^{-c\alpha}. \end{aligned}$$

Using the above, we now have

$$\begin{aligned} \theta^{(u+1)/2} &\geq e^{-c\alpha(u+1)/2} \\ &\geq e^{-c\beta} \\ &= \frac{\int_\beta^\infty c_0 e^{ct} dt}{\int_0^\infty c_0 e^{ct} dt} \geq \frac{\int_\beta^1 G(t) dt}{\int_0^1 G(t) dt}, \end{aligned}$$

thus resulting in a contradiction to Equation (4.19) and proving the claim. ■

Corollary 4.37. Let K be a convex body in \mathbb{R}^n and $\theta = \text{vol}(K \setminus B_2^n) / \text{vol}(K)$. Then $\text{vol}(K \setminus uB_2^n) \leq \theta^{(u+1)/2} \text{vol}(K)$.

Before we conclude this section, we give two more lemmas that will be useful in the future.

Lemma 4.38. Let K be a convex body and $\theta = \text{vol}(K \setminus B_2^n) / \text{vol}(K)$. Then $K \subseteq \frac{2n}{1-\theta} B_2^n$.

Proof. Let $x \in K$ be the point farthest from the origin and $R = \|x\|$. It suffices to show the result for $\text{Conv}(K \cap B_2^n) \cup \{x\}$ (Why?). Assume K to be of this form.

Note that K is contained in

$$\left\{ x + \left(\frac{R+1}{R-1} \right) v : x + v \in K \setminus B_2^n \right\}.$$

Then,

$$\text{vol}(K) \leq \left(\frac{R+1}{R-1} \right)^n \text{vol}(K \setminus B_2^n) \leq \theta \left(\frac{R+1}{R-1} \right)^n \text{vol}(K).$$

Therefore,

$$R \leq \frac{2}{1-\theta^{1/n}} \leq \frac{2n}{1-\theta}. \quad \blacksquare$$

³⁶Multiplying by the appropriate factors leaves Equation (4.18) unchanged in the restricted segment, and one of the two intervals will also satisfy the restriction of Equation (4.19).

Lemma 4.39. Let $0 \leq t \leq 1$. If $\text{vol}(K \setminus (x + K)) \leq 1/2 \text{vol}(K)$, then $\text{vol}(K \setminus (tx + K)) \leq (2t/3) \text{vol}(K)$.

Proof. Define $\psi : [0, 1] \rightarrow \mathbb{R}$ by

$$\psi(u) = \frac{\text{vol}(K \cap (ux + K))}{\text{vol}(K)}.$$

Corollary 4.29 (or rather, the line right after it) implies that ψ is log-concave. We have $\psi(0) = 1$ and $\psi(1) \geq 1/2$. Therefore, $\psi(t) \geq 2^{-t}$ so

$$\text{vol}(K \setminus (tx + K)) \leq (1 - 2^{-t}) \text{vol}(K) \leq \frac{2t}{3} \text{vol}(K). \quad \blacksquare$$

4.6. An $\mathcal{O}^*(n^7)$ Algorithm using Ball-Step

As in most volume estimation algorithms, the basic idea remains nearly the same, the changes being only in the walk. The algorithm used here involves the “ball-step” mentioned earlier. It is worth noting instead of the “ball” in ball-step, one could use any other symmetric convex body G . An obvious choice is the cube, which is quite convenient to draw points uniformly randomly from from a programming perspective. Our analysis shall be done in this general case.

4.6.1. Ball-Step and Bounding Conductance

The basic walk \mathcal{M} is as follows: when we are at v_k , we let $v_{k+1} = v_k$ with probability $1/2$. Otherwise, we generate a random vector u from the uniform distribution on G . If $v_k + u \in K$, set $v_{k+1} = v_k + u$ and otherwise, set $v_{k+1} = v_k$. This is termed as the *lazy random walk in K with G -steps*.

In this particular algorithm, we further filter it to obtain a Metropolis chain (recall that we defined this in Definition 4.14). That is, for any measurable A such that $x \notin A$,

$$P_x(A) = \frac{1}{2 \text{vol}(G)} \int_{(x+G) \cap A} \min \left\{ 1, \frac{F(y)}{F(x)} \right\} dy = \frac{1}{2 \text{vol}(G)} \int_{(x+G) \cap A} \min \left\{ \frac{1}{F(y)}, \frac{1}{F(x)} \right\} d\mu_F(y)$$

and

$$P_x(x) = \frac{1}{2} + \frac{1}{2 \text{vol}(G)} \int_{x+G} \max \left\{ 0, 1 - \frac{F(y)}{F(x)} \right\} dy.$$

Recall from the discussion after Definition 4.11 that we denote by H_t (for $0 \leq t \leq 1/2$) the set of points such that

$$\int_{x+G} \min\{F(x), F(y)\} dy < tF(x) \text{vol}(G),$$

the set of points where the probability of moving out is less than t . We also saw that the $(Q_F(H_t)/2)$ -conductance of the chain is at most $2t$.

The main result of this section, which is an improvement of a previous result, says that if the local conductance is large and the “diameter” (not the usual Euclidean diameter) of K is small, then the overall conductance is large.

Theorem 4.40. Let $0 \leq t \leq 1/2$, $0 < \theta < 1$, and $s = Q_F(H_t)$. Assume that for all $x, y \in K$,

$$\text{vol}(G \cap (\theta(x - y) + G)) \leq \frac{1}{2} \text{vol}(G). \quad (4.20)$$

Then the $(7s/t)$ -conductance of $\mathcal{M}(K, G)/F$ is at least $t^2\theta/18$.

Our idea of diameter here is $1/\theta$ (where θ is the minimal value satisfying the required in the above theorem). It is seen that $1/\theta$ is the usual diameter under the norm whose unit ball is $\{x : \text{vol}(G \cap (x + G)) \geq \text{vol}(G)/2\}$. If G is the Euclidean ball, then $1/\theta$ grows as \sqrt{nd} , where d is the usual Euclidean diameter of K .

Proof. Alternatively, the above result states that if we split K into measurable sets S_1 and S_2 ,

$$\int_{S_1} \int_{S_2 \cap (x+G)} \min\{F(x), F(y)\} dy dx \geq \frac{t^2 \theta \text{vol}(G)}{18} \min \left\{ Q_F(S_1) - \frac{7s}{t}, Q_F(S_2) - \frac{7s}{t} \right\}.$$

We may assume that $Q_F(S_1)$ and $Q_F(S_2)$ are both greater than $7s/t$. For $i = 1, 2$, define

$$\begin{aligned} S'_i &= \left\{ x \in S_i : \mu_F((x+G) \cap S_{3-i}) \geq \frac{t}{3} \text{vol}(G)F(x) \right\}, \\ S''_i &= (S_i \setminus S'_i) \setminus H_t, \text{ and} \\ S_3 &= S'_1 \cup S'_2 \cup H_t. \end{aligned}$$

Note that S'_1 , S''_2 , and S_3 are disjoint (and cover the entirety of K). Each S'_i represents the “good” points in S_i – the probability of transitioning to S_{3-i} is decently high, or rather, sufficiently higher than the probability of even being at that point in the first place.

The only problematic points are those in the S''_i .

Claim. If $x_1 \in S'_1$ and $x_2 \in S''_2$, then $\text{vol}((x_1+G) \setminus (x_2+G)) \geq \frac{t}{3} \text{vol}(G)$.

Suppose otherwise. Observe that the expression under consideration is symmetric in x_1 and x_2 so we may assume that $F(x_1) \leq F(x_2)$. Define $G_i = x_i + G$ for $i = 1, 2$. Since S''_i and H_t are disjoint,

$$\int_{G_i} \min\{F(x_i), F(y)\} dy \geq t \text{vol}(G)F(x_i).$$

We also have (by the contradiction assumption) that

$$\int_{G_2 \setminus G_1} \min\{F(x_2), F(y)\} dy < \frac{t}{3} \text{vol}(G)F(x_2).$$

Therefore,

$$\int_{G_2 \cap G_1} \min\{F(x_2), F(y)\} dy \geq \frac{2t}{3} \text{vol}(G)F(x_2).$$

Since $x_2 \notin S'_2$,

$$\int_{G_2 \cap G_1 \cap S_1} \min\{F(x_2), F(y)\} dy \leq \int_{G_2 \cap S_1} \min\{F(x_2), F(y)\} dy < \frac{t}{3} \text{vol}(G)F(x_2).$$

Because $S_1 \cup S_2 = K$,

$$\int_{G_2 \cap G_1 \cap S_2} \min\{F(x_2), F(y)\} dy > \frac{t}{3} \text{vol}(G)F(x_2).$$

Multiplying by $F(x_1)/F(x_2)$ on either side,

$$\int_{G_2 \cap G_1 \cap S_2} \min\{F(x_1), F(y)\} dy > \frac{t}{3} \text{vol}(G)F(x_1)$$

and so,

$$\int_{G_1 \cap S_2} \min\{F(x_1), F(y)\} dy > \frac{t}{3} \text{vol}(G)F(x_1).$$

However, this means that $x_1 \in S'_2$, proving the claim.

Observe that the above claim is equivalent to saying that if $x_1 \in S'_1$ and $x_2 \in S''_2$, $\text{vol}(G \cap ((x_2 - x_1) + G)) > \frac{t}{3} \text{vol}(G)$. Therefore, Lemma 4.39 implies that

$$\text{vol} \left(G \cap \left(\frac{2}{t}(x_2 - x_1) + G \right) \right) > \frac{1}{2} \text{vol}(G).$$

If we have some $a, b \in K$ such that $S_1'' \cap [a, b]$ and $S_2'' \cap [a, b]$ are non-empty and the distance between them is $\rho \|b - a\|$, then the claim above together with Equation (4.20) imply that $\rho > t\theta/2$. Using Theorem 4.34,

$$\mu_F(S_3) \geq \frac{t\theta}{1 - t\theta/2} \min\{\mu_F(S_1''), \mu_F(S_2'')\}.$$

Further note that

$$\mu_F(S_i'') \geq \mu_F(S_i) - \mu_F(S_i') - \mu_F(H_t) \geq \mu_F(S_i) - \mu_F(S_3) - s.$$

That is,

$$\left(1 + \frac{t\theta}{2}\right) \mu_F(S_3) \geq \frac{t\theta}{1 - t\theta/2} \min\{\mu_F(S_1) - s, \mu_F(S_2) - s\},$$

so

$$\mu_F(S_3) \geq t\theta \min\{\mu_F(S_1) - s, \mu_F(S_2) - s\}.$$

We also have

$$\begin{aligned} \int_{S_1} \int_{S_2 \cap (x+G)} \min\{F(x), F(y)\} dy dx &\geq \int_{S_1'} \int_{S_2 \cap (x+G)} \min\{F(x), F(y)\} dy dx \\ &\geq \int_{S_1'} \frac{t}{3} \text{vol}(G) F(x) dx = \frac{t}{3} \text{vol}(G) \mu_F(S_1'). \end{aligned}$$

A similar inequality holds with $\mu_F(S_2')$ instead of $\mu_F(S_1')$ as well (invoking time-reversibility). Finally,

$$\begin{aligned} \int_{S_1} \int_{S_2 \cap (x+G)} \min\{F(x), F(y)\} dy dx &\geq \frac{t}{6} \text{vol}(G) \mu_F(S_1' \cup S_2') \\ &= \frac{t}{6} \text{vol}(G) \mu_F(S_3 \setminus H_t) \\ &\geq \frac{t}{6} \text{vol}(G) (\mu_F(S_3) - s) \\ &\geq \frac{t}{6} \text{vol}(G) (t\theta \min\{\mu_F(S_1) - s, \mu_F(S_2) - s\} - s) \\ &= \frac{t^2\theta}{6} \min\left\{\mu_F(S_1) - s \left(1 + \frac{1}{t\theta}\right), \mu_F(S_2) - s \left(1 + \frac{1}{t\theta}\right)\right\} \\ &\geq \frac{t^2\theta}{6} \min\left\{\mu_F(S_1) - \frac{7s}{t}, \mu_F(S_2) - \frac{7s}{t}\right\}. \end{aligned}$$

■

Corollary 4.41. If the local conductance of $\mathcal{M}(K, G)$ is at least t at each point, its conductance is at least $t^2\theta/18$.

4.6.2. The Walk

A simple albeit important problem is that of deciding how to sample from the body G we are considering. As mentioned at the beginning of this section, a cube is quite convenient from a programmer's perspective. The Euclidean ball is not too problematic either. Letting ξ_1, \dots, ξ_n be iid standard normal distributions and η be uniformly distributed in $[0, 1]$, we see that

$$v_0 = \left(\eta^{1/n} \frac{\xi_1}{\sqrt{\sum_i \xi_i^2}}, \dots, \eta^{1/n} \frac{\xi_n}{\sqrt{\sum_i \xi_i^2}} \right)$$

is uniformly distributed in B_2^n .

We modify the G -walk described above into a suitable Metropolis chain, with the primary function being quite similar to that we used in the $\mathcal{O}^*(n^8)$ algorithm described in a previous section. Define

$$\phi_K(x) = \min\{t \geq 0 : x \in tK\}$$

and $F_K(x) = e^{-\phi_K(x)}$. Clearly, $0 < F_K \leq 1$. We often refer to these functions as just ϕ and F if it is clear from context what convex body we are talking about (this is almost always K). First of all, we can use Equations (1.2) and (1.3) to get

$$\int_{\mathbb{R}^n} F = n \operatorname{vol}(K) \int_0^\infty t^{n-1} e^{-t} dt.$$

That is,

$$\operatorname{vol}(K) = \frac{1}{n!} \int_{\mathbb{R}^n} F. \quad (4.21)$$

Let $h : \mathbb{R}^+ \rightarrow \mathbb{R}$ be any function such that $\int_0^\infty h(t)t^{n-1} dt$ exists. Then another useful corollary of Equations (1.2) and (1.3) is that

$$\int_{\mathbb{R}^n} h(\phi(x)) = n \operatorname{vol}(K) \int_0^\infty h(t)t^{n-1} dt. \quad (4.22)$$

Now, define

$$\lambda(s) = \frac{1}{s} \left(\frac{1}{(n-1)!} \int_0^s e^{-t} t^{n-1} dt \right)^{1/n}.$$

The reason for choosing such a convoluted function is made clear by the following lemma.

Lemma 4.42. Let v be randomly distributed in \mathbb{R}^n with density $e^{-\phi(v)}/(n-1)!$. Then

$$H(v) = \lambda(\phi(v))v$$

is uniformly distributed on K .

Proof. Set $h(t) = e^{-t}/(n-1)!$ and fix some $0 \leq s \leq 1$. Observe that the set sK is mapped by H to $s\lambda(s)K$.³⁷ Obviously, the probability of $s\lambda(s)K$ under the uniform distribution on K is $(s\lambda(s))^n$. The probability of sK under the given density h is

$$\int_{sK} \frac{e^{-\phi(x)}}{(n-1)!} dx = \int_0^s h(t)t^{n-1} dt.$$

By the definition of λ , these two quantities are equal. Since we can similarly restrict ourselves to any fixed cone similarly, the assertion holds and $H(v)$ is uniform. \blacksquare

While we used usual (deterministic) sandwiching in our earlier algorithm, it turns out that we can get an algorithm that gives a better sandwiching ratio without being too costly in terms of time by introducing randomness.

The sandwiching we take is such that more than $2/3$ of the volume of B_2^n is in K and for a $1 \leq m \leq n^{3/2}$, more than $2/3$ of the volume of K is contained in the convex body mB_2^n .

There exists a randomized algorithm to obtain a $m = n$ in the above (which we describe later), but for now, we shall analyze it for a general m .

Set $q = 2mn \log(4/\varepsilon)$ and $t = 10^{10} n q^2 (n \log n + \log(2/\varepsilon))$.

In the algorithm, start with the uniform distribution on B_2^n and do a lazy random walk in qB_2^n up till time t with B_2^n -steps, filtered by F (as defined earlier in the section). Compute $w = H(v_t)$. We claim that w is close to being drawn from the uniform distribution. This is stated more rigorously in the following, which is the main result of this section.

Theorem 4.43. For any (Lebesgue) measurable set $A \subseteq K$, the random point w described above satisfies

$$\left| \Pr[w \in A] - \frac{\operatorname{vol}(A)}{\operatorname{vol}(K)} \right| < \varepsilon.$$

Moreover, it requires $\mathcal{O}(n^3 m^2 \log^2(1/\varepsilon)(n \log n + \log(1/\varepsilon)))$ membership tests and $\mathcal{O}(n^4 m^2 \log(1/\varepsilon)(n \log n + \log(1/\varepsilon)))$ arithmetic operations involving numbers of $\mathcal{O}(\log n)$ bits.

³⁷if $x \in s\partial K$, then $H(x) = \lambda(s)x$.

The remainder of this section is dedicated to proving the above.

Lemma 4.44. Let H be a halfspace in \mathbb{R}^n and B a unit ball whose center is at distance t from H . Then

(i) if $t \leq 1/\sqrt{n}$,

$$\text{vol}(B \cap H) > \left(\frac{1}{2} - \frac{t\sqrt{n}}{2} \right) \text{vol}(B_2^n).$$

(ii) if $t > 1/\sqrt{n}$,

$$\frac{1}{10t\sqrt{n}}(1-t^2)^{(n+1)/2} \text{vol}(B_2^n) < \text{vol}(H \cap B) < \frac{1}{t\sqrt{n}}(1-t^2)^{(n+1)/2} \text{vol}(B_2^n).$$

Observe that the above is just a (better) bound on the volume of a spherical cap, which we rudimentarily bounded back in Lemmas 1.1 and 1.2. We omit the proof of the above.

The above with the sandwiching we are taking implies that $(1/3n^{1/2})B_2^n \subseteq K$. Also, Lemma 4.38 implies that $K \subseteq 3nmB_2^n$. Therefore, for any $x \in K$,

$$\frac{\|x\|}{3nm} \leq \phi(x) \leq 3\sqrt{n}\|x\|. \quad (4.23)$$

The first lemma justifies why we can restrict ourselves to qB_2^n .

Lemma 4.45. Given the above,

$$\left(1 - \frac{\varepsilon}{4}\right) \text{vol}(K) < \frac{1}{n!} \int_{qB_2^n} F(x) \, dx.$$

Proof. Let $\overline{K} = K \cap mB_2^n$. Note that for any x , $F_{\overline{K}}(x) \leq F(x)$. We then have

$$\begin{aligned} \int_{2nmB_2^n} F(x) \, dx &\geq \int_{2n\overline{K}} F(x) \, dx && (2n\overline{K} \subseteq 2nmB_2^n) \\ &\geq \int_{2n\overline{K}} \overline{F}(x) \, dx \\ &= n \text{vol}(\overline{K}) \int_0^{2n} e^{-t} t^{n-1} \, dt && \left(\text{using Equation (4.22) on } h(t) = \begin{cases} e^{-t}, & 0 \leq t \leq 2n, \\ 0, & \text{otherwise.} \end{cases} \right) \\ &> \frac{39}{40} n! \text{vol}(\overline{K}) \\ &\geq \frac{13}{20} n! \text{vol}(K) && (\text{at least } 2/3 \text{ of the volume of } K \text{ is in } mB_2^n) \end{aligned}$$

for sufficiently large n .

Alternatively,

$$\int_{\mathbb{R}^n \setminus 2nmB_2^n} F(x) \, dx < \frac{7}{20} n! \text{vol}(K) = \frac{7}{20} \int_{\mathbb{R}^n} F(x) \, dx.$$

We can then use Theorem 4.36 to get

$$\int_{\mathbb{R}^n \setminus 2nm \log(4/\varepsilon) B_2^n} F(x) \, dx < \left(\frac{7}{20} \right)^{\log(4/\varepsilon)} \int_{\mathbb{R}^n} F(x) \, dx \leq \frac{\varepsilon}{4} n! \text{vol}(K)$$

for sufficiently small ε , thus proving the required. ■

The second lemma bounds the conductance of the chain.

Lemma 4.46. If $p \geq 10\sqrt{n}$, then the conductance of $\mathcal{M}(pB_2^n, B_2^n)/F_K$ is at least $1/(20000p\sqrt{n})$.

Proof. The first step is bounding the local conductance, much like we did for the earlier algorithm. Let $x \in pB_2^n$ and y be chosen randomly from $x + B_2^n$. By the condition that $p \geq 10\sqrt{n}$, $y \notin pB_2^n$ with probability at most $5/9$. Since $2/3$ of the volume of B_2^n is in K , $y \notin K$ with probability at most $1/3$. Therefore, $y \in pB_2^n \cap K$ with probability at least $1/9$. Fix such a y . Then

$$y \in x + K \subseteq \phi(x)K + K = (\phi(x) + 1)K,$$

so $\phi(y) \leq \phi(x) + 1$. Therefore, $F_K(y) \geq F_K(x)/e$. This bounds the local conductance below by $1/9e > 1/25$. In the context of Corollary 4.41, the minimum value of θ is bounded below by $2/3pn^{1/2}$ (using Lemma 4.44).³⁸ Corollary 4.41 then yields the result. \blacksquare

Let us now move on to the proof of the main theorem.

For $A \subseteq \mathbb{R}^n$, define

$$Q_F(A) = \frac{\int_A F(u) \, du}{\int_{\mathbb{R}^n} F(u) \, du}$$

and

$$Q'_F(A) = \frac{\int_{A \cap qB_2^n} F(u) \, du}{\int_{qB_2^n} F(u) \, du}.$$

For measurable $A \subseteq K$,

$$\Pr[w \in A] = \Pr[v_t \in H^{-1}(A)] = Q_t(H^{-1}(A)).$$

By Lemma 4.42,

$$Q_F(H^{-1}(A)) = \frac{\text{vol}(A)}{\text{vol}(K)}.$$

Clearly, it suffices to show that for any measurable $U \subseteq \mathbb{R}^n$,

$$|Q_F(U) - Q_t(U)| < \varepsilon.$$

Using Lemma 4.45,

$$\begin{aligned} Q_F(U) - Q'_F(U) &= \frac{\mu_F(U)}{\mu_F(\mathbb{R}^n)} - \frac{\mu_F(U \cap qB_2^n)}{\mu_F(qB_2^n)} \\ &\leq \frac{\mu_F(U)}{\mu_F(\mathbb{R}^n)} - \frac{\mu_F(U \cap qB_2^n)}{\mu_F(\mathbb{R}^n)} \\ &= \frac{\mu_F(U \setminus qB_2^n)}{\mu_F(\mathbb{R}^n)} \\ &\leq \frac{\mu_F(\mathbb{R}^n \setminus qB_2^n)}{\mu_F(\mathbb{R}^n)} \leq \frac{\varepsilon}{4} \\ Q'_F(U) - Q_F(U) &= \frac{\mu_F(U \cap qB_2^n)}{\mu_F(qB_2^n)} - \frac{\mu_F(U)}{\mu_F(\mathbb{R}^n)} \\ &\leq \frac{\mu_F(U \cap qB_2^n)}{\mu_F(qB_2^n)} - \frac{\mu_F(U \cap qB_2^n)}{\mu_F(\mathbb{R}^n)} \\ &= \frac{\mu_F(U \cap qB_2^n)\mu_F(\mathbb{R}^n \setminus qB_2^n)}{\mu_F(qB_2^n)\mu_F(\mathbb{R}^n)} \\ &\leq \frac{\mu_F(\mathbb{R}^n \setminus qB_2^n)}{\mu_F(\mathbb{R}^n)} \leq \frac{\varepsilon}{4} \end{aligned}$$

³⁸try bounding the distance d such that $\text{vol}(B_2^n \cap (de_1 + B_2^n)) \geq \text{vol}(B_2^n)/2$ and going from there.

Therefore, it suffices to bound $|Q'_F(U) - Q_t(U)|$ by $3\varepsilon/4$. To do so, we use Corollary 4.22. To estimate M (in the context of Corollary 4.22),

$$\begin{aligned}
M &= \sup_A \frac{Q_0(A)}{Q'_F(A)} \\
&= \frac{\mu_F(qB_2^n)}{\mu_F(B_2^n)} && \text{(the supremum is attained for } A = B_2^n \text{)} \\
&\leq \frac{n! \operatorname{vol}(K)}{e^{-3\sqrt{n}} \operatorname{vol}(B_2^n)} && \text{(Equation (4.23))} \\
&\leq n^{3n} && \left(n! \leq n^n, \frac{\operatorname{vol}(K)}{\operatorname{vol}(B_2^n)} \leq \frac{3}{2} m^n, e^{-3\sqrt{n}} \leq \frac{2}{3} n^{n/2} \right)
\end{aligned}$$

for sufficiently large n . By Lemma 4.46,

$$\Phi \geq \frac{1}{20000q\sqrt{n}}.$$

Therefore,

$$\begin{aligned}
|Q_t(U) - Q'_F(U)| &\leq n^{3n/2} \left(1 - \frac{\Phi^2}{2}\right)^t \\
&= n^{3n/2} \left(1 - \frac{25}{2t} (n \log(n) + \log(2/\varepsilon))\right)^t \\
&\leq n^{3n/2} \exp\left(-\frac{25}{2} (n \log(n) + \log(2/\varepsilon))\right) \leq \frac{\varepsilon}{2}.
\end{aligned}$$

This proves Theorem 4.43.

It is actually possible to perform the above algorithm with a far smaller value of t ($\mathcal{O}^*(n^4 m^2)$) while taking $\frac{\varepsilon}{1000n} B_2^n$ -steps, but the analysis is more complicated so we omit it (we would have to use s -conductance in the proof instead).

4.6.3. Better Sandwiching and Ignoring the Error Probability

One of the basic assumptions in our algorithm was that of the sandwiching. Our body K is such that

- At least $2/3$ of the volume of B_2^n is in K .
- At least $2/3$ of the volume of K is in mB_2^n for some $1 \leq m \leq n^{3/2}$.

We have already seen in Section 4.1.2 that it is possible to deterministically obtain $B_2^n \subseteq K \subseteq n^{3/2} B_2^n$. Sticking with $n^{3/2}$ would cost us a running time of n in the main part, so how do we do better?

Suppose we have $n^{-1/2} B_2^n \subseteq K \subseteq n B_2^n$. First, we randomly select $T = 3 \log n$ points in B_2^n independently and then check if they are in K . If one of them is not, we have a point in $B_2^n \setminus K$ to perform the ellipsoid step. Otherwise, we shall conclude that at least $2/3$ of the volume of B_2^n is in K . Indeed, if not, the probability that we do not find a point in $B \setminus K$ is less than $(2/3)^{3 \log n} \leq 1/(100n^2 \log n)$. The procedure itself lasts at most $25n^2 \log n$ steps, so the probability that it halts with K containing less than $2/3$ of B_2^n (which it has) is less than $1/4$.

This gives a randomized algorithm that achieves the required with error probability less than $1/4$.

It is worth noting that here, we have the second condition for $m = n$ in a stronger sense with at least $2/3$ of the volume of B_2^n in K and $K \subseteq mB_2^n$.

We now discuss another tactic to obtain the first condition in a strong sense and the second condition in a weaker sense using the polar.

Suppose we have $B_2^n \subseteq K \subseteq n^{3/2} B_2^n$. If K contains some point x with $\|x\| > 6n$, then we first expand the body by a factor of $(1 + 1/n)$ in all directions orthogonal to x , shrink it by a factor of 3 along x , and then translate it by $(-2/3)(x/\|x\|)$. This affine transformation of K still contains B_2^n (Why?). We can repeat this until we get $B_2^n \subseteq K \subseteq 6n B_2^n$ (or rather, some affine transformation of K).

However, there is still one problem – how do we find a valid x or determine that no such x exists? That is, we wish to determine if $K \subseteq 6nB_2^n$ and if not, find a point in $6B_2^n \setminus K$. We can do this by generating $\log_{3/2}(10n \log n)$ independent random points in K (!) and test if they belong to $6nB_2^n$. If one of them does, we have a point to carry out the ellipsoid step. If all of them belong to $6nB_2^n$, then we shall conclude that at least $2/3$ of the volume is in $6nB_2^n$. Indeed, if not, the probability of not finding a point in $6nB_2^n \setminus K$ is less than $(2/3)^{\log_{3/2}(10n \log n)} \leq 1/(10n \log n)$. Generating points in K is quite expensive however, especially because the whole reason we are sandwiching is to make generating points easy.

If we use the sampling algorithm discussed in Theorem 4.43, we require $\mathcal{O}(n^4 m^2 \log n)$ membership test and $\mathcal{O}(n^5 m^2 \log n)$ arithmetic operations.

With a neat little trick however, we may in fact take $m = \mathcal{O}(n)$ here. Let $K' = K \cap 18nB_2^n$. If $\text{vol}(K \setminus 6nB_2^n) = \theta \text{vol}(K)$ ($\theta > 1/3$), then by Corollary 4.37, $\text{vol}(K \setminus 18nB_2^n) \leq \theta^2 \text{vol}(K)$. Therefore,

$$\begin{aligned} \text{vol}(K' \setminus 6nB_2^n) &= \text{vol}(K \cap 18nB_2^n) - \text{vol}(K \cap 6nB_2^n) \\ &\geq (1 - \theta^2) \text{vol}(K) - (1 - \theta) \text{vol}(K) \\ &= (\theta - \theta^2) \text{vol}(K) \\ &= \theta \text{vol}(K \cap 6nB_2^n) = \theta \text{vol}(K' \cap 6nB_2^n) \\ (1 + \theta) \text{vol}(K' \setminus 6nB_2^n) &\geq \theta \text{vol}(K') \\ \text{vol}(K' \setminus 6nB_2^n) &\geq \frac{\theta}{1 + \theta} \text{vol}(K') \geq \frac{1}{4} \text{vol}(K'). \end{aligned}$$

We need to generate $\mathcal{O}(n \log^2 n)$ random points overall, which makes the cost of this phase $\mathcal{O}(n^7 \log^3 n)$, which is at most a log factor more than that of the main part.

The reader might be wondering why we even introduced this alternate way to obtain a sandwiching; it does not seem to be any better than what we did earlier with the strong satisfaction of the second condition. In special cases however, this method turns out to be extremely powerful.

If K is a polytope with polynomially many (in n) facets, the two conditions can be attained with $m = \mathcal{O}(\sqrt{n} \log n)$. If K is a symmetric polytope with polynomially many facets, then we can in fact achieve $m = \mathcal{O}(\log n)$!

We mentioned in Section 4.6.2 that while it seems like we sacrifice precision and get a bad error probability δ , this is not really the case. This is due to a neat statistical trick from [JVV86] which claims that it suffices to solve the problem for $\delta = 1/3$. Fix some $\varepsilon > 0$ and suppose we have some algorithm that calculates a ζ such that $\zeta \in [(1 - \varepsilon) \text{vol}(K), (1 + \varepsilon) \text{vol}(K)]$ with probability at least $2/3$. Let $s = 10 \log(1/\delta)$ and repeat the algorithm $2s + 1$ times to obtain $\zeta_1, \zeta_2, \dots, \zeta_{2s+1}$. Arranging the (ζ_i) in increasing order, let $\zeta = \zeta_{s+1}$ (the median).

We claim that $\Pr[\zeta \in [(1 - \varepsilon) \text{vol}(K), (1 + \varepsilon) \text{vol}(K)]] \geq 1 - \delta$.

If ζ is not in the interval, at least $(s + 1)$ of the $(2s + 1)$ (ζ_i) are outside the interval. We can then use Chernoff's inequality, which yields that out of $2s + 1$ independent events, each having a probability at most $1/3$ of occurring, the probability that more than half occur is at most $e^{-s/10} \leq \delta$.

4.6.4. Bringing Everything Together and a Final Analysis

We have now built the various parts of the algorithm, and all that remains is to put the pieces together.

Let K be a convex body with $(2/3) \text{vol}(B_2^n) \leq \text{vol}(K \cap B_2^n)$ and $(2/3) \text{vol}(K) \leq \text{vol}(K \cap mB_2^n)$. We have described how to attain this (in a randomized manner) in Section 4.6.3.

Although we have described the primary algorithm in detail before, we restate it here because it is slightly different. Set $q = 4mn \log(1/\varepsilon)$, $k = 4n \log n$, and $t = 10^{11} n k q^2 \varepsilon^{-2}$.

For each i , define

$$F_i(x) = \min\{F(x), \exp(-\|x\| n^{1/2} 2^{-i/n})\}$$

where F is defined as in the beginning of Section 4.6.2.

Now, for each i , perform a lazy walk taking $3t$ steps in qB_2^n with B_2^n -steps, filtered by F_i . Let these steps be $v_{i,1}, \dots, v_{i,3t}$. The stationary distribution of this walk Q_{F_i} is such that $Q_{F_i}(A) = \mu_F(A)/\mu_F(qB_2^n)$. Here, the first t steps are to get close to the stationary distribution, the next t are what we use for the algorithm, and the last t are

to ensure independence from the next phase.

The i th walk begins where the $(i-1)$ th ends. For each i , compute

$$\Lambda_i = \frac{1}{t} \sum_{j=t+1}^{2t} \frac{F_{i-1}(v_{i,j})}{F_i(v_{i,j})}.$$

Note that

$$\Lambda_i \approx \int_{qB_2^n} \frac{F_{i-1}(x)}{F_i(x)} dQ_{F_i}(x) = \frac{\int_{qB_2^n} F_{i-1}(x) dx}{\int_{qB_2^n} F_i(x) dx} \approx \frac{\text{vol}(K_{i-1})}{\text{vol}(K_i)},$$

where $K_i = 2^{i/n} B_2^n \cap K$. Finally, we return our estimate of $\text{vol}(K)$ as

$$\widetilde{\text{vol}}(K) = (\Lambda_1 \Lambda_2 \cdots \Lambda_k)^{-1} \text{vol}(B_2^n).$$

Let us now analyze this beast.

Theorem 4.47. If K is a convex body such that $\text{vol}(K \cap B_2^n) \geq (2/3) \text{vol}(B_2^n)$ and $\text{vol}(K \cap mB_2^n) \geq (2/3) \text{vol}(K)$ and ζ is the estimate returned by the above algorithm, then

$$\Pr[(1-\varepsilon)\zeta \leq \text{vol}(K) \leq (1+\varepsilon)\zeta] \geq 3/4.$$

Further, the algorithm uses

$$\mathcal{O}\left(n^3 m^2 \varepsilon^{-2} (n + \log(1/\varepsilon))^2 (\log m + \log \log(1/\varepsilon))^2 \log^2(1/\varepsilon)\right)$$

membership oracle calls.

Corollary 4.48. Let K be a convex body given by a well-guaranteed membership oracle. Then it is possible to compute a ζ such that

$$\Pr[(1-\varepsilon)\zeta \leq \text{vol}(K) \leq (1+\varepsilon)\zeta] \geq 1-\delta$$

in

$$\mathcal{O}\left(n^7 \varepsilon^{-2} \log^2(n) \log^2(1/\varepsilon) \log(1/\delta)\right)$$

oracle calls. Further, if K is a polytope with polynomially many (in n) facets, we only require $\mathcal{O}(n^6 \varepsilon^{-2} \log^4(n) \log^2(1/\varepsilon) \log(1/\delta))$ oracle calls and if K is a centrally symmetric polytope with polynomially many facets, we only require $\mathcal{O}(n^5 \varepsilon^{-2} \log^4(n) \log^2(1/\varepsilon) \log(1/\delta))$ oracle calls.

The rest of this section is dedicated to proving the above, which we have already done most of the work for over the past 3 subsections. For each i , let $W_i = \int_{qB_2^n} F_i$. By Lemma 4.46,

$$\left(1 - \frac{\varepsilon}{4}\right) \text{vol}(K) \leq \frac{1}{n!} W_i \leq \text{vol}(K).$$

First, we claim that for any i ,

$$\frac{1}{2} \leq \frac{W_{i-1}}{W_i} \leq 1.$$

Indeed, the latter inequality is trivial and for the former,

$$\begin{aligned} W_i &= \int_{qB_2^n} F_i(x) dx \\ &\leq \int_{2^{i/n} qB_2^n} F_i(x) dx \\ &= \frac{1}{2} \int_{qB_2^n} F_i(2^{i/n} x) dx \\ &\leq \frac{1}{2} \int_{qB_2^n} F_{i-1}(x) dx = \frac{1}{2} W_{i-1}. \end{aligned}$$

We also see that W_0 is easily computed to be $n^{-n/2}n! \text{vol}(B_2^n)$.

What are the possible (probabilistic) sources of error in our algorithm?

1. The distribution of the point $v_{i,t+1}$ generated is not exactly $(1/W_i)Q_{F_i}$.
2. The points $v_{i,t+1}$ are not independent.
3. The sum used to estimate W_{i-1}/W_i has variance.

Let us look at each of these separately, starting with the first.

Let $P_{i,p}$ represent the distribution of $v_{i,p}$. As defined in Section 4.4, let $h_{i,p}$ be the distance function between $P_{i,p}$ and Q_{F_i} . Because Q_{F_i} is atom-free,

$$h_{i,p}(x) = \sup_{\substack{A \subseteq qB_2^n \\ Q_{F_i}(A)=x}} P_{i,p}(A) - x.$$

Also let $h_{0,p}(x) = 0$. Define $\Phi = \min_i \Phi_i$. By Lemma 4.46, $\Phi \geq 1/(20000q\sqrt{n})$. Also define

$$\eta = \left(1 - \frac{\Phi^2}{2}\right)^t \leq e^{-t\Phi^2/2}$$

Lemma 4.49. For every $0 \leq x \leq 1$,

$$h_{i,p}(x) \leq \begin{cases} 2\eta \min\{\sqrt{x}, \sqrt{1-x}\}, & \text{if } t \leq p \leq 3t, \\ 4 \min\{\sqrt{x}, \sqrt{1-x}\} & \text{otherwise.} \end{cases}$$

Proof. We prove this with induction on i . The claim is trivially true for $i = 0$. Let $i > 0$. Then for some $A \subseteq qB_2^n$ with $Q_{F_i}(A) = x$,

$$h_{i,0}(x) = P_{i,0}(A) - x.$$

Let $y = Q_{F_{i-1}}(A)$. Then

$$y = \frac{1}{W_{i-1}} \int_A F_{i-1}(u) du \leq \frac{2}{W_i} \int_A F_i(u) du = 2x.$$

Therefore, using the inductive hypothesis,

$$\begin{aligned} h_{i,0}(x) &= P_{i,0}(A) - x \\ &= P_{i-1,3t}(A) - x \\ &= (P_{i-1,3t}(A) - y) + (y - x) \\ &\leq h_{i-1,3t}(y) + \min\{x, 1-x\} && (y - x \leq x) \\ &\leq 2\eta \min\{\sqrt{y}, \sqrt{1-y}\} + \min\{\sqrt{x}, \sqrt{1-x}\} \\ &\leq (1 + 2\sqrt{2}\eta) \min\{\sqrt{x}, \sqrt{1-x}\} < (1 + 4\eta) \min\{\sqrt{x}, \sqrt{1-x}\}. \end{aligned}$$

We can then use Theorem 4.21 to conclude that for $p \geq t$,

$$\begin{aligned} h_{i,p}(x) &< (1 + 4\eta) \min\{\sqrt{x}, \sqrt{1-x}\} \left(1 - \frac{\Phi^2}{2}\right)^p \\ &\leq (\eta + 4\eta^2) \min\{\sqrt{x}, \sqrt{1-x}\} \leq 2\eta \min\{\sqrt{x}, \sqrt{1-x}\}. \end{aligned}$$

The case for $p < t$ follows similarly (with the last two inequalities above slightly modified). ■

The above lemma resolves the first of the issues by bounding how far the distribution of $v_{i,t+1}$ can get from the required.

Next, let us look at the second issue. Let $u = v_{i,a}$ and $w = v_{j,b}$ for some $i < j$ and $t < a, b \leq 2t$. Let $f(u) = F_{i-1}(u)/F_i(u)$ and $g(w) = F_{j-1}(w)/F_j(w)$. We wish to bound the correlation between the two random variables.

Lemma 4.50. Let f , g , u , and w be defined as above. Then

$$|\mathbf{E}[f(u)g(w)] - \mathbf{E}[f(u)]\mathbf{E}[g(w)]| \leq 4\eta.$$

Proof. Let us consider another random walk $\bar{v}_{i,a}, \dots, \bar{v}_{j,b}$ defined as follows. The transition probability from a \bar{v} to another is exactly the same as that for the v , but the distribution of the starting point $\bar{v}_{i,a}$ is slightly different. Set

$$c_f = \frac{1}{\int_{qB_2^n} f \, dP_{i,a}} = \frac{W_i}{W_{i-1}}.$$

Further, let

$$\bar{P}_{i,a}(A) = \Pr[\bar{v}_{i,a} \in A] = \frac{\int_A f \, dP_{i,a}}{\int_{qB_2^n} f \, dP_{i,a}} = c_f \int_A f \, dP_{i,a}.$$

Similarly, for each $i \leq k \leq j$ and $0 \leq r \leq 2t$, let $\bar{P}_{k,r}$ be the distribution of $\bar{v}_{k,r}$. Then

$$\begin{aligned} \mathbf{E}[f(u)g(w)] &= \int_{qB_2^n} \mathbf{E}[f(u)g(w) \mid u = x] \, dP_{i,a}(x) \\ &= \int_{qB_2^n} \mathbf{E}[g(w) \mid u = x] f(x) \, dP_{i,a}(x) \\ &= \int_{qB_2^n} \mathbf{E}[g(w) \mid u = x] \, d\bar{P}_{i,a}(x) \int_{qB_2^n} f(x) \, dP_{i,a}(x) \\ &= \mathbf{E}[g(\bar{v}_{j,b})] \mathbf{E}[f(u)]. \end{aligned}$$

Therefore,

$$\begin{aligned} |\mathbf{E}[f(u)g(w)] - \mathbf{E}[f(u)]\mathbf{E}[g(w)]| &= \mathbf{E}[f(u)] |\mathbf{E}[g(\bar{v}_{j,b}) - g(v_{j,b})]| \\ &= \mathbf{E}[f(u)] \left| \int_{qB_2^n} g(y) (\, d\bar{P}_{j,b} - dP_{j,b} \,) \right| \\ &\leq \sup_{A \in \mathcal{A}} |\bar{P}_{j,b}(A) - P_{j,b}(A)| \left(\frac{1}{2} \leq \mathbf{E}[f(u)] \leq 1 \text{ and Equation (4.15)} \right) \\ &\leq \sup_{A \in \mathcal{A}} |\bar{P}_{j,b}(A) - Q_{F_i}(A)| + |Q_{F_i}(A) - P_{j,b}(A)| \end{aligned}$$

By Lemma 4.49, the second quantity is at most 2η . For each $i \leq k \leq j$ and $0 \leq r \leq 2t$, let $\bar{h}_{k,r}$ be the distance between $\bar{P}_{k,r}$ and Q_{F_k} . To bound the first quantity, let $A \subseteq qB_2^n$ with $Q_{F_i}(A) = z$. Let $y = \int_A f \, dQ_{F_i} \leq z$. Then

$$\begin{aligned} \bar{P}_{i,a}(A) - Q_{F_i}(A) &= \int_A c_f f \, dP_{i,a} - z \\ &= \int_A c_f f (\, dP_{i,a} - dQ_{F_i} \,) + \int_A c_f f \, dQ_{F_i} - z \\ &\leq c_f h_{i,a}(y) + c_f y - z \\ &\leq 2h_{i,a}(y) + 2y - z. \end{aligned}$$

By Lemma 4.49 and because $1 \leq c_f \leq 2$,

$$\begin{aligned} \bar{h}_{i,a}(z) &\leq 4\eta \min\{\sqrt{y}, \sqrt{1-y}\} + 2y - z \\ &\leq 4\eta\sqrt{z} + z \leq 5\sqrt{z}. \end{aligned}$$

We also trivially have

$$\bar{h}_{i,a}(z) \leq 1 - z \leq 5\sqrt{1-z}.$$

Applying the proof of Lemma 4.49 to the alternate chain,

$$\bar{h}_{j,b}(z) \leq 2\eta \min\{\sqrt{z}, \sqrt{1-z}\} \leq 2\eta,$$

completing the proof. ■

The third issue has already been taken care of in Theorem 4.25.

For each i , let $1 + \beta_i = \Lambda_i / \mathbf{E}[\Lambda_i]$. We shall then show that

$$\Pr \left[1 - \frac{\varepsilon}{2} \leq \prod_{i=1}^k (1 + \beta_i) \leq 1 + \frac{\varepsilon}{2} \right] > \frac{3}{4}. \quad (4.24)$$

Obviously, $\mathbf{E}[\beta_i] = 0$ for any i . We split the proof into two cases.

1. $\sum_{i=1}^k \beta_i^2 > \varepsilon/8$. By Markov's inequality,

$$\Pr \left[\sum_{i=1}^k \beta_i^2 > \frac{\varepsilon}{8} \right] \leq \frac{\mathbf{E} \left[\sum_{i=1}^k \beta_i^2 \right]}{\varepsilon/8}.$$

Let $F = F_{i-1}/F_i$. Applying Theorem 4.25,

$$\mathbf{Var}[t\Lambda_i] \leq \frac{4t}{\Phi^2} \leq \frac{4t}{\Phi^2}.$$

Therefore,

$$\mathbf{E}[\beta_i^2] = \frac{\mathbf{Var}[\Lambda_i]}{\mathbf{E}[\Lambda_i]^2} \leq \frac{4t/\Phi^2}{1/4} \leq \frac{\varepsilon^2}{8k}$$

and

$$\Pr \left[\sum_{i=1}^k \beta_i^2 > \frac{\varepsilon}{8} \right] \leq \frac{1}{8}.$$

2. $\sum_{i=1}^k \beta_i^2 \leq \varepsilon/8$. We may assume that each $|\beta_i| \leq \frac{1}{2}$.
Suppose that $|\prod_i (1 + \beta_i) - 1| > \varepsilon/2$. Then,

$$\log \left(1 - \frac{\varepsilon}{2} \right) > \sum_i \log(1 + \beta_i) \text{ or } \sum_i \log(1 + \beta_i) > \log \left(1 + \frac{\varepsilon}{2} \right)$$

so

$$\left| \sum_{i=1}^k \log(1 + \beta_i) \right| > \frac{\varepsilon}{4}.$$

Then note that $|\log(1 + \beta_i) - \beta_i| < \beta_i^2$. Therefore,

$$\begin{aligned} \sum_i \beta_i^2 &> \sum_i |\log(1 + \beta_i) - \beta_i| \\ &\geq \sum_i |\log(1 + \beta_i)| - \sum_i |\beta_i| \\ &\geq \left| \sum_i \log(1 + \beta_i) \right| - \left| \sum_i \beta_i \right| \\ \left| \sum_i \beta_i \right| &> \left| \sum_i \log(1 + \beta_i) \right| - \sum_i \beta_i^2 \geq \frac{\varepsilon}{8}. \end{aligned}$$

The probability of this occurring can be computed using Chebyshev's inequality. We have

$$\begin{aligned}
\mathbf{Var} \left(\sum_i \beta_i \right) &= \mathbf{E} \left[\left(\sum_i \beta_i \right)^2 \right] \\
&= \sum_i \mathbf{E}[\beta_i^2] + 2 \sum_{1 \leq i < j \leq n} \mathbf{E}[\beta_i \beta_j] \\
&\leq \frac{\varepsilon^2}{8} + 2 \sum_{1 \leq i < j \leq n} \mathbf{E}[\beta_i \beta_j]. \\
\mathbf{E}[\beta_i \beta_j] &= \frac{\mathbf{E}[\Lambda_i \Lambda_j]}{\mathbf{E}[\Lambda_i] \mathbf{E}[\Lambda_j]} - 1.
\end{aligned}$$

Using Lemma 4.50,

$$\begin{aligned}
\mathbf{E}[\Lambda_i \Lambda_j] &= \frac{1}{t^2} \sum_{a=t+1}^{2t} \sum_{b=t+1}^{2t} \mathbf{E}[f(v_{i,a})g(v_{j,b})] \\
&\leq \frac{1}{t^2} \sum_{a=t+1}^{2t} \sum_{b=t+1}^{2t} \mathbf{E}[f(v_{i,a})] \mathbf{E}[g(v_{j,b})] + 4\eta \\
&= \mathbf{E}[\Lambda_i] \mathbf{E}[\Lambda_j] + 4\eta.
\end{aligned}$$

Because $\mathbf{E}[\Lambda_i] \geq \frac{1}{2}$, $\mathbf{E}[\beta_i \beta_j] \leq 16\eta < \varepsilon^2/8k^2$. Therefore,

$$\mathbf{Var} \left(\sum_i \beta_i \right) \leq \frac{\varepsilon^2}{4}.$$

Using Chebyshev's inequality,

$$\Pr \left[\left| \sum_i \beta_i \right| > \frac{\varepsilon}{8} \right] \leq \frac{64 \mathbf{Var} [\sum_i \beta_i]}{\varepsilon^2} \leq$$

This proves the required.

How large is the running time? We make kt “moves”, where each move constitutes

- An update of n coordinates.
- One test of membership in qB_2^n .
- The evaluation of $\phi(x)$.
- Some constant number of arithmetic operations.

We can evaluate $\phi(x)$ using binary search with error ε/n^2 in $\mathcal{O}(\log n + \log(1/\varepsilon))$ membership tests. Thus, the algorithm makes $\mathcal{O}(kt(\log n + \log(1/\varepsilon)))$ membership tests.

It is worth noting that we have assumed that we can compute membership in an affine image of K in a single step. This is indeed true for sensible encodings such as linear or algebraic inequalities, but it may become important if it takes n^2 or more operations.

§5. The KLS Conjecture

5.1. An Isoperimetric Problem

5.1.1. Introduction

In the context of ball-step, let us look at the mixing time of the chain for a general (not necessarily convex) body. As discussed, it suffices to look at the conductance of the chain, which relates to finding a “cut” of the body of relatively small surface area. For example, in a dumbbell, we could have a cut down the central bottleneck, which would result in a very low conductance.

What about convex bodies? It is seen that hyperplanes are not bad (this is made precise in Theorem 5.10). A natural next question is: could we have some convoluted cut that ends up being a bottleneck? In [KLS95], Kannan, Lovász, and Simonovits conjectured that this in fact cannot happen. In particular, they claim that up to a constant factor, hyperplane cuts are in fact the “worst” cuts.

We first formalize this notion of a cut to get an expression similar to that of conductance, discuss some localization lemmata similar to those discussed earlier (to reduce n -dimensional integrals to 1-dimensional integrals), prove an improvement of Theorem 4.34 in Theorems 5.7 and 5.9, and finish off with the statement of the conjecture.

Suppose we have a convex body K and we want to find a surface that divides K into two parts, whose measure is minimum relative to that of the two parts.

Definition 5.1. The *isoperimetric coefficient* of a convex body $K \subseteq \mathbb{R}^n$ is defined as the largest number $\psi = \psi(K)$ such that for any measurable $S \subseteq K$,

$$\psi = \inf_{S \subseteq K} \frac{\text{vol}_{n-1}(\partial S)}{\min\{\text{vol}(S), \text{vol}(K \setminus S)\}}$$

More generally, for any log-concave density p on \mathbb{R}^n (instead of $\mathbb{1}_K$ taken above), we can define ψ_p , the isoperimetric constant for p , as

$$\psi_p = \inf_{S \subseteq \mathbb{R}^n} \frac{p(\partial S)}{\min\{p(S), p(\mathbb{R}^n \setminus S)\}}.$$

In some texts, the above definition is replaced with

$$\psi_p = \inf_{S \subseteq \mathbb{R}^n} \frac{p(\partial S)}{p(S)p(\mathbb{R}^n \setminus S)}.$$

Since both definitions are within a factor of 2 of each other, this does not make much difference in our estimations.

This problem turns out to be very intimately related to that of volume computation we explored in the previous section.

[LS90] bounds the isoperimetric coefficient below by $1/d$, where d is the diameter of the body. Note that this is quite obvious if the separating surface ∂S is a (section of a) hyperplane.

[AK91] gives a more general result where the measure is replaced by that with density equal to any log-concave function and bounds it below by $2/d$. This is in fact as tight as we can get in terms of the diameter and indeed, the bound is attained for a thin long cylinder.

However, the bodies we are interested in (in say, volume computation) tend to have a certain structure to them. In particular, sandwiching makes the bodies somewhat round.

The main result of this section is that for every convex body K ,

$$\psi(K) \geq \frac{\ln 2}{M_1(K)},$$

where $M_1(K)$ is the average distance of a point in K from the center of gravity of K .

5.1.2. Needles and Localization Lemmas

To begin, consider the following motivated by Theorem 4.31.

Definition 5.2. A *needle* is a segment $[a, b] \in \mathbb{R}^n$ together with a non-negative linear function $\ell : I \rightarrow \mathbb{R}^{\geq 0}$ not identically 0. If $N = (I, \ell)$ is a needle and f is an integrable function defined on I , denote

$$\int_N f = \int_0^{|b-a|} f(a+tu)\ell(a+tu)^{n-1} dt,$$

where $u = (b-a)/|b-a|$.

Lemma 5.1. Let f_1, f_2, f_3, f_4 be non-negative continuous functions defined on \mathbb{R}^n and $\alpha, \beta > 0$. The following are equivalent.

- For every convex body K in \mathbb{R}^n ,

$$\left(\int_K f_1\right)^\alpha \left(\int_K f_2\right)^\beta \leq \left(\int_K f_3\right)^\alpha \left(\int_K f_4\right)^\beta.$$

- For every needle N in \mathbb{R}^n ,

$$\left(\int_N f_1\right)^\alpha \left(\int_N f_2\right)^\beta \leq \left(\int_N f_3\right)^\alpha \left(\int_N f_4\right)^\beta.$$

Proof. The first implying the second is quite easy to show. For the converse, suppose that the second holds but the first does not.

Adding a sufficiently small quantity to f_3 and f_4 , we may further assume that they are (strictly) positive. We may also assume that f_1 and f_2 are positive (Why?). Choose some A such that

$$\frac{(\int_K f_1)^\alpha}{(\int_K f_3)^\alpha} > A > \frac{(\int_K f_4)^\beta}{(\int_K f_2)^\beta}.$$

Then,

$$\int_K f_1 - A^{1/\alpha} f_3 > 0 \text{ and } \int_K A^{1/\beta} f_2 - f_4 > 0.$$

Using Theorem 4.31, there is some needle N such that

$$\int_N f_1 - A^{1/\alpha} f_3 > 0 \text{ and } \int_N A^{1/\beta} f_2 - f_4 > 0.$$

This implies that

$$\frac{(\int_N f_1)^\alpha}{(\int_N f_3)^\alpha} > A > \frac{(\int_N f_4)^\beta}{(\int_N f_2)^\beta},$$

thus proving the claim. ■

Observe that we can extend this more generally to the case where f_1 and f_2 are upper semicontinuous and f_3 and f_4 are lower semicontinuous by considering an appropriate sequence of continuous functions. In particular, this allows us to restrict ourselves from \mathbb{R}^n to some subset T of \mathbb{R}^n by multiplying the functions with the indicator function $\mathbb{1}_T$ (the functions extend to upper semicontinuous functions if T is closed and lower semicontinuous functions if T is open).

Corollary 5.2. Let T be a bounded open convex set in \mathbb{R}^n , g a bounded lower semicontinuous function on T , and h a continuous function on T such that

$$\int_T g > 0 \text{ and } \int_T h = 0.$$

Then there is a needle $N = (I, \ell)$ with $I \subseteq T$ such that

$$\int_N g > 0 \text{ and } \int_N h = 0.$$

Proof. Choose some $0 < \delta < \int_T g$ and let $\varepsilon > 0$. Then,

$$\int_T \left(g - \delta + \frac{1}{\varepsilon} h \right) > 0 \text{ and } \int_T (\varepsilon^2 - h) > 0.$$

Extending these functions to functions on \mathbb{R}^n (multiplying with the indicator function) and using Theorem 4.31, we get a needle $N_\varepsilon = (I_\varepsilon, \ell_\varepsilon)$ with $I_\varepsilon \subseteq T$ (Why?) such that

$$\int_{N_\varepsilon} \left(g - \delta + \frac{1}{\varepsilon} h \right) > 0 \text{ and } \int_{N_\varepsilon} (\varepsilon^2 - h) > 0. \quad (5.1)$$

Observe that $\int_{N_\varepsilon} (g - \delta + \varepsilon) > 0$.

Taking M as the supremum of g on \mathbb{R}^n ,

$$-M\varepsilon \int_{N_\varepsilon} 1 < \int_{N_\varepsilon} h < \varepsilon^2 \int_{N_\varepsilon} 1. \quad (5.2)$$

Consider these needles for $\varepsilon = 1/k$ ($k \in \mathbb{N}$). Scaling appropriately, we may assume that the maximum of each linear function $\ell_{1/k}$ is 1. Using the Bolzano-Weierstrass Theorem, there is some subsequence of these needles that converges (in the sense that the endpoints of the $I_{1/k}$ and the $\ell_{1/k}$ converge)³⁹ to some needle $N = (I, \ell)$. Combining Equations (5.1) and (5.2) implies that N satisfies the required (we get $\int_N (g - \delta) \geq 0$ and $\int_N h = 0$). ■

While these results are quite nice, exponents of a linear function are not very convenient to deal with. This motivates the following.

5.1.3. Exponential Needles

Definition 5.3. An *exponential needle* is a segment $[a, b] \in \mathbb{R}^n$ together with a real γ . If $E = (I, \gamma)$ is a needle and f is an integrable function defined on I , denote

$$\int_E f = \int_0^{|b-a|} f(a + tu) e^{\gamma t} dt,$$

where $u = (b - a) / \|b - a\|$.

If we manage to prove our results for an exponential needle instead, it is extremely convenient because taking exponents does not change the underlying structure of the function itself.

Lemma 5.3. Let f_1, f_2, f_3 , and f_4 be four non-negative continuous functions defined on an interval $[a, b]$ in \mathbb{R} and $\alpha, \beta > 0$. Then the following are equivalent.

- For every log-concave function F defined on \mathbb{R} ,

$$\left(\int_a^b F(t) f_1(t) dt \right)^\alpha \left(\int_a^b F(t) f_2(t) dt \right)^\beta \leq \left(\int_a^b F(t) f_3(t) dt \right)^\alpha \left(\int_a^b F(t) f_4(t) dt \right)^\beta.$$

- For every subinterval $[a', b'] \subseteq [a, b]$ and real γ ,

$$\left(\int_{a'}^{b'} e^{\gamma t} f_1(t) dt \right)^\alpha \left(\int_{a'}^{b'} e^{\gamma t} f_2(t) dt \right)^\beta \leq \left(\int_{a'}^{b'} e^{\gamma t} f_3(t) dt \right)^\alpha \left(\int_{a'}^{b'} e^{\gamma t} f_4(t) dt \right)^\beta.$$

Proof. The first implying the second is obvious (on setting $F = \mathbb{1}_{[a', b']} e^{\gamma t}$).

Note that if for some $t_0 \in [a, b]$, $f_1(t_0)^\alpha f_2(t_0)^\beta > f_3(t_0)^\alpha f_4(t_0)^\beta$, then both the assertions above fail since we can consider

³⁹We can think of an needle $N = ([a, b], \ell)$ as an element $(a, b, \ell(a), \ell(b) - \ell(a)) \in \mathbb{R}^{2n+2}$. In our case, this sequence is bounded because each interval is in the bounded set T and each ℓ is between 0 and 1.

- the log-concave function $e^{-c(t-t_0)^2}$ for a sufficiently large c , or
- a sufficiently small interval containing t_0 .

Therefore, we may assume that for all $t \in [a, b]$,

$$f_1(t)^\alpha f_2(t)^\beta \leq f_3(t)^\alpha f_4(t)^\beta. \quad (*)$$

Suppose the second holds and the first does not for some log-concave function F .

We may assume that $F \neq 0$ (so $F > 0$) on $[a, b]$. Otherwise, we can replace it with its convolution with e^{-ct^2} for a sufficiently large c , which is still log-concave by Lemma 4.27 and would still satisfy the inequality (Why?). We may also assume that $F \geq 1$ on $[a, b]$ by scaling up appropriately. Let $F = e^G$, where G is a non-negative concave function on $[a, b]$.

For each n , define $K_n \subseteq \mathbb{R}^{n+1}$ by

$$K_n = \left\{ (t, x) : t \in [a, b], x \in \mathbb{R}^n, \|x\| \leq 1 + \frac{G(t)}{n} \right\}.$$

Let $\hat{f}_i : \mathbb{R}^{n+1} \rightarrow \mathbb{R}$ by defined by $\hat{f}_i(t, x) = f_i(t)$.

For sufficiently large n , we have $(1 + G(t)/n)^n \approx e^{G(t)} = F(t)$, so we can write

$$\left(\int_{K_n} \hat{f}_1(t) dt \right)^\alpha \left(\int_{K_n} \hat{f}_2(t) dt \right)^\beta > \left(\int_{K_n} \hat{f}_3(t) dt \right)^\alpha \left(\int_{K_n} \hat{f}_4(t) dt \right)^\beta.$$

Using Lemma 5.1, there exists a needle N_n such that

$$\left(\int_{N_n} \hat{f}_1(t) dt \right)^\alpha \left(\int_{N_n} \hat{f}_2(t) dt \right)^\beta > \left(\int_{N_n} \hat{f}_3(t) dt \right)^\alpha \left(\int_{N_n} \hat{f}_4(t) dt \right)^\beta.$$

If N_n is orthogonal to the t -axis, then $(*)$ immediately breaks so we arrive at a contradiction. Otherwise, we may project the needle onto the t -axis to get some $[a_n, b_n] \subseteq [a, b]$ and a linear function ℓ_n such that

$$\left(\int_{a_n}^{b_n} \ell_n(t)^n \hat{f}_1(t) dt \right)^\alpha \left(\int_{a_n}^{b_n} \ell_n(t)^n \hat{f}_2(t) dt \right)^\beta > \left(\int_{a_n}^{b_n} \ell_n(t)^n \hat{f}_3(t) dt \right)^\alpha \left(\int_{a_n}^{b_n} \ell_n(t)^n \hat{f}_4(t) dt \right)^\beta. \quad (5.3)$$

By the Bolzano-Weierstrass Theorem, there is a subsequence such that a_{n_k}, b_{n_k} converge, to say a_0 and b_0 . By $(*)$, $a_0 < b_0$. Suppose that $\ell_n(a_0) < \ell_n(b_0)$ for infinitely many indices – if not, then exchange a_0 and b_0 in the following argument. Now, let each ℓ_n be normalized such that $\ell_n(b_0) = 1$. Let $\gamma_n = \ell_n(a_0)$ for each n .

For some subsequence, let $\gamma_n \rightarrow \gamma$ and $n(1 - \gamma_n) \rightarrow \gamma'$, where $0 \leq \gamma \leq 1$ and $0 \leq \gamma' \leq \infty$. Henceforth, we restrict ourselves to this subsequence.

- If $\gamma \neq 1$, $\ell_n(t)^n \rightarrow 0$ for all $a_0 \leq t < b_0$. Dividing Equation (5.3) by $\left(\int_{a_n}^{b_n} \ell_n(t)^n dt \right)^{\alpha+\beta}$ and letting $n \rightarrow \infty$, we get

$$f_1(b_0)^\alpha f_2(b_0)^\beta \geq f_3(b_0)^\alpha f_4(b_0)^\beta.$$

If instead of f_3 and f_4 everywhere in the proof above, we instead take $f_3 + \varepsilon$ and $f_4 + \varepsilon$ for a sufficiently small ε , we get a strict inequality above and arrive at a contradiction to $(*)$.

- Therefore, $\gamma = 1$. We then have

$$\ell_n(t)^n = \left((1 - (1 - \ell_n(t)))^{1/(1 - \ell_n(t))} \right)^{n(1 - \ell_n(t))}.$$

The inner expression goes to $1/e$. If $\gamma' = \infty$, then we again get $\ell_n(t)^n \rightarrow 0$ for $t < b_0$, so we arrive at a contradiction similar to the first case above. Otherwise, we have

$$\ell_n(t) \rightarrow e^{\gamma'(t-b_0)/(b_0-a_0)}.$$

Letting $\gamma'' = \gamma'/(b_0 - a_0)$ and letting $n \rightarrow \infty$, we get

$$\left(\int_{a_0}^{b_0} e^{\gamma''(t-b_0)} f_1(t) dt \right)^\alpha \left(\int_{a_0}^{b_0} e^{\gamma''(t-b_0)} f_2(t) dt \right)^\beta > \left(\int_{a_0}^{b_0} e^{\gamma''(t-b_0)} f_3(t) dt \right)^\alpha \left(\int_{a_0}^{b_0} e^{\gamma''(t-b_0)} f_4(t) dt \right)^\beta.$$

However, this (after multiplying by $e^{\gamma''b_0(\alpha+\beta)}$ on either side to remove the b_0 in the exponent) contradicts the original assumption that the opposite inequality holds for any exponential needle, thus completing the proof. \blacksquare

The next result is essentially a generalized version of the above lemma, so is relatively straight-forward to prove since we have various tools for localization in our repertoire at this point.

Theorem 5.4. Let f_1, f_2, f_3 , and f_4 be non-negative functions on \mathbb{R}^n and $\alpha, \beta > 0$. The following are equivalent.

- For every log-concave function F on \mathbb{R}^n with compact support,

$$\left(\int_{\mathbb{R}^n} F(t) f_1(t) dt \right)^\alpha \left(\int_{\mathbb{R}^n} F(t) f_2(t) dt \right)^\beta \leq \left(\int_{\mathbb{R}^n} F(t) f_3(t) dt \right)^\alpha \left(\int_{\mathbb{R}^n} F(t) f_4(t) dt \right)^\beta.$$

- For every exponential needle E in \mathbb{R}^n ,

$$\left(\int_E f_1 \right)^\alpha \left(\int_E f_2 \right)^\beta \leq \left(\int_E f_3 \right)^\alpha \left(\int_E f_4 \right)^\beta.$$

Proof. Going from the first to the second isn't too difficult. Given the exponential needle over $[a, b]$ and constant γ , consider the function F defined by $t \mapsto e^{\gamma \langle t, u \rangle}$, where $u = (b - a) / \|b - a\|$ restricted to some ε -neighbourhood of $[a, b]$. Letting $\varepsilon \rightarrow 0$, we get the required.

On the other hand, let the second hold but not the first for some function F . Then applying Lemma 5.1 on the $F f_i$, we get some $[a, b]$ and linear function ℓ on $[a, b]$ such that

$$\begin{aligned} & \left(\int_0^{\|b-a\|} f_1(a+tu) F(a+tu) \ell(a+tu)^{n-1} dt \right)^\alpha \left(\int_0^{\|b-a\|} f_2(a+tu) F(a+tu) \ell(a+tu)^{n-1} dt \right)^\beta \\ & > \left(\int_0^{\|b-a\|} f_3(a+tu) F(a+tu) \ell(a+tu)^{n-1} dt \right)^\alpha \left(\int_0^{\|b-a\|} f_4(a+tu) F(a+tu) \ell(a+tu)^{n-1} dt \right)^\beta, \end{aligned}$$

where u has the usual meaning of $(b - a) / \|b - a\|$.

However, $F \ell^{n-1}$ is log-concave, so by Lemma 5.3, there exists an exponential needle that violates the assumption. \blacksquare

5.1.4. An Example Using the Equivalences

Let K be a convex body and $f : K \rightarrow \mathbb{R}$ be integrable. Define its L_p norm by

$$\|f\|_p = \left(\frac{1}{\text{vol } K} \int_K |f(x)|^p dx \right)^{1/p}.$$

It is easy to see that if $0 < p < q$, $\|f\|_p \leq \|f\|_q$.

Theorem 5.5. Let $0 < p < q$. There exists a constant $c_{p,q}$ such that for any dimension n , convex body $K \subseteq \mathbb{R}^n$ and linear function $f : K \rightarrow \mathbb{R}$,

$$\|f\|_q \leq c_{p,q} \|f\|_p$$

Proof. We wish to show that for any K ,

$$\left(\int_K |f|^q \right)^{1/q} \left(\int_K 1 \right)^{1/p} \leq c_{p,q} \left(\int_K 1 \right)^{1/q} \left(\int_K |f|^p \right)^{1/p}.$$

Equivalently, we wish to show that for any exponential needle E ,

$$\left(\int_E |f|^q \right)^{1/q} \left(\int_E 1 \right)^{1/p} \leq c_{p,q} \left(\int_E 1 \right)^{1/q} \left(\int_E |f|^p \right)^{1/p}.$$

That is, we wish to show that for any linear function f , $a, b \in \mathbb{R}$, and real γ ,

$$\left(\frac{\int_a^b e^{\gamma t} |f(t)|^q dt}{\int_a^b e^{\gamma t} dt} \right)^{1/q} \leq c_{p,q} \left(\frac{\int_a^b e^{\gamma t} |f(t)|^p dt}{\int_a^b e^{\gamma t} dt} \right)^{1/p},$$

Since f is linear, we may assume without loss of generality that $f(a + tu) = t$ on $[a, b]$ and that $\gamma = 1$; for the general case where $\gamma \neq 0$, we can just substitute appropriately. The cases where $\gamma = 0$ or f is constant on $[a, b]$ are easily shown.

$$\varphi(a, b) = \left(\frac{\int_a^b e^t |f(t)|^q dt}{\int_a^b e^t dt} \right)^{1/q} \left(\frac{\int_a^b e^t |f(t)|^p dt}{\int_a^b e^t dt} \right)^{-1/p}.$$

We wish to show that $c_{p,q} = \sup_{a < b} \varphi(a, b)$ is finite. Note that φ is continuous for $a < b$. Further, for any α , $\varphi(a, b) \rightarrow 1$ as $a, b \rightarrow \alpha$. That is, we may extend the function continuously to $a \leq b$ defining $\varphi(a, a) = 1$.

Now, observe that for fixed a , as $b \rightarrow \infty$, $\varphi(a, b) \rightarrow 1$.⁴⁰ On the other hand, for fixed b and $a \rightarrow \infty$, $\varphi(a, b)$ remains bounded. The continuity implies that φ is bounded (and its supremum is finite). ■

The actual calculation of the supremum above is quite tedious, however.

5.1.5. Isotropy

The content of this section is closely related to that of volume computation, primarily Section 4.6.3, which discussed sandwiching.

Given a convex body $K \subseteq \mathbb{R}^n$ and $f : K \rightarrow \mathbb{R}^m$, denote by $\mathbf{E}_K(f)$ the “average of f over K ”. That is,

$$\mathbf{E}_K(f) = \frac{1}{\text{vol}(K)} \int_K f(x) dx.$$

Denote by $b(K) = \mathbf{E}_K(x)$ the center of gravity of K , also known as the “baricenter” of K . If K is clear from context, we often denote it as just b . Denote by $A(K)$ the $n \times n$ matrix of inertia

$$A(K) = \mathbf{E}_K((x - b)(x - b)^\top).$$

Denote by $M_p(K)$ the p th moment of K

$$M_p(K) = \mathbf{E}_K(\|x - b\|^p).$$

It is seen that $M_2(K)$ is the trace of $A(K)$. Further, the average squared distance between points in K is

$$\frac{1}{\text{vol}(K)^2} \int_K \int_K \|x - y\|^2 dx dy = 2M_2(K).$$

It is seen that as $p \rightarrow \infty$, $M_p(K)^{1/p}$ converges to $\sup_{x \in K} \|x - b\|$.

⁴⁰ $\int_a^b e^t |f(t)|^p dt$ grows as $e^{-b} b^p$ and $\int_a^b e^t dt$ grows as e^b .

Definition 5.4 (Isotropic). A body K is said to be in *isotropic position* if $b = 0$ and $A(K) = I$, the identity matrix.⁴¹ Similarly, a function $f : \mathbb{R}^n \rightarrow [0, \infty)$ is said to be *isotropic* if its covariance matrix is the identity matrix.

Observe that a convex body is in isotropic position iff its indicator function is isotropic.

It may be shown the affine family of a convex body (the set of its image under affine transformations) has a unique body in isotropic position.

First, let us show how isotropic position is related to sandwiching.

Theorem 5.6. If K is in isotropic position, then

$$\sqrt{\frac{n+2}{n}} B_2^n \subseteq K \subseteq \sqrt{n(n+2)} B_2^n.$$

Observe that these inequalities are tight for the regular simplex and also imply the second part of Theorem 1.5. If K is in isotropic position, then for any unit u ,

$$\int_K \langle u, x \rangle^2 dx = \text{vol}(K).$$

Proof.

- Suppose that $\sqrt{(n+2)/n} B_2^n \not\subseteq K$. Choosing our basis appropriately, we may assume that K is contained in the half-space $x_1 > -\sqrt{(n+2)/n}$. Now, we have

$$\int_K x_1 = 0 \text{ and } \int_K (x_1^2 - 1) = 0.$$

Using Corollary 5.2 (or rather, an extension of it with a weak inequality on $\int g$), we get some needle $N = ([a, b], \ell)$. We may assume that $[a, b]$ is contained in the x_1 axis. so that

$$\int_a^b x_1 \ell(x_1)^{n-1} = 0 \text{ and } \int_a^b x_1^2 \ell(x_1)^{n-1} \geq \int_a^b \ell(x_1)^{n-1}.$$

We have $a > -\sqrt{\frac{n+2}{n}}$. It is easy to see⁴² that we may assume that ℓ is decreasing, and thus may suppose that is of the form $t - x$ for some $\lambda \geq b$. We can then manually (and tediously) compute the integrals to arrive at a contradiction.

- Let v be the point in K furthest from 0 (assume that K is closed so this is well-defined). We wish to show that $\|v\| \leq \sqrt{n(n+2)}$. Let $v^\circ = v / \|v\|$ and for each unit u , let $\varphi(u) = \sup\{t \geq 0 : v + tu \in K\}$. Then,

$$\text{vol}(K) = \int_{\partial B_2^n} \int_0^{\varphi(u)} t^{n-1} dt du = \int_{\partial B_2^n} \frac{\varphi(u)^n}{n} du.$$

⁴¹Some texts use $\text{vol}(K) = 1$ and $A(K) = \lambda_K I$ for some constant λ_K . It remains an open problem as to whether the value of λ_K across convex bodies $K \subseteq \mathbb{R}^n$ is bounded above.

⁴²If $|b| > |a|$, then the first equality implies that ℓ cannot be increasing. Otherwise, we can use the second inequality to justify the assumption.

We also have

$$\begin{aligned}
1 &= \frac{1}{\text{vol}(K)} \int_K \langle v^\circ, x \rangle^2 dx \\
&= \frac{1}{\text{vol}(K)} \int_{\partial B_2^n} \int_0^{\varphi(u)} t^{n-1} \langle v^\circ, v + tu \rangle^2 dt du \\
&= \frac{1}{\text{vol}(K)} \int_{\partial B_2^n} \left(\frac{\varphi(u)^n}{n} \|v\|^2 + 2 \frac{\varphi(u)^{n+1}}{n+1} \langle v^\circ, u \rangle + \frac{\varphi(u)^{n+2}}{n+2} \langle v^\circ, u \rangle^2 \right) du \\
&= \frac{1}{\text{vol}(K)} \int_{\partial B_2^n} \left(\frac{\varphi(u)^n}{n} \left(\frac{\sqrt{n(n+2)}}{n+1} \|v\| + \sqrt{\frac{n}{n+2}} \varphi(u) \langle v^\circ, u \rangle \right)^2 + \frac{\varphi(u)^n}{n(n+1)^2} \|v\|^2 \right) du \\
&= \frac{1}{\text{vol}(K)} \left(\int_{\partial B_2^n} \frac{\varphi(u)^n}{n} \left(\frac{\sqrt{n(n+2)}}{n+1} \|v\| + \sqrt{\frac{n}{n+2}} \varphi(u) \langle v^\circ, u \rangle \right)^2 du \right) + \frac{\|v\|^2}{(n+1)^2}
\end{aligned}$$

Note that this gives a bound of $\|v\| \leq n+1$. To get the bound mentioned in the theorem, it remains to bound the integral by a suitable positive quantity. Now, we have

$$\begin{aligned}
0 = b(K) &= \frac{1}{\text{vol}(K)} \int_{\partial B_2^n} \int_0^{\varphi(u)} t^{n-1} (v + tu) dt du \\
&= \frac{1}{\text{vol}(K)} \int_{\partial B_2^n} \frac{\varphi(u)^n}{n} v + \frac{\varphi(u)^{n+1}}{n+1} u du \\
&= v + \frac{1}{\text{vol}(K)} \int_{\partial B_2^n} \frac{\varphi(u)^{n+1}}{n+1} u du.
\end{aligned}$$

Therefore,

$$\begin{aligned}
\frac{1}{\text{vol}(K)} \int_{\partial B_2^n} \frac{\varphi(u)^n}{n} \left(\frac{\sqrt{n(n+2)}}{n+1} \|v\| + \sqrt{\frac{n}{n+2}} \varphi(u) \langle v^\circ, u \rangle \right) du \\
= \left(\frac{\sqrt{n(n+2)}}{n+1} - \frac{n+1}{\sqrt{n(n+2)}} \right) \|v\| = -\frac{1}{(n+1)\sqrt{n(n+2)}} \|v\|.
\end{aligned}$$

We can then use the Cauchy-Schwarz inequality to get

$$\left(\frac{1}{\text{vol}(K)} \int_{\partial B_2^n} \frac{\varphi(u)^n}{n} \left(\frac{\sqrt{n(n+2)}}{n+1} \|v\| + \sqrt{\frac{n}{n+2}} \varphi(u) \langle v^\circ, u \rangle \right)^2 du \right) \cdot 1 \geq \frac{1}{(n+1)^2 n(n+2)} \|v\|^2.$$

That is,

$$1 \geq \left(\frac{1}{(n+1)^2 n(n+2)} + \frac{1}{(n+1)^2} \right) \|v\|^2 = \frac{\|v\|^2}{n(n+2)},$$

proving the result. ■

5.1.6. The KLS Conjecture

Let us now move on to the main result of this section.

Theorem 5.7. For any convex body K ,

$$\psi(K) \geq \frac{\ln 2}{M_1(K)}.$$

In Definition 5.1, let K_3 be the intersection of K with the open $\varepsilon/2$ -neighbourhood of ∂S . Further, let $K_1 = S \setminus K_3$ and $K_2 = (K \setminus S) \setminus K_3$. Then, it suffices to prove the following, which is yet another improvement of Theorems 4.15 and 4.34.

Theorem 5.8. Let K be a convex body and $K = K_1 \cup K_2 \cup K_3$ a decomposition of K into three measurable sets such that $d(K_1, K_2) = \varepsilon > 0$. Then

$$\text{vol}(K_1) \text{vol}(K_2) \leq \frac{M_1(K)}{\varepsilon \ln 2} \text{vol}(K) \text{vol}(K_3).$$

Proof. We may assume that K_1 and K_2 are closed. Assume that $b(K) = 0$. Let f_1, f_2 , and f_3 be the indicator functions on K_1, K_2 , and K_3 respectively and $f_4(x) = \|x\| / \varepsilon \ln 2$. We then wish to show that

$$\int_K f_1 \int_K f_2 \leq \int_K f_3 \int_K f_4.$$

By Lemma 5.3, it suffices to show that for any exponential needle E ,

$$\int_E f_1 \int_E f_2 \leq \int_E f_3 \int_E f_4.$$

Let E be an arbitrary exponential defined by $[a, b]$ and γ . As before, we may assume that $\gamma = 1$ by rescaling appropriately. The case $\gamma = 0$ is taken care of by going to the appropriate limits.

First of all, we may assume that $0 \in [a, b]$. Indeed, otherwise, we can move the body such that 0 goes to the point on $[a, b]$ closest to it initially. Then the integral of f_4 decreases while the others remain the same, so proving it for this case suffices.

So let us restate the problem in the one-dimensional case that we have reduced it to. Let $[a, b]$ be an interval, $u \in [a, b]$ and $[a, b] = J_1 \cup J_2 \cup J_3$ be a decomposition of $[a, b]$ into three measurable sets, where $d(J_1, J_2) \geq \varepsilon > 0$. We wish to show that

$$\int_{J_1} e^t dt \int_{J_2} e^t dt \leq \int_{J_3} e^t dt \int_a^b \frac{|t - u|}{\varepsilon \ln 2} e^t dt.$$

Here, each J_i corresponds to the intersection of K_i with the interval and u corresponds to the position of 0 in $[a, b]$. Let us first prove the result for the case where J_3 is a single interval. Let $a \leq s < s + \varepsilon \leq b$ (Why does it suffice to prove it for the case where the interval is of length ε ?). Then we claim that

$$\int_a^s e^t dt \int_{s+\varepsilon}^b e^t dt \leq \int_s^{s+\varepsilon} e^t dt \int_a^b \frac{|t - u|}{\varepsilon \ln 2} e^t dt.$$

Equivalently,

$$\int_a^s e^t dt \int_\varepsilon^{b-s} e^t dt \leq \int_0^\varepsilon e^t dt \int_a^b \frac{|t - u|}{\varepsilon \ln 2} e^t dt.$$

Now, note that the expression on the left is maximized when $s = (a + b - \varepsilon)/2$ and that on the right is minimized when $u = \ln((e^a + e^b)/2)$. Substituting these values on each side and simplifying, it suffices to show that

$$(e^{(b-a)/2} - e^{\varepsilon/2})^2 \leq \frac{1}{\ln 2} \frac{e^\varepsilon - 1}{\varepsilon} \left(-\ln \left(\frac{e^{a-b} - 1}{2} \right) e^{b-a} + \ln \left(\frac{e^{b-a} - 1}{2} \right) \right).$$

On decreasing ε , the left increases whereas the right decreases. Therefore, it suffices to prove the above in the limit case where $\varepsilon = 0$. Letting $z = e^{(b-a)/2} \geq 1$, we want to prove that

$$\ln 2(z - 1)^2 + z^2 \ln \left(\frac{z^{-2} - 1}{2} \right) - \ln \left(\frac{z^2 - 1}{2} \right) \leq 0.$$

This is a computational task and is not too difficult.⁴³

For the general case, let $[c_i, d_i]$ be maximal intervals in J_3 for $1 \leq i \leq k$. They are each of length at least ε . Then we get

$$\sum_{i=1}^k \int_a^{c_i} e^t dt \int_{d_i}^b e^t dt \leq \int_{J_3} dt \int_a^b \frac{|t-u|}{\varepsilon \ln 2} e^t dt.$$

We then have

$$\sum_{i=1}^k \int_a^{c_i} e^t dt \int_{d_i}^b e^t dt \geq \int_{J_1} e^t dt \int_{J_2} e^t dt,$$

completing the proof. ■

Let K be an arbitrary convex body and for each $x \in K$, let $\chi_K(x)$ denote the longest segment in K that has midpoint x . Let

$$\chi(K) = \frac{1}{\text{vol}(K)} \int_K \chi_K(x) dx.$$

Note that $\chi(K) = \text{diam}(K \cap (2x - K))$.

Theorem 5.9. For any convex body K ,

$$\psi(K) \geq \frac{1}{\chi(K)}.$$

Proof. As before, it is equivalent to show that for any decomposition $K = K_1 \cup K_2 \cup K_3$, where $d(K_1, K_2) = \varepsilon > 0$,

$$\text{vol}(K_1) \text{vol}(K_2) \leq \frac{1}{\varepsilon} \text{vol}(K_3) \int_K \chi_K(x) dx.$$

The proof of this is very similar to the that of the previous theorem. It suffices to show that for any interval $[a, b]$ and any decomposition $[a, b] = J_1 \cup J_2 \cup J_3$ into three measurable sets such that $d(J_1, J_2) \geq \varepsilon$,

$$\int_{J_1} e^t dt \int_{J_2} e^t dt \leq \frac{1}{\varepsilon} \int_{J_3} e^t dt \int_a^b \min\{t-a, b-t\} e^t dt.$$

Similar to earlier, this can be shown without too much difficulty in the case where J_3 is a single interval, and similarly extending it to the general case. ■

The two bounds Theorems 5.7 and 5.9 are not comparable however. For example, Theorem 5.7 gives $\psi(K) = \Omega(n^{-1/2})$ for any body in isotropic position whereas Theorem 5.9 gives $\Omega(1)$ for the isotropic ball and $\Omega(n^{-1})$ for the isotropic simplex.

For any convex body K , let $\alpha(K)$ be the largest eigenvalue of $A(K)$.

Theorem 5.10. For any convex body K ,

$$\psi(K) \leq \frac{10}{\sqrt{\alpha(K)}}.$$

This is proved using the following result.

Theorem 5.11. Let K be a convex body in \mathbb{R}^n and assume that $b(K) = 0$. Let $u \in \mathbb{R}^n$ have unit norm and $\beta = \mathbf{E}_K(\langle u, x \rangle^2)$. Then

$$\text{vol}(K \cap \{x : \langle u, x \rangle < 0\}) \text{vol}(K \cap \{x : \langle u, x \rangle > 0\}) \geq \frac{1}{10} \sqrt{\beta} \text{vol}(K) \text{vol}_{n-1}(K \cap \{x : \langle u, x \rangle = 0\}).$$

The above can be proved by projecting the body onto the u -axis and considering the resulting log-concave function (using **Brunn's Theorem**).

⁴³Show that the function f on the left is monotone decreasing and use the fact that $f(1) = 0$.

Conjecture (KLS Conjecture). There is a constant c (independent of dimension) such that for any log-concave density p on \mathbb{R}^n ,

$$\psi_p \geq c \cdot \inf_{H \text{ is a halfspace}} \frac{p(\partial H)}{\min\{p(H), p(\mathbb{R}^n \setminus H)\}}.$$

The **KLS Conjecture** asserts that up to a constant factor, a hyperplane cut is the “worst” cut (involved in the isoperimetric coefficient).

[Che21] has made the most progress in recent times, proving that there is a constant c such that

$$\psi(K) \geq \frac{1}{\sqrt{n^{c(\log \log n / \log n)^{1/2}} \alpha(K)}}.$$

5.2. A More Detailed Look

Henceforth, we write $a \gtrsim b$ if there is some constant c (independent of dimension and all parameters under consideration) such that $a \geq cb$.

Generalizing Theorem 5.10 to an arbitrary log-concave density (by a similar proof), it just says that

$$\inf_{H \text{ is a halfspace}} \frac{p(\partial H)}{\min\{p(H), p(\mathbb{R}^n \setminus H)\}} \gtrsim \frac{1}{\sqrt{\|A\|_{\text{op}}}},$$

where A is the covariance matrix of p and $\|A\|_{\text{op}}$ is the largest eigenvalue of A .

In this context, the **KLS Conjecture** can be restated as follows.

Conjecture (KLS Conjecture (Reformulated)). For any log-concave density p with covariance matrix A , $\psi_p \gtrsim \|A\|_{\text{op}}^{-1/2}$. Equivalently, $\psi_p \gtrsim 1$ for any isotropic log-concave density p .

Theorem 5.7 then says that for any isotropic log-concave p , $\psi_p \gtrsim n^{-1/2}$.

For the sake of brevity, if p is a log-concave density with covariance matrix A , let $\rho(p) = \|A\|_{\text{op}}$.

Next, we look at a few consequences of the KLS Conjecture.

5.2.1. The Slicing Conjecture

The slicing conjecture essentially asks whether a convex body of unit volume in \mathbb{R}^n has a hyperplane section whose $(n-1)$ -volume is at least some universal constant.

Conjecture (Slicing Conjecture). Any convex body $K \subseteq \mathbb{R}^n$ of volume 1 has at least one hyperplane section H such that

$$\text{vol}_{n-1}(K \cap H) \gtrsim 1.$$

[Ba188] showed that the above is in fact equivalent to asking how much volume is present around the origin. This makes sense because if a large proportion of volume is there around the origin, then no hyperplane will intersect a lot of volume.

Motivated by this intuition, define

Definition 5.5 (Slicing Constant). For any isotropic log-concave density p on \mathbb{R}^n , define the *isotropic (slicing) constant* by $L_p = p(0)^{1/n}$.

Conjecture (Slicing Conjecture). For any isotropic log-concave density p on \mathbb{R}^n , the slicing constant L_p is $\mathcal{O}(1)$.

5.2.2. The Thin-Shell Conjecture

Conjecture (Thin-Shell Conjecture). Let p be a isotropic log-concave density. Then

$$\sigma_p^2 := \mathbf{E}_{X \sim p} [(\|X\| - \sqrt{n})^2] \lesssim 1.$$

Equivalently, $\mathbf{Var}_{X \sim p}(\|X\|^2) \lesssim 1$.

The above means that a random point X from a log-concave density lies in a constant width annulus (a thin shell) with constant probability.

It was shown in [EK10] that the Thin-Shell conjecture implies the Slicing conjecture and by Ball that the KLS conjecture implies the Thin-Shell conjecture. That is, we have that $L_p \lesssim \sigma_p \lesssim \psi_p$.

5.3. Recent Bounds on the Isoperimetric Constant

5.3.1. A Look At Stochastic Localization

Most of the progress towards proving the conjecture in recent times has been done using a method known as *stochastic localization*. Recall how in the proof of the localization lemma Theorem 4.31, which is possibly one of the most powerful tools we have built thus far, we use a bisection argument, where we bisect the body by a hyperplane at each step. In the general setting, this just corresponds to multiplying the current log-concave measure by $\mathbb{1}_H$, where H is a certain half-space.

For now, let us discuss how it works out in discrete time. Instead of multiplying by this indicator function, we multiply by an affine functional that is very close to 1. That is, we transform the density $p(x)$ to $(1 \pm \varepsilon \langle x - b_\mu, \theta \rangle) p(x)$, where b_μ is the barycenter of the measure (this gives two probability measures) and θ is randomly chosen. This is like a reweighting in favour of one of the half-spaces.

The resulting measures are probability measures since we are reweighting around the barycenter. The average of these two measures is the original measure. Further, each of these measures are log-concave (the product of log-concave functions is log-concave)!

This gives a stochastic process (which is discrete time for now) defined by

$$p_0(x) = p(x) \text{ and } p_{t+\Delta t}(x) = (1 + \langle x - \mu_t, \sqrt{\Delta t} Z_t \rangle) p_t(x). \quad (5.4)$$

The $\sqrt{\Delta t} Z_t$ represents $\pm \varepsilon \theta$ and is the random component. Here, μ_t is the barycenter of the measure corresponding to p_t and the Z_t are iid random which are either uniform on the sphere on $\sqrt{n} S^{n-1}$ or standard Gaussians in \mathbb{R}^n . By the averaging property mentioned, the p_t form a martingale (with respect to the filtration with $\mathcal{F}_t = \sigma\{Z_s : 0 \leq s \leq t\}$).

Now, we would like to make this continuous by making $\Delta t \rightarrow 0$. How do we do this? When the Z_t are Gaussian, Equation (5.4) can be rewritten as a stochastic differential equation

$$dp_t = \langle x - \mu_t, dW_t \rangle p_t(x) = (x - \mu_t)^\top dW_t p_t(x), \quad (5.5)$$

where $p_0 = p$ and μ_t , as before, is $\int_{\mathbb{R}^n} x p_t(x) dx$.

Existence and uniqueness for all $t \geq 0$ can be shown using standard means. Moreover, for any time t , p_t is almost surely continuous. If \mathcal{F}_t is the σ -algebra generated by $(W_s)_{0 \leq s \leq t}$, then $\mathbf{E}[p_t(x) \mid \mathcal{F}_s] = p_s(x)$ for $s < t$. That is, it is a martingale. The processes are also \mathcal{F}_t -adapted.

While the above is the basic idea, the following, slightly more complicated form is what is slightly more handy. Define the stochastic differential equation

$$c_0 = 0 \text{ and } dc_t = dW_t + \mu_t dt, \quad (5.6)$$

with p_t and μ_t defined by

$$p_t(x) = \frac{e^{\langle c_t, x \rangle - (t/2)\|x\|^2} p(x)}{\int_{\mathbb{R}^n} e^{\langle c_t, y \rangle - (t/2)\|y\|^2} p(y) dy} \text{ and } \mu_t(x) = \mathbf{E}_{x \sim p_t}[x].$$

Sometimes, to add another method to control the covariance, we often add a *control matrix* C_t , to control the covariance A_t of the density p_t at time t . This is incorporated into the previous equations as

$$\begin{aligned} c_0 &= 0, \quad dc_t = C_t^{1/2} dW_t + C_t \mu_t dt, \\ B_0 &= 0, \quad dB_t = C_t dt, \\ p_t(x) &= \frac{e^{\langle c_t, x \rangle - (t/2)\|x\|_{B_t}^2} p(x)}{\int_{\mathbb{R}^n} e^{\langle c_t, y \rangle - (t/2)\|y\|_{B_t}^2} p(y) dy}, \quad \mu_t(x) = \mathbf{E}_{x \sim p_t}[x], \end{aligned} \quad (5.7)$$

where C_t is a Lipschitz function with respect to c_t , μ_t , A_t , and t .

It may be shown that a solution to the above equation exists and is unique (up to almost-sure equivalence).

It is also not too difficult to show using Itô's Lemma that (5.7) implies (5.5).

Now, observe that

$$\begin{aligned} d \log p_t(x) &= (x - \mu_t)^\top dW_t - \frac{1}{2} (x - \mu_t)^\top (x - \mu_t) dt \\ &= x^\top (dW_t + \mu_t dt) - \frac{1}{2} \|x\|^2 dt + g(t) \\ &= x^\top dc_t - \frac{1}{2} \|x\|^2 dt + g(t), \end{aligned}$$

where $g(t)$ is independent of x and the first two terms. This explains the appearance of the Gaussian in (5.7) – the above implies that p_t is more log-concave than $e^{-\|x\|^2/2}$.

As the Gaussian factor dominates more and more, the density converges to a Dirac delta “function”, where the measure of any subset is 0 or 1. This is stated in Theorem 5.15.

The KLS Conjecture has been proven for Gaussian distributions. More generally, for any distribution whose density is the product of the density of $\mathcal{N}(0, \sigma^2 I)$ and any log-concave function, $\psi_p \gtrsim 1/\sigma$ – this can be proved by normal localization.

To get some sort of bound for ψ_p , we want to bound the covariance matrix (in some meaningful sense of the word bound).

Using Itô's Lemma once more on the covariance matrix, we get

$$\begin{aligned} dA_t &= \int_{\mathbb{R}^n} (x - \mu_t)(x - \mu_t)^\top \cdot (x - \mu_t)^\top dW_t \cdot p_t(x) dx - A_t^2 dt \\ &= \mathbf{E}_{x \sim p_t} (x - \mu_t)(x - \mu_t)^\top \cdot (x - \mu_t)^\top dW_t - A_t^2 dt. \end{aligned}$$

One important result that we have not mentioned thus far is due to [Mil08], which claims that the *isoperimetric profile* $I_p : [0, 1] \rightarrow \mathbb{R}^+$, defined by

$$I_p(t) = \inf_{\substack{S \subseteq \mathbb{R}^n \\ p(S)=t}} \frac{p(\partial S)}{\min\{p(S), p(\mathbb{R}^n \setminus S)\}}$$

is concave. In particular, since $I_p(t) = I_p(1-t)$, it attains its maximum at $1/2$. Therefore, to bound the isoperimetric coefficient (and prove the KLS Conjecture), it suffices to check subsets of measure $1/2$.

With this added information, what do we desire from stochastic localization?

1. The covariance matrix should not explode (since the bound on the isoperimetric coefficient that we obtain depends on it) and
2. The measure of a set E of measure $1/2$ (under the initial density) does not change much.

The reason the above works is due to the following series of inequalities for some set E of initial measure $1/2$:

$$\begin{aligned}
p(\partial E) &= \mathbf{E} [p_t(\partial E)] && (p_t \text{ is a martingale}) \\
&\geq \mathbf{E} \left[\frac{1}{2} \|B_t^{-1}\|_2^{-1/2} \min\{p_t(E), p_t(\mathbb{R}^n \setminus E)\} \right] && (p_t \text{ is more log-concave than the Gaussian}) \\
&\geq \frac{1}{4} \cdot \frac{1}{2} \|B_t^{-1}\|_2^{-1/2} \Pr \left[\frac{1}{4} \leq p_t(E) \leq \frac{3}{4} \right] && (p_t(E) \geq 0) \\
&= \frac{1}{4} \|B_t^{-1}\|_2^{-1/2} \Pr \left[\frac{1}{4} \leq p_t(E) \leq \frac{3}{4} \right] \min\{p(E), p(\mathbb{R}^n \setminus E)\}.
\end{aligned}$$

Over the next few sections, we give a $n^{-1/4}$ bound on ψ_p , as described in [LV17]. More precisely, we show that $\psi_p \gtrsim \text{Tr}(A^2)^{-1/4}$.

5.3.2. Towards a $n^{-1/4}$ Bound

Before we begin, define the following for notational convenience.

Definition 5.6. For any stochastic processes x_t and y_t , denote the *quadratic variations* $[x]_t$ and $[x, y]_t$ by

$$[x]_t = \lim_{\|P\| \rightarrow 0} \sum_{n=1}^{\infty} (x_{\tau_n} - x_{\tau_{n-1}})^2$$

and

$$[x, y]_t = \lim_{\|P\| \rightarrow 0} \sum_{n=1}^{\infty} (x_{\tau_n} - x_{\tau_{n-1}})(y_{\tau_n} - y_{\tau_{n-1}}),$$

where $P = \{0 = \tau_0 \leq \tau_1 \leq \dots \uparrow t\}$ is a *stochastic partition* of the non-negative reals and $\|P\| = \max_n(\tau_n - \tau_{n-1})$ is called the *mesh* of P and the limit is defined using convergence in probability.

For example, if x_t and y_t satisfy $dx_t = \mu(x_t) dt + \sigma(x_t) dW_t$ and $dy_t = \nu(x_t) dt + \eta(y_t) dt$, then

$$d[x]_t = \sigma^2(x_t) dt \text{ and } d[x, y]_t = \sigma(x_s)\eta(y_s) dt.$$

The following two results will also come in useful.

Lemma 5.12 (Reflection Principle). Given a Wiener process W_t and $a, t \geq 0$,

$$\Pr \left[\sup_{0 \leq s \leq t} W_s \geq a \right] = 2 \Pr [W_t \geq a].$$

Theorem 5.13 (Dambis, Dubins-Schwarz Theorem). Every continuous local martingale M_t is of the form

$$M_t = M_0 + W_{[M]_t} \text{ for all } t \geq 0,$$

where W_s is a Wiener process.

The first simplest case is when we take the control matrix to just be the identity. That is, the relevant stochastic differential equation is given by (5.6). Denote by A_t the covariance matrix of p_t .

First, we give some “basic estimates”. Let us start by bounding the measure of any set of initial measure $1/2$.

Lemma 5.14. For any $E \subseteq \mathbb{R}^n$ with $p(E) = 1/2$ and $t \geq 0$,

$$\Pr \left[\frac{1}{4} \leq p_t(E) \leq \frac{3}{4} \right] \geq \frac{9}{10} - \Pr \left[\int_0^t \rho(p_s) ds \geq \frac{1}{64} \right].$$

Proof. Let $g_t = p_t(E)$. Then $dg_t = \int_E (x - \mu_t)^\top dW_t p_t(x) dx$. We have

$$\begin{aligned} d[g]_t &= \left\| \int_E (x - \mu_t) p_t(x) dx \right\|_2^2 dt \\ &= \max_{\|\zeta\|_2 \leq 1} \left(\int_E (x - \mu_t)^\top \zeta p_t(x) dx \right)^2 dt \\ &\leq \left(\max_{\|\zeta\|_2 \leq 1} \int_{\mathbb{R}^n} ((x - \mu_t)^\top \zeta)^2 p_t(x) dx \right) \left(\int_{\mathbb{R}^n} p_t(x) dx \right) dt \\ &= \max_{\|\zeta\|_2 \leq 1} \zeta^\top A_t \zeta dt = \rho(p_t) dt. \end{aligned}$$

Using Theorem 5.13, let \tilde{W}_t be a Wiener process such that $g_t - g_0$ has the same distribution as $\tilde{W}_{[g]_t}$. Then,

$$\begin{aligned} \Pr \left[\frac{1}{4} \leq g_t \leq \frac{3}{4} \right] &= \Pr \left[-\frac{1}{4} \leq \tilde{W}_{[g]_t} \leq \frac{1}{4} \right] \\ &\geq 1 - \Pr \left[\max_{0 \leq s \leq 1/64} |\tilde{W}_s| > \frac{1}{4} \right] - \Pr \left[[g]_t > \frac{1}{64} \right] \\ &= 1 - 4 \Pr \left[\tilde{W}_{1/64} > \frac{1}{4} \right] - \Pr \left[[g]_t > \frac{1}{64} \right] \\ &\geq \frac{9}{10} - \Pr \left[\int_0^t \rho(p_s) ds \geq \frac{1}{64} \right]. \end{aligned}$$

In the second-to-last equation, the first two terms simplify on estimates for the concentration of the normal measure and the second term simplifies on using the earlier bound on $\frac{d[g]_t}{dt}$. \blacksquare

We now restate the bound on the isoperimetric constant we mentioned earlier for distributions more log-concave than the Gaussian.

Theorem 5.15. Let

$$h(x) = \frac{f(x)e^{-\|x\|^2/2\sigma^2}}{\int f(y)e^{\|y\|^2/2\sigma^2}},$$

where $f : \mathbb{R}^n \rightarrow \mathbb{R}^+$ is an integrable log-concave function. Then h is log-concave and for any measurable $S \subseteq \mathbb{R}^n$

$$\int_{\partial S} h(x) dx \gtrsim \frac{1}{\sigma} \min \left\{ \int_S h(x) dx, \int_{\mathbb{R}^n \setminus S} h(x) dx \right\}.$$

Now, let us get to the main estimation of the isoperimetric constant using the above results.

Theorem 5.16. Suppose there is $T > 0$ such that

$$\Pr \left[\int_0^T \rho(p_s) ds \leq \frac{1}{64} \right] \geq \frac{3}{4}.$$

Then $\psi_p \gtrsim T^{-1/2}$.

Proof. Let $E \subseteq \mathbb{R}^n$ with $p(E) = 1/2$. We then have

$$\begin{aligned}
 \int_{\partial E} p(x) \, dx &= \mathbf{E} \left[\int_{\partial E} p_T(x) \, dx \right] && (p_t \text{ is a martingale}) \\
 &\gtrsim T^{1/2} \mathbf{E} [\min \{p_T(E), p_T(\mathbb{R}^n \setminus E)\}] \\
 &\gtrsim T^{1/2} \Pr \left[\frac{1}{4} \leq p_T(E) \leq \frac{3}{4} \right] \\
 &\gtrsim T^{1/2} \left(\frac{9}{10} - \Pr \left[\int_0^t \rho(p_s) \, ds \geq \frac{1}{64} \right] \right) \gtrsim T^{1/2}.
 \end{aligned}$$

■

As mentioned earlier, we now need to control the growth of the covariance matrix A_t , preventing it from exploding and ensuring that the condition in above theorem is satisfied for some large T .

5.3.3. Controlling A_t

To control the growth of A_t , we use the potential function $\text{Tr}(A_t^2)$.

Lemma 5.17. Given a log-concave distribution p with mean μ and covariance matrix A , for any positive semi-definite matrix C ,

$$\|\mathbf{E}_{x \sim p} [(x - \mu)(x - \mu)^\top C(x - \mu)]\|_2 \lesssim \|A\|_{\text{op}}^{1/2} \text{Tr}(A^{1/2} C A^{1/2}).$$

Proof. First, consider the case where C is of the form vv^\top . Let $w = A^{1/2}v$ and $y = A^{-1/2}(x - \mu)$. Let the distribution of y be \tilde{p} (it is isotropic and log-concave). Then

$$\begin{aligned}
 \|\mathbf{E}_{x \sim p} [(x - \mu)(x - \mu)^\top C(x - \mu)]\|_2 &= \|\mathbf{E}_{y \sim \tilde{p}} [A^{1/2} y (y^\top w)^2]\|_2 \\
 &= \max_{\|\zeta\|_2 \leq 1} \mathbf{E}_{y \sim \tilde{p}} [(A^{1/2} y)^\top \zeta (y^\top w)^2] \\
 &\leq \max_{\|\zeta\|_2 \leq 1} \sqrt{\mathbf{E}_{y \sim \tilde{p}} [(A^{1/2} y)^\top \zeta]^2} \sqrt{\mathbf{E}_{y \sim \tilde{p}} [(y^\top w)^4]} \\
 &= \max_{\|\zeta\|_2 \leq 1} \sqrt{\zeta^\top A \zeta} \lesssim \|A\|_{\text{op}}^{1/2} \|w\|_2^2.
 \end{aligned}$$

The bound for a general C isn't too difficult to show by writing it as $\sum \lambda_i v_i v_i^\top$ in terms of its eigenvalues $\lambda_i \geq 0$ and eigenvectors v_i . ■

Lemma 5.18. Given a log-concave distribution p with mean μ and covariance matrix C ,

$$\mathbf{E}_{x, y \sim p} [|\langle x - \mu, y - \mu \rangle|^3] \lesssim \text{Tr}(A^2)^{3/2}.$$

Proof. We may assume that $\mu = 0$. For a fixed x , we have

$$\begin{aligned}
 \mathbf{E}_{y \sim p} [|\langle x, y \rangle|^3] &\leq \mathbf{E}_{y \sim p} [|\langle x, y \rangle|^2]^{3/2} \\
 &= (x^\top A x)^{3/2} = \|A^{1/2} x\|^3.
 \end{aligned}$$

Thus,

$$\begin{aligned}
 \mathbf{E}_{x, y \sim p} [|\langle x, y \rangle|^3] &\leq \mathbf{E}_{x \sim p} \left[\|A^{1/2} x\|^3 \right] \\
 &\leq \mathbf{E}_{x \sim p} \left[\|A^{1/2} x\|^2 \right]^{3/2} \\
 &= \text{Tr}(A^2)^{3/2}.
 \end{aligned}$$

■

Theorem 5.19. With the previously used notation, there is a universal constant c_1 such that

$$\Pr \left[\max_{t \in [0, T]} \text{Tr}(A_t^2) \geq 8 \text{Tr}(A_0^2) \right] \leq 0.01 \text{ with } T = \frac{c_1}{\sqrt{\text{Tr}(A_0^2)}}.$$

Before we get onto the proof, we show that the bound on the isoperimetric constant follows from previously mentioned results.

Corollary 5.20. For any log-concave distribution p with covariance matrix A ,

$$\psi_p \gtrsim \text{Tr}(A^2)^{-1/4}.$$

In particular, if p is isotropic log-concave,

$$\psi_p \gtrsim n^{-1/4}.$$

Proof. Theorem 5.19 implies that

$$\Pr \left[\max_{s \in [0, t]} \text{Tr}(A_s^2) \leq 8 \text{Tr}(A_0^2) \right] \geq 0.99,$$

where t is equal to the quantity we denoted as T there. Since $\|A_s\|_{\text{op}} \leq \sqrt{\text{Tr}(A_s^2)}$, we have

$$\Pr \left[\max_{s \in [0, t]} \rho(p_s) \leq \sqrt{8 \text{Tr}(A_0^2)} \right] \geq 0.99.$$

Therefore, letting

$$T = \min \left\{ c_1, \frac{1}{64\sqrt{8}} \right\} \frac{1}{\sqrt{\text{Tr}(A_0^2)}},$$

we have

$$\Pr \left[\int_0^T \rho(p_s) ds \leq \frac{1}{64} \right] \geq 0.99,$$

and the result follows on using Theorem 5.16. ■

Proof of Theorem 5.19. Define the potential function $\Phi_t = \text{Tr}(A_t^2)$.

It is a computational task using Itô's Lemma to check that

$$d\Phi_t = (2\mathbf{E}_{x \sim p_t}(x - \mu_t)^\top A_t(x - \mu_t)(x - \mu_t)^\top) dW_t + (\mathbf{E}_{x, y \sim p_t}((x - \mu_t)^\top (y - \mu_t))^3 - 2 \text{Tr}(A_t^3) dt) dt.$$

Write this as

$$d\Phi_t = \delta_t dt + v_t^\top dW_t.$$

By Lemma 5.18, we get

$$\delta_t \lesssim \text{Tr}(A_t^2)^{3/2} \lesssim \Phi_t^{3/2}$$

by dropping the negative term in the expression (A_t is positive semi-definite). What about the martingale term? Using Lemma 5.17, we have

$$\|v_t\|_2 = 2 \|\mathbf{E}_{x \sim p_t}(x - \mu_t)^\top A_t(x - \mu_t)(x - \mu_t)^\top\|_2 \lesssim \|A_t\|_{\text{op}}^{1/2} \text{Tr}(A_t^2) \leq \Phi_t^{5/4}.$$

Intuitively, this means that the drift term (the dt part) grows as $\Phi_t^{3/2}t$ and the martingale term (the dW_t part) grows as $\Phi_t^{5/4}\sqrt{t}$. So for t up to $\mathcal{O}(\Phi_0^{-1/2})$, the potential Φ_t remains $\mathcal{O}(\Phi_0)$.

To formalize this, define $f(a) = 1/\sqrt{a + \Phi_0}$. Observe that $\Phi_t \geq 8\Phi_0$ if and only if $f(\Phi_t) \geq -1/3\sqrt{\Phi_0}$. We can use Itô's Lemma to get

$$df(\Phi_t) = \left(\frac{1}{2} \frac{v_t^\top dW_t}{(\Phi_t + \Phi_0)^{3/2}} \right) + \left(\frac{1}{2} \frac{\delta_t}{(\Phi_t + \Phi_0)^{3/2}} - \frac{3}{8} \frac{\|v_t\|_2^2}{(\Phi_t + \Phi_0)^{5/2}} \right) dt \leq dY_t + C' dt,$$

where C' is a suitable constant and dY_t is the martingale term. Observe that

$$\frac{d[Y]_t}{dt} = \frac{1}{4} \frac{\|v_t\|_2^2}{(\Phi_t + \Phi_0)^3} \leq \frac{C}{\sqrt{\Phi_0}}$$

for a suitable constant C .

Let \tilde{W}_t be a martingale such that $Y_t = \tilde{W}_{[Y]_t}$ in distribution. Using Lemma 5.12,

$$\begin{aligned} \Pr \left[\max_{t \in [0, T]} Y_t \geq \gamma \right] &\leq \Pr \left[\max_{t \in [0, CT/\sqrt{\Phi_0}]} \tilde{W}_t \geq \gamma \right] \\ &= \Pr \left[\tilde{W}_{CT/\sqrt{\Phi_0}} \geq \gamma \right] \leq 2 \exp \left(-\frac{\gamma^2 \sqrt{\Phi_0}}{2CT} \right). \end{aligned}$$

Therefore,

$$\Pr \left[\max_{t \in [0, T]} f(\Phi_t) \geq -\frac{1}{\sqrt{2\Phi_0}} + C'T + \gamma \right] \leq 2 \exp \left(-\frac{\gamma^2 \sqrt{\Phi_0}}{2CT} \right).$$

Setting $T = 1/256(C + C')\sqrt{\Phi_0}$ and $\gamma = 1/4\sqrt{\Phi_0}$, we get

$$\Pr \left[\max_{t \in [0, T]} f(\Phi_t) \geq -\frac{1}{3\Phi_0} \right] \leq 2 \exp(-8).$$

Using our earlier observation about f ,

$$\Pr \left[\max_{t \in [0, T]} \Phi_t \geq 8\Phi_0 \right] \leq 2 \exp(-8) \leq 0.01.$$

■

Over the next few sections, we look at the best bound attained (as of the time of writing) of the isoperimetric constant, as described in [Che21].

5.3.4. Towards an Almost Constant Bound

Here, we prove that there is a constant c such that for any log-concave p in \mathbb{R}^n and integer $\ell \geq 1$,

$$\psi_p \geq \frac{1}{(c\ell(\log n + 1))^{\ell/2} n^{16/\ell} \sqrt{\rho(p)}}.$$

In particular, setting

$$\ell = \left\lceil \sqrt{\frac{\log n}{\log \log n}} \right\rceil,$$

there exists a constant c' such that

$$\psi_p \geq \frac{1}{n^{c'} \sqrt{\log \log n / \log n} \sqrt{\rho(p)}}.$$

For this, the control matrix C_t in Equation (5.7) as A^{-1} . The resulting stochastic differential equations are then

$$\begin{aligned} c_0 &= 0, \quad dc_t = A^{-1/2} dW_t + A^{-1} \mu_t dt, \\ B_0 &= 0, \quad dB_t = A^{-1} dt, \\ p_t(x) &= \frac{e^{c_t^\top x - \frac{1}{2} x^\top B_t x} p(x)}{\int_{\mathbb{R}^n} e^{c_t^\top y - \frac{1}{2} y^\top B_t y} p(y) dy}, \quad \mu_t(x) = \mathbf{E}_{x \sim p_t}[x], \end{aligned} \tag{5.8}$$

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