

Volume of random real algebraic submanifolds

Thomas Letendre (ENS de Lyon)

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Random geometry

(M, g) compact Riemannian manifold of dimension n (without boundary).
We choose a codimension r submanifold of M “randomly”.

Question

What can we say of the topology or the geometry of the submanifold?
(volume, Euler characteristic, number of connected components, ...)

We look for a statistical answer (mean, variance, distribution, ...) or an almost sure behavior.

Roots of real polynomials

A complex polynomial of degree d has d roots in \mathbb{C} , generically distinct.

Question

How many roots does a real polynomial $P \in \mathbb{R}_d[X]$ have?

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Theorem (Kac, 1943)

Let $P = \sum_{i=0}^d a_i X^i$, where a_0, \dots, a_d are i.i.d. standard Gaussian variables and let $Z_d = P^{-1}(0)$, then

$$\mathbb{E}[\text{card}(Z_d)] \sim \frac{2}{\pi} \log(d).$$

Higher dimensions

Notations

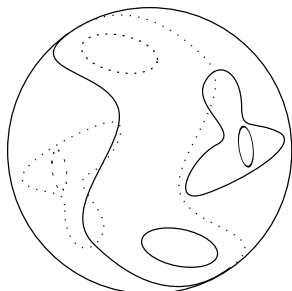
Let $\alpha = (\alpha_0, \dots, \alpha_n) \in \mathbb{N}^{n+1}$, we set:

- $|\alpha| = \alpha_0 + \dots + \alpha_n$,
- $X^\alpha = X_0^{\alpha_0} \dots X_n^{\alpha_n}$,
- $\alpha! = \alpha_0! \dots \alpha_n!$,
- if $|\alpha| = d$, $\binom{d}{\alpha} = \frac{d!}{\alpha!}$.

P homogeneous polynomial in $\mathbb{R}_d^{\text{hom}}[X_0, \dots, X_n]$: $P = \sum_{|\alpha|=d} a_\alpha X^\alpha$.

$P^{-1}(0) \subset \mathbb{R}^{n+1}$ is a cone.

We consider $Z_P = P^{-1}(0) \cap \mathbb{S}^n$.



What is a manifold?

Definition

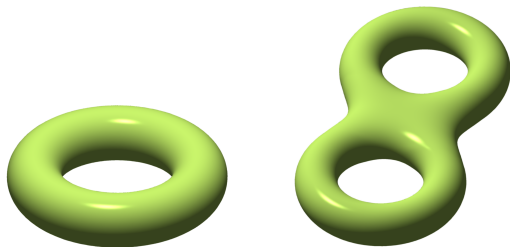
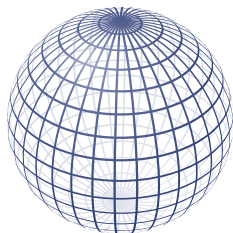
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What is a manifold?

Definition

A dimension n manifold is a space M which is locally diffeomorphic to \mathbb{R}^n .

It generalizes the idea of a non-singular curve or surface (no double points, no cusps, etc.).



Source: en.wikipedia.org

Main point

We can extend the calculus to maps between manifolds.

What is a submanifold?

Let M be a manifold of dimension n and $r \in \{1, \dots, n\}$.

Definition

A codimension r submanifold of M is $Z_f \subset M$ such that $Z_f = f^{-1}(0)$, where:

- $f : M \rightarrow \mathbb{R}^r$ is smooth,
- for all x such that $f(x) = 0$, $d_x f$ is surjective.

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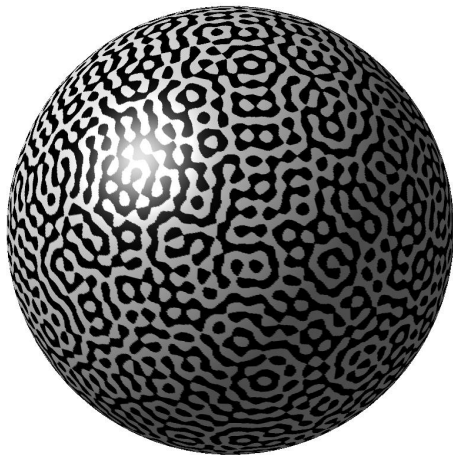
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Main point

Z_f is a manifold of dimension $n - r$.

A random curve on the sphere



Picture by Alex Barnett (Dartmouth).

Riemannian manifold

Definition

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- a natural distance D ,
- a natural volume measure $|dV_M|$.

If Z_f is a codimension r submanifold of M , the restriction of g is a Riemannian metric on Z_f .

We denote by $|dV_f|$ the associated $((n - r)$ -dimensional) volume measure.

Gaussian variables

$(V, \langle \cdot, \cdot \rangle)$ Euclidean space of dimension N ,
 Λ self-adjoint and positive definite.

Definition

A random vector X in V is a centered Gaussian of variance Λ if its distribution admits the density:

$$\frac{1}{(2\pi)^{\frac{N}{2}} \sqrt{\det(\Lambda)}} \exp\left(-\frac{1}{2} \langle \Lambda^{-1}x, x \rangle\right)$$

with respect to the Lebesgue measure. This is denoted by $X \sim \mathcal{N}(\Lambda)$.

We say that $X \sim \mathcal{N}(\text{Id})$ is a standard Gaussian.

In any orthonormal basis (e_1, \dots, e_N) we have $X = \sum a_i e_i$, where $a_i \sim \mathcal{N}(1)$ are i.i.d. real random variables.

Some properties of Gaussian variables

- Two jointly Gaussian vectors are independent iff they are uncorrelated.
- If $X \sim \mathcal{N}(\Lambda)$ in V and $L : V \rightarrow V'$ is linear, then $L(X) \sim \mathcal{N}(L\Lambda L^*)$.
- If (X, Y) is a centered Gaussian vector with variance $\begin{pmatrix} A & B^t \\ B & C \end{pmatrix}$, then the distribution of Y given that $X = 0$ is also a centered Gaussian vector, and its variance is:

$$C - BA^{-1}B^t.$$

Kostlan–Shub–Smale polynomials

We consider a random Kostlan-distributed $P \in \mathbb{R}_d^{\text{hom}}[X_0, \dots, X_n]$. That is:

$$P = \sqrt{\frac{(d+n)!}{\pi^n d!}} \sum_{|\alpha|=d} a_\alpha \sqrt{\binom{d}{\alpha}} X^\alpha,$$

where $(a_\alpha)_{|\alpha|=d}$ are i.i.d. $\mathcal{N}(1)$ real variables.

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Remark

$P \sim \mathcal{N}(\text{Id})$ in $\mathbb{R}_d^{\text{hom}}[X_0, \dots, X_n]$ for the following L^2 scalar product:

$$\langle P, Q \rangle = \frac{1}{2\pi} \int_{\{z \in \mathbb{C}^{n+1} \mid \|z\|=1\}} P(z) \overline{Q(z)} d\theta(z).$$

Kostlan's distribution is invariant under the action of $O_{n+1}(\mathbb{R})$ by:

$$(O \cdot P)(x) = P(O^{-1}x).$$

Kostlan–Shub–Smale polynomials

Let $d, n \in \mathbb{N}^*$ and $r \in \{1, \dots, n\}$,

P_1, \dots, P_r i.i.d. Kostlan-distributed polynomials in $\mathbb{R}_d^{\text{hom}}[X_0, \dots, X_n]$.

We set $Z_d = Z_{P_1} \cap \dots \cap Z_{P_r} \subset \mathbb{S}^n$.

Lemma

Z_d is almost surely a codimension r submanifold of \mathbb{S}^n .

Theorem (Kostlan, 1993)

For all n, r and d , we have: $\mathbb{E}[\text{Vol}(Z_d)] = d^{\frac{r}{2}} \text{Vol}(\mathbb{S}^{n-r})$.

Kostlan–Shub–Smale polynomials

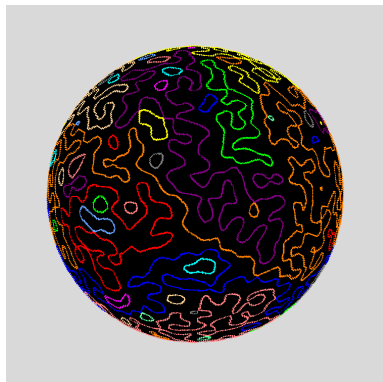
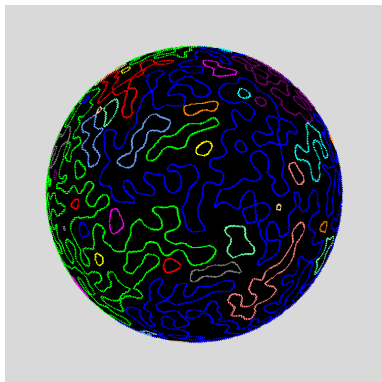


Figure: Degree 56 random curves in \mathbb{S}^2 , Kostlan's model.

Pictures by Maria Nastasescu (Caltech).

Real algebraic framework

M real algebraic manifold of dimension n (for example $M = Z_P \subset \mathbb{S}^{n+1}$), with a natural Riemannian metric.

(P_1, \dots, P_r) replaced by a standard Gaussian section s of $\mathcal{E} \otimes \mathcal{L}^d$, a rank r real holomorphic Hermitian vector bundle, with \mathcal{L} ample line bundle. In this setting, $Z_d = s_d^{-1}(0)$.

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Lemma

If d is large enough, then Z_d is a.s. a codimension r submanifold of M .

Expected volume

$|dV_M|$ Riemannian measure on M , $|dV_d|$ Riemannian measure on Z_d .

We see Z_d as a measure on M : $\forall \phi \in C^0(M)$, $\langle Z_d, \phi \rangle = \int_{Z_d} \phi |dV_d|$.

Theorem (L., 2014)

For all $\phi \in C^0(M)$,

$$\mathbb{E}[\langle Z_d, \phi \rangle] = d^{\frac{r}{2}} \left(\int_M \phi |dV_M| \right) \frac{\text{Vol}(\mathbb{S}^{n-r})}{\text{Vol}(\mathbb{S}^n)} + \|\phi\|_{C^0} O\left(d^{\frac{r}{2}-1}\right),$$

where the error term is independent of ϕ .

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Corollary

As Radon measures, we have: $d^{-\frac{r}{2}} \mathbb{E}[Z_d] \xrightarrow{d \rightarrow +\infty} \frac{\text{Vol}(\mathbb{S}^{n-r})}{\text{Vol}(\mathbb{S}^n)} |dV_M|$.

Variance of the volume

Theorem (L., 2016)

If $1 \leq r < n$, then for all $\phi \in C^0(M)$,

$$\text{Var}(\langle Z_d, \phi \rangle) = d^{r-\frac{n}{2}} \left(\int_M \phi^2 |dV_M| \right) \mathcal{I}_{n,r} + o\left(d^{r-\frac{n}{2}}\right),$$

where $\mathcal{I}_{n,r}$ is explicit and $0 \leq \mathcal{I}_{n,r} < +\infty$.

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Corollary

$$\text{Var}(\text{Vol}(Z_d)) = d^{r-\frac{n}{2}} \text{Vol}(M) \mathcal{I}_{n,r} + o\left(d^{r-\frac{n}{2}}\right).$$

The case of random points

For one Kostlan–Shub–Smale polynomial in \mathbb{S}^1 ($n = r = 1$).

Theorem (Kostlan, 1993)

$$\mathbb{E}[\text{card}(Z_d)] = 2\sqrt{d}.$$

Theorem (Dalmao, 2015)

There exists $\sigma^2 > 0$ explicit such that:

$$\text{Var}(\text{card}(Z_d)) \sim \sigma^2\sqrt{d}.$$

Moreover,

$$\frac{\text{card}(Z_d) - 2\sqrt{d}}{\sigma d^{\frac{1}{4}}} \xrightarrow[d \rightarrow +\infty]{\mathcal{D}} \mathcal{N}(1).$$

Concentration around the mean

Corollary

If $1 \leq r < n$, then for all $\phi \in \mathcal{C}^0(M)$,

$$\mathbb{P} \left(\left| \frac{\langle Z_d, \phi \rangle - \mathbb{E}[\langle Z_d, \phi \rangle]}{d^{\frac{r}{2}}} \right| \geq \frac{1}{d^{\frac{r}{4}}} \right) = O\left(d^{\frac{r-n}{2}}\right).$$

By Markov's inequality,

$$\begin{aligned} \mathbb{P} \left(\left| \frac{\langle Z_d, \phi \rangle - \mathbb{E}[\langle Z_d, \phi \rangle]}{d^{\frac{r}{2}}} \right| \geq \frac{1}{d^{\frac{r}{4}}} \right) &= \mathbb{P} \left(\left| \langle Z_d, \phi \rangle - \mathbb{E}[\langle Z_d, \phi \rangle] \right| \geq d^{\frac{r}{4}} \right) \\ &\leq d^{-\frac{r}{2}} \text{Var}(\langle Z_d, \phi \rangle) \\ &= O\left(d^{\frac{r-n}{2}}\right). \end{aligned}$$

Equidistribution in probability

Corollary

If $1 \leq r < n$, for every open set $U \subset M$, we have:

$$\mathbb{P}(Z_d \cap U = \emptyset) = O\left(d^{-\frac{n}{2}}\right).$$

Equidistribution in probability

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If $1 \leq r < n$, for every open set $U \subset M$, we have:

$$\mathbb{P}(Z_d \cap U = \emptyset) = O\left(d^{-\frac{n}{2}}\right).$$

Let $\phi_U \in C^0(M)$ that vanishes outside U and is positive on U .

Let $\varepsilon > 0$ be such that, for every d large enough,

$$\mathbb{E}[\langle Z_d, \phi_U \rangle] - d^{\frac{r}{2}} \varepsilon > 0.$$

Equidistribution in probability

$$\begin{aligned}\mathbb{P}(Z_d \cap U = \emptyset) &= \mathbb{P}(\langle Z_d, \phi_U \rangle = 0) \\ &\leq \mathbb{P}\left(\langle Z_d, \phi_U \rangle < \mathbb{E}[\langle Z_d, \phi_U \rangle] - d^{\frac{r}{2}}\varepsilon\right) \\ &\leq \mathbb{P}\left(\left|\langle Z_d, \phi_U \rangle - \mathbb{E}[\langle Z_d, \phi_U \rangle]\right| > d^{\frac{r}{2}}\varepsilon\right) \\ &\leq \frac{1}{d^r\varepsilon^2} \text{Var}(\langle Z_d, \phi_U \rangle) \\ &= O\left(d^{-\frac{n}{2}}\right).\end{aligned}$$

Universality of the zero set

Theorem (Gayet–Welschinger, 2013)

Let $\Sigma \subset \mathbb{R}^n$ be a codimension r compact submanifold without boundary and $R > 0$.

Then, there exists $C_{\Sigma,R} \geq 0$ such that, for all d large enough, for all $x \in M$,

$$\mathbb{P} \left(Z_d \cap B \left(x, \frac{R}{\sqrt{d}} \right) \supset \Sigma' \text{ s.t. } \left(B \left(x, \frac{R}{\sqrt{d}} \right), \Sigma' \right) \simeq (\mathbb{R}^n, \Sigma) \right) \geq C_{\Sigma,R}.$$

Moreover, $C_{\Sigma,R} > 0$ for R large enough.

The correlation function

A Kostlan polynomial $P \in \mathbb{R}_d^{\text{hom}}[X_0, \dots, X_n]$ defines a centered Gaussian process $(P(x))_{x \in \mathbb{S}^n}$.

This process is characterized by its correlation function:

$$e_d : (x, y) \mapsto \mathbb{E}[P(x)P(y)].$$

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$$\begin{aligned} \mathbb{E}[P(x)P(y)] &= \frac{(d+n)!}{\pi^n d!} \sum_{|\alpha|=d} \binom{d}{\alpha} x^\alpha y^\alpha = \frac{(d+n)!}{\pi^n d!} (\langle x, y \rangle)^d \\ &= \frac{(d+n)!}{\pi^n d!} \cos(D(x, y))^d. \end{aligned}$$

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Remark

By taking partial differentials, $\frac{\partial e_d}{\partial x_i}(x, y) = \mathbb{E} \left[\frac{\partial P}{\partial x_i}(x) P(y) \right]$.

Scaling limit of the Bergman kernel

In the general real algebraic framework, the correlation function e_d is the Bergman kernel of $\mathcal{E} \otimes \mathcal{L}^d$.

There is a universal scaling limit for e_d (Ma–Marinescu, 2007) :

$$e_d(x, y) \simeq \frac{d^n}{\pi^n} \exp\left(-\frac{d}{2} \|x - y\|^2\right),$$

whenever $D(x, y) \leq K \frac{\log d}{\sqrt{d}}$.

Theorem (Ma–Marinescu, 2015)

There exists $C > 0$ such that, for all $k \in \mathbb{N}$,

$$\|e_d(x, y)\|_{C^k} = O\left(d^{n+\frac{k}{2}} \exp\left(-C\sqrt{d}D(x, y)\right)\right),$$

uniformly in (x, y) .

A heuristic for the mean volume

The Bergman kernel shows a characteristic scale $\frac{1}{\sqrt{d}}$.

We cut M into boxes of size $\frac{1}{\sqrt{d}}$:

$$\simeq \text{Vol}(M) d^{\frac{n}{2}} \text{ boxes.}$$

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Components of size $\frac{1}{\sqrt{d}}$, each one has a volume of order $\left(\frac{1}{\sqrt{d}}\right)^{n-r}$.

Finally, $\text{Vol}(Z_d)$ is of order $\text{Vol}(M) d^{\frac{r}{2}}$.

Kac–Rice formula

In the case of hypersurfaces ($r = 1$).

$P \in \mathbb{R}_d^{\text{hom}}[X_0, \dots, X_n]$ Kostlan-distributed, $Z_d = P^{-1}(0) \cap \mathbb{S}^n$.

Kac–Rice formula

For every ϕ ,

$$\mathbb{E} \left[\int_{Z_d} \phi |dV_d| \right] = \frac{1}{\sqrt{2\pi}} \int_{x \in \mathbb{S}^n} \phi(x) \frac{\mathbb{E} \left[\|d_x P\| \mid P(x) = 0 \right]}{\sqrt{e_d(x, x)}}.$$

$x \mapsto e_d(x, x)$ does not vanish (i.e. for all $x \in M$, $P(x)$ is non-degenerate).
Similar formula in the general case.

Asymptotic of the expectation

$$\mathbb{E}[\langle Z_d, \phi \rangle] = \frac{1}{\sqrt{2\pi}} \int_{x \in \mathbb{S}^n} \phi(x) \frac{\mathbb{E}[\|d_x P\| \mid P(x) = 0]}{\sqrt{e_d(x, x)}}.$$

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$(P(x), d_x P)$ is a centered Gaussian of variance:

$$\Lambda = \begin{pmatrix} e_d(x, x) & \partial_{y_1} e_d(x, x) & \cdots & \partial_{y_n} e_d(x, x) \\ \partial_{x_1} e_d(x, x) & \partial_{x_1} \partial_{y_1} e_d(x, x) & \cdots & \partial_{x_1} \partial_{y_n} e_d(x, x) \\ \vdots & \vdots & \ddots & \vdots \\ \partial_{x_n} e_d(x, x) & \partial_{x_n} \partial_{y_1} e_d(x, x) & \cdots & \partial_{x_n} \partial_{y_n} e_d(x, x) \end{pmatrix}.$$

The conditional distribution of $d_x P$ is a centered Gaussian.

We can compute its variance from Λ .

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We conclude by using the estimates of Ma and Marinescu for e_d .

Asymptotic of the variance

$$\text{Var}(\langle Z_d, \phi \rangle) = \mathbb{E}[\langle Z_d, \phi \rangle^2] - \mathbb{E}[\langle Z_d, \phi \rangle]^2.$$

By the Kac–Rice formula, $\mathbb{E}[\langle Z_d, \phi \rangle]^2$ equals:

$$\frac{1}{2\pi} \int_{x,y \in \mathbb{S}^n} \phi(x)\phi(y) \frac{\mathbb{E}[\|d_x P\| \mid P(x) = 0]}{\sqrt{e_d(x,x)}} \frac{\mathbb{E}[\|d_y P\| \mid P(y) = 0]}{\sqrt{e_d(y,y)}}.$$

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Besides,

$$\mathbb{E} \left[\langle Z_d, \phi \rangle^2 \right] = \mathbb{E} \left[\int_{x,y \in Z_d} \phi(x)\phi(y) |dV_d|^2 \right].$$

Kac–Rice formula 2

For d large enough, we have $\det \begin{pmatrix} e_d(x,x) & e_d(x,y) \\ e_d(y,x) & e_d(y,y) \end{pmatrix} \neq 0$, whenever $x \neq y$ (i.e. $(P(x), P(y))$ is non-degenerate).

Kac–Rice formula

$$\mathbb{E} \left[\int_{x,y \in Z_d} \phi(x)\phi(y) |dV_d|^2 \right] = \frac{1}{2\pi} \int_{x,y \in \mathbb{S}^n} \phi(x)\phi(y) \frac{\mathbb{E} \left[\|d_x P\| \|d_y P\| \mid P(x) = 0 = P(y) \right]}{\sqrt{e_d(x,x)e_d(y,y) - e_d(x,y)^2}}.$$

Asymptotic of the variance

Finally

$$\text{Var}(\langle Z_d, \phi \rangle) = \frac{1}{2\pi} \int_{x,y \in \mathbb{S}^n} \phi(x)\phi(y) \mathcal{D}_d(x,y),$$

where

$$\mathcal{D}_d(x,y) = \frac{\mathbb{E} \left[\|d_x P\| \|d_y P\| \mid P(x) = 0 = P(y) \right]}{\sqrt{e_d(x,x)e_d(y,y) - e_d(x,y)^2}} \\ - \frac{\mathbb{E} \left[\|d_x P\| \mid P(x) = 0 \right]}{\sqrt{e_d(x,x)}} \frac{\mathbb{E} \left[\|d_y P\| \mid P(y) = 0 \right]}{\sqrt{e_d(y,y)}}.$$

Asymptotic of the variance

When $D(x, y) \geq K \frac{\log d}{\sqrt{d}}$, we prove that $\mathcal{D}_d(x, y)$ is $O\left(d^{r-\frac{n}{2}-1}\right)$.

Moreover, $\frac{1}{d^r} \mathcal{D}_d\left(x, x + \frac{z}{\sqrt{d}}\right) \xrightarrow{d \rightarrow +\infty} \mathcal{D}(z)$.

$$\begin{aligned} \int_{x, y \in \mathbb{S}^n} \phi(x) \phi(y) \mathcal{D}_d(x, y) &\simeq \int_{x \in \mathbb{S}^n} \int_{y \in B(x, \frac{\log d}{\sqrt{d}})} \phi(x) \phi(y) \mathcal{D}_d(x, y) \\ &\simeq d^{-\frac{n}{2}} \int_{x \in \mathbb{S}^n} \int_{z \in B(0, \log d)} \phi(x) \phi\left(x + \frac{z}{\sqrt{d}}\right) \mathcal{D}_d\left(x, x + \frac{z}{\sqrt{d}}\right) \\ &\simeq d^{r-\frac{n}{2}} \left(\int_{x \in \mathbb{S}^n} \phi(x)^2 \right) \left(\int_{\mathbb{R}^n} \mathcal{D}(z) \right). \end{aligned}$$

Almost sure equidistribution

We consider a random sequence of polynomials of increasing degree

$$(P_d)_{d \in \mathbb{N}^*} \in \prod_{d \in \mathbb{N}^*} \mathbb{R}_d^{\text{hom}}[X_0, \dots, X_n],$$

distributed as $d\nu$, product measure of the Kostlan distributions.

Corollary

If $n \geq 3$, then $d\nu$ -almost surely we have:

$$\forall \phi \in C^0(\mathbb{S}^n), \quad \frac{1}{\sqrt{d}} \langle Z_{P_d}, \phi \rangle \xrightarrow{d \rightarrow +\infty} \frac{\text{Vol}(\mathbb{S}^{n-1})}{\text{Vol}(\mathbb{S}^n)} \int_{\mathbb{S}^n} \phi.$$

Almost sure equidistribution

Let $\phi \in \mathcal{C}^0(\mathbb{S}^n)$, we have:

$$\mathbb{E} \left[\sum_{d \geq 1} \left(\frac{1}{\sqrt{d}} (\langle Z_{P_d}, \phi \rangle - \mathbb{E}[\langle Z_d, \phi \rangle]) \right)^2 \right] = \sum_{d \geq 1} \frac{1}{d} \text{Var}(\langle Z_d, \phi \rangle) < +\infty,$$

since $\text{Var}(\langle Z_d, \phi \rangle) = O(d^{1-\frac{3}{2}})$. Then $d\nu$ -a.s.

$$\sum_{d \geq 1} \left(\frac{1}{\sqrt{d}} (\langle Z_{P_d}, \phi \rangle - \mathbb{E}[\langle Z_d, \phi \rangle]) \right)^2 < +\infty,$$

and

$$\frac{1}{\sqrt{d}} \langle Z_{P_d}, \phi \rangle \xrightarrow[d \rightarrow +\infty]{d\nu\text{-p.s.}} \frac{\text{Vol}(\mathbb{S}^{n-1})}{\text{Vol}(\mathbb{S}^n)} \int_{\mathbb{S}^n} \phi.$$

We conclude by using the separability of $\mathcal{C}^0(\mathbb{S}^n)$.

The end

Thank you for your attention.