

# On the number of roots of random homogeneous polynomials

Based on joint works with D.Armentano, JM. Azaïs, JR. León  
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# Plan of the talk:

1. Introduction.
2. Random Homogeneous polynomials.
  - 2.1 Kostlan's classification.
  - 2.2 Some concrete examples.
3. The expectation of the number of roots.
4. The variance of the number of roots.
  - 4.1 General aspects.
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  - 4.3 The limit.
  - 4.4 On the positivity of the limit variance.

# Introduction

# Introduction

We are interested in the distribution of the number of roots of random polynomial systems of equations.

This is a natural continuation of the study of the number of roots of random polynomials.

- ▶ We shall concentrate on **square systems**, but one can consider instead the geometric measure (depending on the dimension: the length, the area, etc.) of the zero set of non-square systems with the same methods.
- ▶ Assuming **homogeneity** is not an important restriction.
- ▶ **Invariance under isometries** is natural in some frameworks and greatly simplifies the treatment.

# Introduction

In the **early nineties**, **Kostlan** and **Shub & Smale** proposed the study of an invariant Gaussian polynomial system which appears naturally in the analysis of algorithms for solving polynomial systems of equations.

Via geometric/analytic arguments they computed the exact expected number of roots of such systems.

In **2005** **Azaïs & Wschebor**, using probabilistic tools, gave a new proof for the expectation and computed the asymptotic variance of these systems when the size of the system (number of equations = number of variables) tends to infinity while the degree remains controlled.

# Introduction

In the last five years the asymptotic variance of the number of roots of these systems, as the degree tends to infinity, has been obtained by Letendre, Letendre & Puchol and Armentano, Azaïs, D & León.

A Central Limit Theorem was established by the latter authors.

# Random Homogeneous Polynomials

# Random Homogeneous Polynomials

We are interested in **random homogeneous polynomials** which distributions are invariant under the action of the orthogonal group  $\mathcal{O}(n+1)$ :

$$f(Ux) \stackrel{(d)}{=} f(x), \quad \text{for all } U \in \mathcal{O}(n+1).$$

Here  $\stackrel{(d)}{=}$  means *equal distributed r.v.s.*

## Remark

*In the complex case there is a unique invariant Gaussian distribution in the space of (complex) homogeneous polynomials. This is not the case for real polynomials.*

# Random Homogeneous Polynomials

A Gaussian distribution in the space of homogeneous polynomials can be associated with an inner product on the underlying parameter space:

$$p(f) = \text{Const} \cdot \exp \left( -\frac{1}{2} \langle f, f \rangle \right).$$

Taking profit of this correspondence [Kostlan](#) in [2002](#) classified all orthogonally invariant centered Gaussian distributions on the space of real homogeneous polynomials.

We start recalling this classification.

# Random Homogeneous Polynomials

Let  $\mathcal{P}_{d,n}$  be the space of real homogeneous polynomials of degree  $d$  in  $n + 1$  variables and let  $\mathcal{H}_{d,n}$  denote the subspace of *harmonic homogeneous polynomials*,

$$\mathcal{H}_{d,n} = \{f \in \mathcal{P}_{d,n} : \partial_{x_0}^2 f + \cdots + \partial_{x_n}^2 f \equiv 0\}.$$

Restrictions of harmonic homogeneous polynomials in  $\mathcal{H}_{d,n}$  to the unit sphere  $\mathbb{S}^n = \{x \in \mathbb{R}^{n+1} : |x| = 1\}$  are called *spherical harmonics*; these are eigenfunctions of the spherical Laplace operator corresponding to the eigenvalue  $-d(d + n - 1)$ .

# Random Homogeneous Polynomials

It is well-known that

$$\mathcal{P}_{d,n} = \mathcal{H}_{d,n} \oplus |x|^2 \mathcal{H}_{d-2,n} \oplus \cdots \oplus |x|^{2[d/2]} \mathcal{H}_{d-2[d/2],n},$$

is a direct sum decomposition and

$$|x|^{2k} \mathcal{H}_{d-2k,n} = \{|x|^{2k} h : h \in \mathcal{H}_{d-2k,n}\}, \quad k = 0, \dots, [d/2],$$

are irreducible subspaces of  $\mathcal{P}_{d,n}$  under the standard action of the orthogonal group.

# Random Homogeneous Polynomials

Kostlan proved that (up to a multiplicative constant) there is a unique inner product in  $\mathcal{H}_{d-2k,n} : k = 0, \dots, \lfloor d/2 \rfloor$  which is invariant under the action of the orthogonal group.

Therefore, each invariant inner product in  $\mathcal{P}_{d,n}$  is a (positive) linear combination of the inner products in  $\mathcal{H}_{d-2k,n} : k = 0, \dots, \lfloor d/2 \rfloor$ .

From the point of view of the Gaussian distribution this means that:

*There is (up to a scale constant) a unique invariant Gaussian distribution on  $\mathcal{H}_{d-2k,n} : k = 0, \dots, \lfloor d/2 \rfloor$  and any invariant Gaussian distribution on  $\mathcal{P}_{d-2k,n}$  is a convolution of the distributions on  $\mathcal{H}_{d-2k,n} : k = 0, \dots, \lfloor d/2 \rfloor$ .*

# Random Homogeneous Polynomials

Hence, a random homogeneous polynomial can be realised as

$$f(x) = \sum_{k=0}^{\lfloor \frac{d}{2} \rfloor} w_{d-2k} \sum_{i=1}^{D_{d-2k}} \xi_{d-2k}^i Y_{d-2k}^i(x), \quad x \in \mathbb{S}^n.$$

Here,  $\{Y_{d-2k,n}^i\}_{i=1}^{D_{d-2k,n}}$  is any  $\langle \cdot, \cdot \rangle_{d-2k,n}^{\text{RFS}}$ -orthonormal basis of  $\mathcal{H}_{d-2k,n}$  and  $\xi_{d-2k,n}^i$ ,  $i = 1, \dots, D_{d-2k,n}$ ,  $k = 0, \dots, \lfloor d/2 \rfloor$ , are independent standard Gaussian random variables.

The  $\{w_{d-2k}\}_k$  are positive weights that parameterise the different Gaussian models.

**Some particular examples.**

# Kostlan Polynomial systems

This distribution is associated with the **Bombieri-Weyl** inner product. For  $m \in \mathbb{N}$ , consider homogeneous polynomials

$$f_\ell(x) = \sum_{|j|=d} a_j^{(\ell)} x^j; \quad \ell = 1, \dots, m,$$

where we use the notations

- ▶  $j = (j_0, \dots, j_m) \in \mathbb{N}^{m+1}$ ;
- ▶  $x = (x_0, \dots, x_m) \in \mathbb{R}^{m+1}$ ;
- ▶  $|j| = \sum_{k=0}^m j_k$  and  $x^j = \prod_{k=0}^m x_k^{j_k}$ .
- ▶  $a_j^{(\ell)} \in \mathbb{R}$ .

We assume that the random variables  $a_j^{(\ell)}$  are independent centered Gaussian with variances

$$\text{var} \left( a_j^{(\ell)} \right) = \binom{d}{j} = \frac{d!}{\prod_{k=0}^m j_k!}.$$

# Kostlan Polynomials

**Remark** If we ask the polynomials to be invariant in distribution and the monomials to be independent, then, the polynomials must be Gaussian. [Kostlan](#).

The covariance function for  $f_\ell$  is:

$$r_d(s, t) := \mathbf{E}(f_\ell(s)f_\ell(t)) = \langle s, t \rangle^d;$$

where  $\langle \cdot, \cdot \rangle$  is the standard inner product in  $\mathbb{R}^{n+1}$ .

This is clearly invariant under orthogonal transformations.

# Random Homogeneous Polynomials

The *real Fubini-Study scalar product* on  $\mathcal{P}_{d,n}$  (or  $L^2(\mathbb{S}^n)$ -product) is defined by

$$\langle f, g \rangle_{d,n}^{\text{RFS}} = \int_{\mathbb{S}^n} f(x)g(x) d\mathbb{S}^n(x), \quad f, g \in \mathcal{P}_{d,n},$$

where  $d\mathbb{S}^n$  is the standard volume measure on the sphere  $\mathbb{S}^n$ . One can easily see that this scalar product is invariant under orthogonal changes of coordinates on  $\mathcal{P}_{d,n}$ .

This implies that the restriction of the real Fubini-Study scalar product to  $\mathcal{H}_{d,n}$  is the unique (up to a multiple) orthogonally invariant scalar product on  $\mathcal{H}_{d,n}$ . Equivalently, there is a unique centered Gaussian probability distribution on  $\mathcal{H}_{d,n}$  that is invariant under orthogonal changes of variables.

# Random Spherical Harmonics

A random spherical harmonic  $h \in \mathcal{H}_{d,n}$  is modelled as

$$h(x) = \sum_{i=1}^{D_{d,n}} \xi_{d,n}^i Y_{d,n}^i(x), \quad x \in \mathbb{S}^n,$$

where  $D_{d,n} = \dim \mathcal{H}_{d,n}$ ,  $\{Y_{d,n}^i\}_{i=1}^{D_{d,n}}$  is any  $\langle \cdot, \cdot \rangle_{d,n}^{\text{RFS}}$ -orthonormal basis of  $\mathcal{H}_{d,n}$  and  $\xi_{d,n}^i$ ,  $i = 1, \dots, D_{d,n}$ , are independent standard Gaussian random variables.

Normalization:  $h \mapsto \nu h$  with  $\nu = \sqrt{\frac{|\mathbb{S}^n|}{\dim(\mathcal{H}_{d,n})}}$ .

**Remark** In the case of  $\mathbb{S}^2$ , if the terms in the above sum are independent then the form is Gaussian [Baldi & Marinucci](#).

# Real Fubini-Study

A random form  $f \in \mathcal{P}_{d,n}$ , is modelled as

$$f(x) = \sum_{k=0}^{[d/2]} \sum_{i=1}^{D_{d-2k,n}} \xi_{d-2k,n}^i Y_{d-2k,n}^i(x), \quad x \in \mathbb{S}^n.$$

Here,  $\{Y_{d-2k,n}^i\}_{i=1}^{D_{d-2k,n}}$  is any  $\langle \cdot, \cdot \rangle_{d-2k,n}^{\text{RFS}}$ -orthonormal basis of  $\mathcal{H}_{d-2k,n}$  and  $\xi_{d-2k,n}^i$ ,  $i = 1, \dots, D_{d-2k,n}$ ,  $k = 0, \dots, [d/2]$ , are independent standard Gaussian random variables.

Normalization:  $f \mapsto \omega f$  with  $\omega = \sqrt{\frac{|\mathbb{S}^n|}{\dim(\mathcal{P}_{d,n})}}$ .

## RSH and RFS as Gaussian fields

Centered Gaussian fields are characterized by its covariance functions.

Addition Theorem for spherical harmonics and the properties of Gegenbauer (a.k.a. ultraspherical) polynomials yield:

$$\mathbf{E}(h(x)h(y)) = \frac{P_d^{(\lambda)}(\langle x, y \rangle)}{P_d^{(\lambda)}(1)};$$
$$\mathbf{E}(f(x)f(y)) = \frac{P_d^{(\lambda+1)}(\langle x, y \rangle)}{P_d^{(\lambda+1)}(1)};$$

where  $P_d^{(\lambda)}$  is the *standard Gegenbauer polynomial of parameter*  $\lambda = \frac{n-1}{2}$  *of degree*  $d$ .

# Real Fubini-Study

Using the addition theorem for spherical harmonics: for  $x, y \in S^n$  and  $t = x \cdot y$ ,

$$\begin{aligned}\mathbf{E}(f(x)f(y)) &= \omega^2 \sum_{k=0}^{[d/2]} \sum_{i=1}^{D_{d-2k,n}} Y_{d-2k,n}^i \left( \frac{x}{|x|} \right) Y_{d-2k,n}^i \left( \frac{y}{|y|} \right) \\ &= \sum_{k=0}^{[d/2]} \frac{D_{d-2k,n}}{\dim(\mathcal{P}_{d,n})} \frac{P_{d-2k}^{(\lambda)}(t)}{P_{d-2k}^{(\lambda)}(1)},\end{aligned}$$

where  $P_k^{(\lambda)}$  is the Gegenbauer polynomials of degree  $k$  and parameter  $\lambda = \frac{n-1}{2}$ .

# Real Fubini-Study

We have,

$$\frac{D_{d-2k,n}}{P_{d-2k}^{(\lambda)}(1)} = \frac{\binom{n+d-2k}{d-2k} - \binom{n+d-2k-2}{d-2k-2}}{\binom{n+d-2k-2}{d-2k}} = \frac{2(d-2k) + n - 1}{n - 1}.$$

Now,  $\dim(\mathcal{P}_{d,n}) = \binom{n+d}{d} = P_d^{(\lambda+1)}(1)$  and  $n - 1 = 2\lambda$ . Hence, we get

$$\begin{aligned} K(t) &= \frac{2}{2\lambda \dim(\mathcal{P}_{d,n})} \sum_{k=0}^{[d/2]} [d - 2k + \lambda] P_{d-2k}^{(\lambda)}(t) \\ &= \frac{1}{2\lambda P_d^{(\lambda+1)}(1)} \frac{d}{dx} P_{d+1}^{(\lambda)}(t) = \frac{P_d^{(\lambda+1)}(t)}{P_d^{(\lambda+1)}(1)}. \end{aligned}$$

## Bonus

We consider an extra example based on the spectral function in [Nicolae](#) defined by

$$f(x) = \sum_{k=0}^d \sum_{i=1}^{D_{d-k,n}} \xi_{d-k,n}^i Y_{d-k,n}^i(x), \quad x \in \mathbb{S}^n.$$

This model does not suit our framework since it includes all  $k = 0, \dots, d$ .

# Coherent families

When studying the asymptotic behaviour as  $d \rightarrow \infty$  one can think in changing the model for each  $d$  while preserving some consistency in the sequence.

As invariant polynomial distributions are parameterised by the weights  $w_{d-2k}$ , it is natural to put conditions on them.

Fyodorov, Lerario & Lundberg proposed the following coherence condition: there exists  $0 < \lambda \leq 1$  such that

$$w_d(d^\lambda x) d^\lambda \rightarrow_d \psi(x), \quad x \in [0, 1).$$

Besides, a subgaussian domination takes place.

Sodin asks a similar condition but directly on the covariance of the polynomials.

**Main results.**

## Main results.

Let  $F = (f_1, \dots, f_n)$  with  $f_i$  i.i.d. copies of one of the models above.

Then, the expectation of the number of roots on the sphere  $N_0$  can be computed explicitly and

### Theorem

There exist constants  $V_K, V_{RSH}, V_{RFS}$  such that:

Kostlan  $\lim_{d \rightarrow \infty} \frac{\text{Var}(N_0)}{d^{n/2}} = V_K;$

RFS  $\lim_{d \rightarrow \infty} \frac{\text{Var}(N_0)}{d^n} = V_{RFS};$

RSH  $\lim_{d \rightarrow \infty} \frac{\text{Var}(N_0)}{d^n} = V_{RSH};$

We know  $0 < V_{RFS}, V_K < \infty$  and  $V_{RSH} < \infty$ .

## Remark - Uni- and bi-variate cases

Let us look now at the case  $n = 1$ .

We have

$$\begin{aligned}\mathbf{E}(f(x)f(y)) &= \frac{1}{\pi} \left[ \frac{1 + (-1)^d}{4} + \sum_{k=0}^{[(d-1)/2]} \cos((d-2k)\theta) \right] \\ &= \frac{\sin((d+1)(\varphi - \psi))}{2\pi \sin(\varphi - \psi)}.\end{aligned}$$

This is similar to the covariance of cosine polynomials which was previously studied.

The bivariate for RSH case was studied by [Wigman](#) in 2011.

**On the expectation.**

## On the expectation.

By Rice formula, we have

$$\mathbf{E}(N_0) = \int_{\mathbb{S}^n} \mathbf{E}(|F'(s)| \mid F(s) = 0) p_{F(s)}(0) ds.$$

Here  $F'$  is the derivative (matrix) of  $F$  on the tangent space;  $ds$  is the surface measure and  $|\cdot|$  is a shorthand for  $|\det(\cdot)|$ .

## On the expectation.

Direct computations show that:

For Kostlan polynomials

$$\mathbf{E}(N_0) = 2d^{n/2}.$$

For RFS polynomials

$$\mathbf{E}(N_0) = 2 \left[ \frac{d(d+n+1)}{n+2} \right]^{n/2} \underset{d \rightarrow \infty}{\sim} c_n d^n.$$

For RSH (it suffices to replace  $n$  by  $n-2$  in the variance).

$$\mathbf{E}(N_0) = 2 \left[ \frac{d(d+n-1)}{n} \right]^{n/2}.$$

This is coherent with [Kostlan's](#) results.

**On the variance.**

## Variance - general aspects

To compute the variance we use Rice formula for the second factorial moment.

$$\begin{aligned} \mathbf{E}(N_0(N_0 - 1)) \\ = v_d^{2n} \int_{(\mathbb{S}^n)^2} \mathbf{E}[|\det \overline{F'}(s) \det \overline{F'}(t)| | F(s) = F(t) = 0] \\ \cdot p_{F(s), F(t)}(0, 0) ds dt. \end{aligned}$$

Here  $ds$  and  $dt$  are the (non-normalized) surface measure on  $\mathbb{S}^n$ ,  $\overline{F'}$  is the normalized derivative,  $p_{F(s), F(t)}(0, 0)$  is the joint density of  $F(s)$  and  $F(t)$  evaluated at  $(0, 0)$ .

This can be strongly simplified thanks to the invariance of the distribution of  $F$  as done in [AADL].

## Variance - general aspects

Let  $\{e_0, e_1, \dots, e_n\}$  be the canonical basis of  $\mathbb{R}^{n+1}$  and

$$s = e_0, \quad t = \cos(\theta)e_0 + \sin(\theta)e_1. \quad (1)$$

We fix the bases  $\{e_1, \dots, e_n\}$  and  $\{\sin(\theta)e_0 - \cos(\theta)e_1, e_2, \dots, e_n\}$  for  $s^\perp$  and  $t^\perp$ .

Then,

$$\mathbf{E}(N_0(N_0 - 1)) = v_d^{2n} \frac{|\mathbb{S}^n| |\mathbb{S}^{n-1}|}{(2\pi)^n} \int_0^\pi \frac{\sin^{n-1}(\theta) \mathcal{E}(\cos(\theta))}{(1 - \mathcal{C}^2(\cos(\theta)))^{n/2}} d\theta,$$

where  $\mathcal{E}(\cos(\theta))$  is the conditional expectation written for  $s, t$  as in (1) and  $\mathcal{C}(\theta)$  is the covariance function.

## Variance - general aspects

In order to compute the conditional expectation  $\mathcal{E}(\cos(\theta))$  we need to know the joint distribution of  $V(\theta) := \left(f_\ell(s), f_\ell(t), \frac{f'_\ell(s)}{v_d}, \frac{f'_\ell(t)}{v_d}\right)$  at the given basis (1),

Its variance-covariance matrix at the given basis (1), can be written in the following form

$$\left[ \begin{array}{c|c|c} A_{11} & A_{12} & A_{13} \\ \hline A_{12}^\top & I_n & A_{23} \\ \hline A_{13}^\top & A_{23}^\top & I_n \end{array} \right], \quad (2)$$

where  $I_n$  is the  $n \times n$  identity matrix...

## Variance - general aspects

$$A_{11} = \begin{bmatrix} 1 & \mathcal{C} \\ \mathcal{C} & 1 \end{bmatrix}, \quad A_{12} = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ -\mathcal{A} & 0 & \cdots & 0 \end{bmatrix},$$
$$A_{13} = \begin{bmatrix} \mathcal{A} & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \end{bmatrix},$$

and  $A_{23}$  is the  $n \times n$  diagonal matrix  $\text{diag}(\mathcal{B}, \mathcal{D}, \dots, \mathcal{D})$ .

Here,  $\mathcal{A}, \mathcal{B}, \mathcal{C}$  and  $\mathcal{D}$  are the covariances between the different coordinates of  $V$ .

## Variance - general aspects

Gaussian regression formulas imply that the conditional distribution of the vector  $(\frac{f'_\ell(s)}{v_d}, \frac{f'_\ell(t)}{v_d})$  (conditioned on  $F(s) = F(t) = 0$ ) is centered normal with variance-covariance matrix given by

$$\left[ \begin{array}{c|c} B_{11} & B_{12} \\ \hline B_{12}^\top & B_{22} \end{array} \right], \quad (3)$$

with  $B_{11} = B_{22} = \text{diag}(\sigma^2, 1, \dots, 1)$  and  $B_{12} = \text{diag}(\sigma^2 \rho, \mathcal{D}, \dots, \mathcal{D})$ .

Here,

$$\sigma^2 = 1 - \frac{\mathcal{A}^2}{1 - \mathcal{C}^2}, \quad \rho = \frac{\mathcal{B}(1 - \mathcal{C}^2) - \mathcal{A}^2 \mathcal{C}}{1 - \mathcal{C}^2 - \mathcal{A}^2}.$$

## Variance - particular aspects

In the case of RFS polynomials:

$$\mathcal{A}(\theta) = \frac{2(\lambda+1)}{v_d} \frac{P_{d-1}^{(\lambda+2)}(\cos(\theta))}{P_d^{(\lambda+1)}(1)} \sin(\theta).$$

$$\begin{aligned} \mathcal{B}(\theta) = & \frac{4(\lambda+1)(\lambda+2)}{v_d^2 \cdot P_d^{(\lambda+1)}(1)} \cdot P_{d-2}^{(\lambda+3)}(\cos(\theta)) \sin^2(\theta) \\ & - \frac{2(\lambda+1)}{v_d^2 \cdot P_d^{(\lambda+1)}(1)} \cdot P_{d-1}^{(\lambda+2)}(\cos(\theta)) \cos(\theta). \end{aligned}$$

$$\mathcal{C}(\theta) = \frac{P_d^{(\lambda+1)}(\cos(\theta))}{P_d^{(\lambda+1)}(1)}.$$

$$\mathcal{D}(\theta) = \frac{2(\lambda+1)}{v_d^2} \frac{P_{d-1}^{(\lambda+2)}(\cos(\theta))}{P_d^{(\lambda+1)}(1)}.$$

**On the variance - the limit.**

## Variance - particular aspects

After the scaling  $\theta \mapsto \frac{\theta}{\sqrt{d}}$  or  $\theta \mapsto \frac{\theta}{d}$  we get pointwise limits and dominations in order to pass to the limit.

In Kostlan's case:

$$C\left(\frac{\theta}{\sqrt{d}}\right) = \cos^d\left(\frac{\theta}{\sqrt{d}}\right) \xrightarrow{d \rightarrow \infty} e^{-\frac{1}{2}\theta^2}.$$

In the RFS case:

$$C\left(\frac{\theta}{d}\right) = \frac{P_d^{(\lambda+1)}(\cos(\theta/d))}{P_d^{(\lambda+1)}(1)} \xrightarrow{d \rightarrow \infty} \Gamma\left(\lambda + \frac{3}{2}\right) \left(\frac{2}{\theta}\right)^{\lambda + \frac{1}{2}} J_{\lambda + \frac{1}{2}}(\theta),$$

where  $J_{\lambda + \frac{1}{2}}$  is Bessel function of the first kind of order  $\lambda + \frac{1}{2}$ .

## Variance - particular aspects

The domination in Kostlan's case is obtained by direct computations.

In the RFS case we use a bound by [Elderly, Magnus & Nevai](#) which in our setting can be written as: for  $d \geq 0$

$$\max_{x \in [-1,1]} (1-x^2)^\lambda \left[ \frac{P_d^{(\lambda)}(x)}{d^{\lambda-1}} \right]^2 \leq \kappa_\lambda, \quad (4)$$

for some positive constant  $\kappa_\lambda$ .

we get

$$C \left( \frac{\theta}{d} \right) \leq \frac{C}{\theta^{\lambda+1}}.$$

We used that for  $u \in [0, \pi/2]$ , we have  $\sin(u) \geq \frac{2u}{\pi}$ .

**Some words about the positivity of the limit variance.**

## Some words about the positivity of the limit variance.

We borrow the chaotic expansion from [AADL],

$$N_d = v_d^n \sum_{q=0}^{\infty} \sum_{|\alpha|+|\beta|=q} b_{\alpha} f_{\beta} \int_{\mathbb{S}^n} H_{\alpha}(\tilde{F}(t)) H_{\beta}\left(\frac{\tilde{F}'(t)}{v_d}\right) dt$$

Here, the  $v_d^n$  comes from the homogeneity of the determinant.

Now, for  $q = 2$  we have:

$$I_{2,d} = v_d^n \sum_{\ell=1}^n b_0^{n-1} \int_{\mathbb{S}^n} \left[ b_2 f_0 H_2(f_{\ell}(t)) + b_0 f_2 \sum_{r=1}^n H_2\left(\frac{\partial_r f_{\ell}(t)}{v_d}\right) \right] dt,$$

where  $v_d^2 = \mathbf{Var}(\partial_r f_{\ell}(t)) = \frac{d(d+n+1)}{n+2}$ . Besides,

$$f_0 = n f_2 \quad \text{and} \quad b_2 = -b_0.$$

## Some words about the positivity of the limit variance.

Now, using Green theorem we get

$$\begin{aligned}\sum_{r=1}^n \int_{\mathbb{S}^n} H_2\left(\frac{\partial_r f_\ell(t)}{v_d}\right) dt &= \sum_{r=1}^n \int_{\mathbb{S}^n} \left(\frac{\partial_r f_\ell(t)^2}{v_d^2} - 1\right) dt \\ &= \sum_{r=1}^n \int_{\mathbb{S}^n} \left(-\frac{f_\ell(t) \partial_{rr}^2 f_\ell(t)}{v_d^2} - 1\right) dt \\ &= \int_{\mathbb{S}^n} \left(\frac{f_\ell(t)(-\Delta) f_\ell(t)}{v_d^2} - n\right) dt.\end{aligned}$$

But,

$$\begin{aligned}-\Delta f(t) &= \omega \sum_{k=0}^{[d/2]} \sum_{i=1}^{D_{d-2k,n}} \xi_{d-2k,n}^i (-\Delta) Y_{d-2k,n}^i(t) \\ &= \omega \sum_{k=0}^{[d/2]} \sum_{i=1}^{D_{d-2k,n}} \xi_{d-2k,n}^i \lambda_{d-2k} Y_{d-2k,n}^i(t),\end{aligned}$$

where  $\lambda_{d-2k} = (d-2k)(d-2k+n-1)$  are the eigenvalues of  $-\Delta$ .

## Some words about the positivity of the limit variance.

Hence,

$$\begin{aligned}\sum_{r=1}^n \int_{\mathcal{S}^n} H_2\left(\frac{\partial_r f_\ell(t)}{v_d}\right) dt &= \int_{\mathcal{S}^n} \left( \frac{f_\ell(t)(-\Delta)f_\ell(t)}{v_d^2} \pm n f_\ell(t)^2 - n \right) dt \\ &= \omega^2 \sum_{k=0}^{[d/2]} \left( \frac{\lambda_{d-2k}}{v_d^2} - n \right) \sum_{i=1}^{D_{d-2k,n}} (\xi_{d-2k,n}^i)^2 \\ &\quad + \int_{\mathcal{S}^n} n H_2(f_\ell(t)) dt.\end{aligned}$$

Here we used the orthogonality of the  $Y$ 's.

## Some words about the positivity of the limit variance.

Putting all together we have

$$\begin{aligned}
 I_{2,d} = & v_d^n \sum_{\ell=1}^n b_0^{n-1} \underbrace{(b_2 f_0 + n b_0 f_2)}_{=0} \int_{S^n} H_2(f_\ell(t)) dt \\
 & + \underbrace{b_0^n f_2 \, v_d^n \omega^2 \sum_{k=0}^{[d/2]} \left( \frac{\lambda_{d-2k}}{v_d^2} - n \right) \sum_{i=1}^{D_{d-2k,n}} (\xi_{d-2k,n}^i)^2}_{:=\zeta_d}.
 \end{aligned}$$

Now,

$$\frac{\lambda_{d-2k}}{v_d^2} - n = (n+2) \frac{(d-2k)(d-2k+n-1)}{d(d+n+1)} - n \rightarrow_d 2.$$

So, since  $\sum_{k=0}^{[d/2]} \sum_{i=1}^{D_{d-2k,n}} (\xi_{d-2k,n}^i)^2 \sim \chi_{\dim(\mathcal{P}_{n,d})}^2$ , we have

$$\mathbf{Var}(\zeta_d) \approx \underbrace{v_d^{2n}}_{\sim d^{2n}} \underbrace{\omega^4}_{\sim d^{-2n}} \underbrace{2 \binom{d+n}{d}}_{\sim d^n} \sim_{d \rightarrow \infty} d^n.$$

**¡THANKS FOR YOUR ATTENTION!**