

# On the spatial distribution of critical points of Random Plane Waves

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# Random Plane Wave

- A 1-dim version of the Random Wave was used by Rice to investigate the likelihood of a given signal to exceed a level.
- In 1950 Longuet-Higgins generalised Rice's model to 2-dim plane to describe ocean waves.
- In 1977 M. Berry conjectured that *high energy behaviour of eigenfunctions* in the chaotic case is universal and have statistically the same behaviour as random plane wave.

# Random Plane Wave

- Space of spherical harmonics of degree  $l$  is of dimension  $2l + 1$ , let  $\{\phi_i\}_{i=1, \dots, 2l+1}$  be an arbitrary  $L^2$ -orthonormal basis. Define random Gaussian spherical harmonic

$$f_l = \sum_{i=1}^{2l+1} c_i \phi_i$$

$c_i$  are i.i.d. standard Gaussian variables. *RPW is the scaling limit of the Gaussian spherical harmonic.*

- We can relate high energy Gaussian spherical harmonics with to the the behaviour of RPW inside a big ball.
- Here we focus on critical points in *small balls and repulsion.*

# Random Plane Wave

## Definition

The **Random Plane Wave** with energy  $E = k^2$  is the centred Gaussian field on  $\mathbb{R}^2$  with covariance kernel

$$K(x, y) = J_0(k|x - y|).$$

One may think of RPW as a *random Gaussian solution* of

$$\Delta f + k^2 f = 0$$

i.e.

$$F(x) = \sum_{n=-\infty}^{\infty} c_n J_{|n|}(kr) e^{in\theta}$$

$c_n$  are standard Gaussian independent save to  $c_{-n} = \bar{c}_n$ .

# Critical Points

We study the **critical point set**

$$\{x \in \mathbb{R}^2 : \nabla F(x) = 0\}.$$

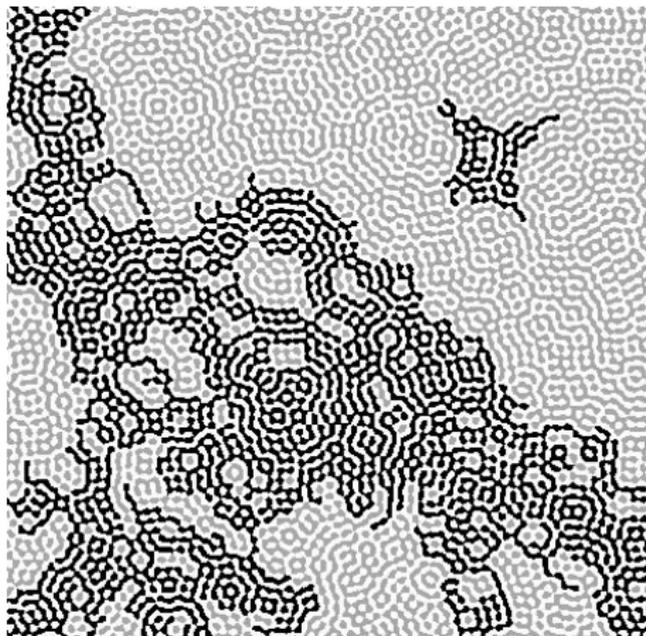
We are interested in the **spatial distribution** of critical points across the surface.

We fix  $k = 1$  since RPW with different values of  $k$  differ by the scaling.

# Motivations

Nodal lines  $\{x \in \mathbb{R}^2 : F(x) = 0\}$

Nodal domains  $\mathbb{R}^2 \setminus \{x \in \mathbb{R}^2 : F(x) = 0\}$

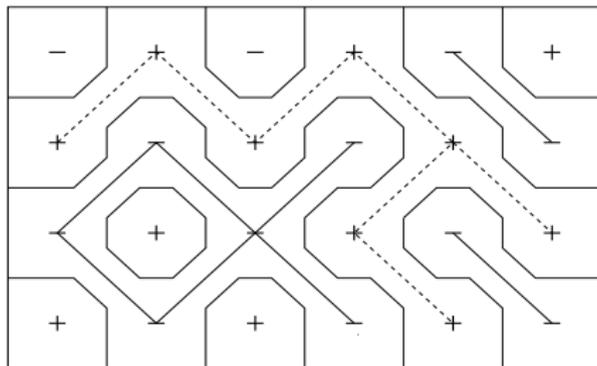


Nodal domains for  
 $k = 100$ .

Two nodal  
domains are  
highlighted  
[Bogomolny-  
Schmit  
2002]

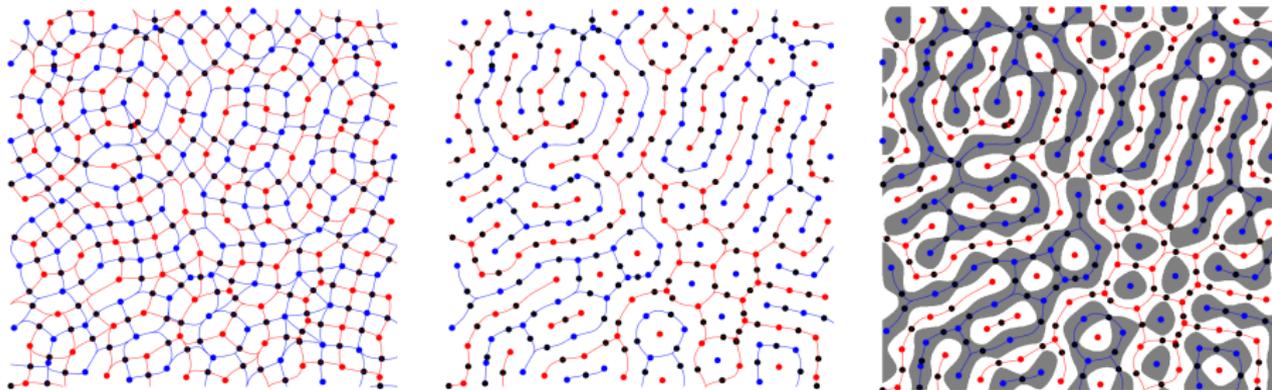
# Motivations

[**Bogomolny-Schmit 2002**] introduce a bond percolation model on the square lattice to describe nodal domains.



# Motivations

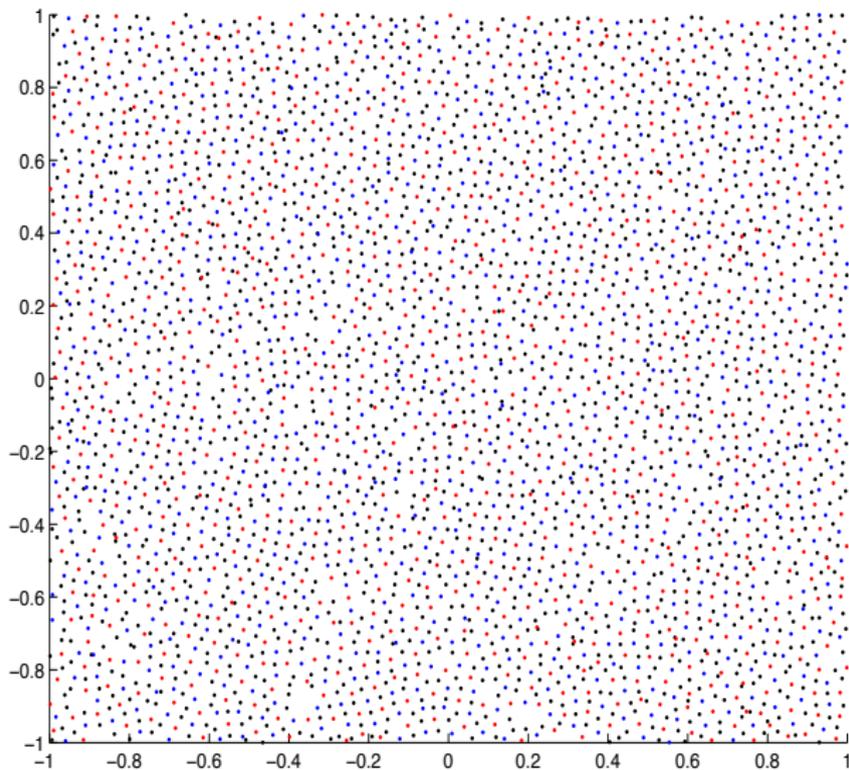
**[Beliaev-Kereta 2013]** introduce a bond percolation on a random graph where nodes are local maxima and edges are gradient streamlines passing through saddles.



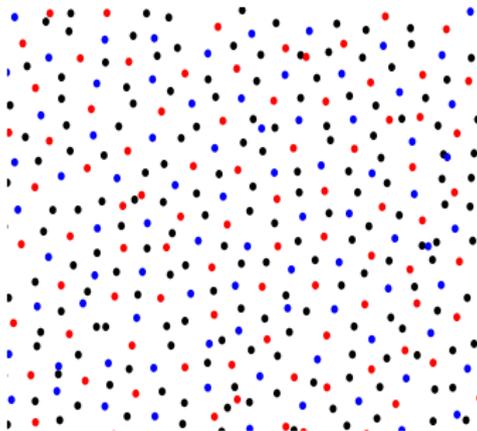
Pictures by D. Beliaev and T. Sharpe.

# Motivations

Critical points of RPW. Picture by D. Beliaev.



# Motivations



**Figure :** Critical points



**Figure :** Poisson

Repulsion?

# Expectation and Variance

$$\mathcal{N}_\rho^c = \#\{x \in \mathcal{B}(\rho) : \nabla F(x) = 0\}$$

## Theorem (Beliaev-C.-Wigman)

For every  $\rho > 0$

$$\mathbb{E}[\mathcal{N}_\rho^c] = \frac{1}{2\sqrt{3}}\rho^2.$$

As  $\rho \rightarrow 0$

$$\mathbb{E}[\mathcal{N}_\rho^c (\mathcal{N}_\rho^c - 1)] = \frac{1}{2^5 3 \sqrt{3}} \rho^4 + O(\rho^6).$$

# Proof

- Critical points density  $K_1 : \mathbb{R}^2 \rightarrow \mathbb{R}$

$$K_1(x) = \phi_{\nabla F(x)}(\mathbf{0}, \mathbf{0}) \cdot \mathbb{E}[|\det H_F(x)| | \nabla F(x) = 0]$$

- Two-point correlation function  $K_2 : \mathbb{R}^2 \times \mathbb{R}^2 \rightarrow \mathbb{R}$

$$K_2(x, y) = \phi_{(\nabla F(x), \nabla F(y))}(\mathbf{0}, \mathbf{0}) \\ \cdot \mathbb{E}[|\det H_F(x)| \cdot |\det H_F(y)| | \nabla F(x) = \nabla F(y) = 0].$$

# Proof

We apply a suitably modified version of Kac-Rice formula for counting the number of zeros of the gradient of  $F$ :

$$\mathbb{E}[\mathcal{N}_\rho^c] = \int_{\mathcal{B}(0,\rho)} K_1(x) dx,$$

and, for  $x \neq y$ ,

$$\mathbb{E}[\mathcal{N}_\rho^c \cdot (\mathcal{N}_\rho^c - 1)] = \iint_{\mathcal{B}(0,\rho) \times \mathcal{B}(0,\rho)} K_2(x, y) dx dy;$$

provided that the Gaussian distribution of  $(\nabla F(x), \nabla F(y)) \in \mathbb{R}^4$  is non-degenerate for all  $(x, y) \in \mathcal{B}(0, \rho) \times \mathcal{B}(0, \rho)$ .

# Proof

## Lemma

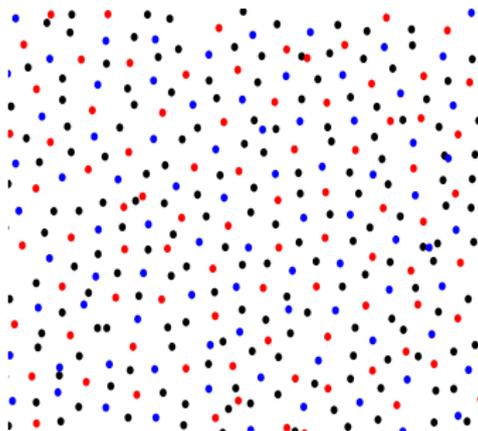
For every  $x \in \mathbb{R}^2$

$$K_1(x) = \frac{1}{2\sqrt{3}\pi}.$$

As  $r = d(x, y) \rightarrow 0$

$$K_2(r) = \frac{1}{96\sqrt{3}\pi^2} + O(r^2).$$

# No repulsion!



**Figure :** Critical points



**Figure :** Poisson

As  $r \rightarrow 0$

$$\frac{K_2(r)}{(K_1(r))^2} = \frac{1}{2^3\sqrt{3}} + O(r^2)$$

$r > 0$

$$\frac{K_2(r)}{(K_1(r))^2} = 1$$

# Probability of 0, 1 pts

$$\mathcal{N}_\rho^c = \#\{x \in \mathcal{B}(\rho) : \nabla F(x) = 0\}$$

## Corollary

As  $\rho \rightarrow 0$

$$\mathbb{P}(\mathcal{N}_\rho^c = 0) = 1 - \frac{1}{2\sqrt{3}}\rho^2 + O(\rho^4),$$

$$\mathbb{P}(\mathcal{N}_\rho^c = 1) = \frac{1}{2\sqrt{3}}\rho^2 + O(\rho^4).$$

# Proof

$$\mathbb{P}(\mathcal{N}_\rho^c = 1) \leq \mathbb{P}(\mathcal{N}_\rho^c \geq 1) \leq \sum_{k=1}^{\infty} k \mathbb{P}(\mathcal{N}_\rho^c = k) = \mathbb{E}[\mathcal{N}_\rho^c] = \frac{1}{2\sqrt{3}}\rho^2.$$

We note that

$$\mathbb{E}[\mathcal{N}] = \mathbb{P}(\mathcal{N} = 1) + \sum_{k=2}^{\infty} k \mathbb{P}(\mathcal{N} = k)$$

and

$$\begin{aligned} \mathbb{P}(\mathcal{N} = 1) &= \mathbb{E}[\mathcal{N}] - \sum_{k=2}^{\infty} k \mathbb{P}(\mathcal{N} = k) \geq \mathbb{E}[\mathcal{N}] - \sum_{k=2}^{\infty} k(k-1) \mathbb{P}(\mathcal{N} = k) \\ &= \mathbb{E}[\mathcal{N}] - \mathbb{E}[\mathcal{N}(\mathcal{N}-1)] \end{aligned}$$

then

$$\mathbb{P}(\mathcal{N}_\rho^c = 1) \geq \frac{1}{2\sqrt{3}}\rho^2 - \frac{1}{2^5 3 \sqrt{3}} \rho^4 + O(\rho^6).$$

## Proof - Lemma

- Critical point density  $K_1$

$$K_1(x) = \phi_{\nabla F(x)}(0, 0) \cdot \mathbb{E}[|\det H_F(x)| | \nabla F(x) = 0],$$

where

$$\phi_{\nabla F(x)}(0, 0) = \frac{1}{\pi},$$

and

$$\mathbb{E}[|\det H_F(x)| | \nabla F(x) = 0] = \mathbb{E}[|\det H_F(x)|] = \frac{1}{2\sqrt{3}}.$$

- Two-point correlation function  $K_2$  around the origin  $\implies$  **perturbation theory.**

## Proof - Lemma

- Write the two-point correlation  $K_2$  function as a function of the perturbing elements of the covariance matrix  $\Delta(r)$  of  $(\nabla^2 F(x), \nabla^2 F(y) | \nabla F(x) = \nabla F(y) = 0)$ .
- The Gaussian expectations  $K_2$  is analytic functions of the of the perturbing elements of  $\Delta(r)$ .
- $K_2$  is a smooth function, defined on some neighbourhood of the origin.
- We can Taylor expand  $K_2$  around the origin.

## Proof - Lemma

$$K_2(r) = \frac{1}{(2\pi)^5 \sqrt{\det A(r)}} \int_{\mathbb{R}^6} |x_1 x_3 - x_2^2| \cdot |x_4 x_6 - x_5^2| \\ \times \frac{1}{\sqrt{\det \Delta(r)}} \exp \left\{ -\frac{1}{2} \mathbf{x}^t \Delta(r)^{-1} \mathbf{x} \right\} d\mathbf{x}.$$

- For every  $r > 0$   $\Delta(r)$  is symmetric  $\implies$  we diagonalise  $\Delta(r)$ :  
 $\Delta(r) = P(r)^t \Lambda(r) P(r)$
- Compute the eigenvalues and eigenvectors of the perturbed matrix  $\Delta(r)$ .
- Note that

$$\frac{1}{\sqrt{\det \Delta(r)}} \exp \left\{ -\frac{1}{2} \mathbf{x}^t \Delta(r)^{-1} \mathbf{x} \right\} = \frac{1}{\sqrt{\prod \lambda_i(r)}} \exp \left\{ -\frac{1}{2} (P(r)\mathbf{x})^t \Lambda(r)^{-1} P(r)\mathbf{x} \right\}.$$

- Change variable:  $\mathbf{z} = P(r)\mathbf{x}$  i.e.  $\mathbf{x} = P(r)^{-1}\mathbf{z}$ .

# Proof - Lemma

- Finally

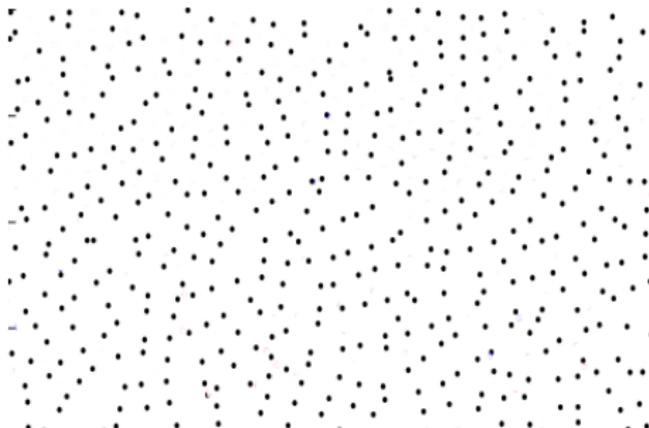
$K_2(r)$

$$\begin{aligned} &= \frac{1}{(2\pi)^5 \sqrt{\det A(r)}} \int_{\mathbb{R}^6} |f(r, \mathbf{z})| \exp \left\{ -\frac{1}{2} \sum_{i=1}^6 z_i^2 \right\} d\mathbf{z} \\ &= \frac{1}{\pi^5 2\sqrt{3}r^2 + O(r^4)} \left[ \frac{r^2}{384} \int_{\mathbb{R}^6} z_4^2 z_6^2 \exp \left\{ -\frac{1}{2} \sum_{i=1}^6 z_i^2 \right\} d\mathbf{z} + O(r^4) \right] \\ &= \frac{1}{96\sqrt{3}\pi^2} + O(r^2). \end{aligned}$$

# And...

- $\mathbb{E}[\mathcal{N}_\rho^c (\mathcal{N}_\rho^c - 1) (\mathcal{N}_\rho^c - 2)]_* = *O(\rho^6)$   
 $\implies \mathbb{P}(\mathcal{N}_\rho^c = 2)_* = * \frac{1}{2^6 3 \sqrt{3}} \rho^4 + O(\rho^6)$

- Repulsion between saddles?



**Thank You!**