

# Outline





# Model : random Gaussian landscape

Hamiltonian (energy)



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Hamiltonian (energy)



# Glass transition for single particle at zero temperature

$$\mathcal{H}(\mathbf{x}) = \frac{\mu}{2} \sum_{k=1}^N \mathbf{x}_k^2 + V(\mathbf{x}_1, \dots, \mathbf{x}_N) : \text{random energy surface (} N \text{ dimensions)}$$

Replica trick analysis (temperature  $T$ )  $\Rightarrow$  **critical value**  $\mu_c = \overline{f''(0)}$ .

[Mézard, Parisi (1991)] [Fyodorov, Sommers (2007)]

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At  $T = 0$  :

$$\mu < \mu_c$$

|

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# Computing the mean number of minima $\langle \mathcal{N} \rangle$

$$\langle \mathcal{N}_m \rangle = \int m(\mathbf{x}) d^N \mathbf{x} \quad \text{with } m(\mathbf{x}) = \text{density of minima.}$$

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Recall :  $\mathcal{H} = \frac{\mu}{2} \sum_{k=1}^N x_k^2 + V(x_1, \mathbf{m}(\mathbf{x}))$



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Kac-Rice expression for  $m$  :

$\mu N$

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Kac-Rice expression for  $m$  :

$$m(\mathbf{x}) = \frac{1}{\sqrt{\det \left( \frac{\partial^2 \mathcal{H}}{\partial i,j} \right)}} \prod_{k=1}^N \left( \frac{\partial \mathcal{H}}{\partial x_k} \right)$$

minima
stationary points

**Heaviside** :  $(A) = \begin{cases} 1 & \text{if } A \text{ positive definite matrix} \\ 0 & \text{otherwise} \end{cases}$

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$$\langle \mathcal{N}_m \rangle = \int m(\mathbf{x}) d^N \mathbf{x} \quad \text{with } m(\mathbf{x}) = \text{density of minima.}$$

Recall :  $\mathcal{H} = \frac{\mu}{2} \sum_{k=1}^N x_k^2 + 607.97011JR2Td[(04JR6491=4JR8672]TJR21190-$

## Link with RMT

$$m(\mathbf{x}) = \left\langle \det \left[ \sum_{i,j} x_{ij} \mathcal{H} \right] \prod_{k=1}^N \left( \sum_k \mathcal{H} \right) \right\rangle_{\mathbf{V}}$$

**Translational invariant**

## Link with RMT

$$m(\mathbf{x}) = \left\langle \det \left( \frac{2}{i,j} \mathcal{H} \right) \prod_{k=1}^N \left( \frac{2}{k} \mathcal{H} \right) \right\rangle_V$$

**Translational invariant covariance structure of  $V$**

$$\Rightarrow \langle V_i V_j \rangle = 0 \text{ (at same } \mathbf{x}) \text{ and } \langle V_j V_k \rangle = -\delta_{j,k} f'(\mathbf{0}) \equiv \delta_{j,k}^{-2}.$$

Thus

$$m(\mathbf{x}) = \frac{1}{(\sqrt{2}^{-2})^N} e^{-\frac{\mu^2 \mathbf{x}^2}{2\sigma^2}} \langle |\det(\mu \text{Id} - M)| \rangle_M$$

$$\text{Hessian} = \frac{2}{i,j} \mathcal{H} = \mu \text{Id} - M \text{ with } M_{i,j} = -\langle V_i V_j \rangle$$

## Link with RMT

$$m(\mathbf{x}) = \left\langle \det \begin{pmatrix} \mathcal{H}_{i,j} & \mathcal{H}_{i,k} \\ \mathcal{H}_{k,j} & \mathcal{H}_{k,k} \end{pmatrix} \prod_{k=1}^N \langle \mathcal{H}_{k,k} \rangle \right\rangle_V$$

**Translational invariant covariance structure of  $V$**

$$\Rightarrow \langle \mathcal{H}_{k,l} \mathcal{H}_{i,j} \rangle = 0 \text{ (at same } \mathbf{x} \text{) and } \langle \mathcal{H}_{j,k} \mathcal{H}_{k,l} \rangle = -\mathcal{H}_{j,k} f'(\mathbf{0}) \equiv \mathcal{H}_{j,k}^2.$$

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$$\text{Hessian} = \mathcal{H}_{i,j} = \mu \text{Id} - M \text{ with } M_{i,j} = -\mathcal{H}_{i,j}$$

$M =$  **Gaussian random matrix**, law independent of  $\mathbf{x}$  :

$$\begin{aligned} \langle M_{i,j} \rangle &= 0 \\ \langle M_{k,l} M_{i,j} \rangle &= \frac{\mu_c^2}{N} (\delta_{i,k} \delta_{j,l} + \delta_{i,l} \delta_{j,k} + \delta_{i,j} \delta_{k,l}) \text{ with } \mu_c^2 = f''(\mathbf{0}). \end{aligned}$$

# Link with RMT

$$m(\mathbf{x}) = \left\langle \det \begin{pmatrix} \mathcal{H} & \mathbf{v} \\ \mathbf{v}^T & \mathbb{I} \end{pmatrix} \right\rangle_V$$

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$$\langle \mathcal{N}_m \rangle = \frac{1}{\mu^N} \langle |\det(\mu \text{Id} - M)| \langle \mu \text{Id} - M \rangle_M \rangle$$

## Link with standard Gaussian ensembles of matrices

$$\langle \mathcal{N}_m \rangle = \frac{1}{\mu^N} \langle |\det(\mu - M)| \quad (\mu - M) \rangle_M \quad \text{with} \quad \mathcal{P}(M) \propto e^{-\frac{N}{4\mu^2} \left[ \text{tr} M^2 - \frac{(\text{tr} M)^2}{N+2} \right]}$$



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Introduce additional Gaussian integration :

$$\langle \mathcal{N}_m \rangle = \frac{1}{\mu^N} \int_{-\infty}^{+\infty} dt \quad \frac{N}{2} e^{-N \frac{t^2}{2}} K_N(z_t) \quad \text{with} \quad z_t = \mu + \mu_c t$$

$$K_N(z) = \langle |\det(z - M_0)| (z - M_0) \rangle_{M_0}$$

**Gaussian Orthogonal Ensemble (GOE) :**

$$P(M_0) = C_N \exp$$

# From the matrix to the eigenvalues

$$K_N(z) = \langle |\det(z - M_0)| \quad (z - M_0) \rangle_{M_0} \quad \text{with} \quad P(M_0) = C_N e^{-\frac{N}{4\mu\tilde{c}} \text{tr}M_0^2}$$

# From the matrix to the eigenvalues

$$K_N(z) = \left\langle |\det(z - M_0)| \delta(z - M_0) \right\rangle_{M_0} \quad \text{with} \quad P(M_0) = C_N e^{-\frac{N}{4\mu\epsilon} \text{tr}M_0^2}$$

- $O(N)$  invariance of **GOE** measure  
 $\Rightarrow$  introduce the **eigenvalues**  $\lambda_i$  of  $M_0$

$$K_N(z) = \frac{1}{z^N} \prod_{i=1}^N \int_{-\infty}^z d\lambda_i \prod_{i < j} |\lambda_i - \lambda_j| \prod_{i=1}^N |z - \lambda_i| e^{-\frac{N}{4\mu\epsilon} \lambda_i^2}$$

$\prod_{i < j} |\lambda_i - \lambda_j|$  : Vandermonde determinant (Jacobian).



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# Relation with maximal eigenvalue of GOE

- We want to compute :

$$\tilde{p}_N(y) = \frac{1}{d_1 \dots d_N} \prod_{i < j} | \lambda_i - \lambda_j | \prod_{i=1}^N (y - \lambda_i) e^{-\frac{\lambda_i^2}{2}}$$

# Relation with maximal eigenvalue of GOE

- We want to compute :

$$\tilde{P}_N(y) = \frac{1}{D_N} \prod_{i < j} |y_i - y_j| \prod_{i=1}^N (y_i)^{\frac{\alpha}{2}} e^{-\frac{\lambda_i^2}{2}}$$

- For standard GOE, ie  $P(M_{\text{GOE}}) \propto e^{-\frac{1}{2} \text{tr} M_{\text{GOE}}^2}$  :

$$P(y_1, \dots, y_N) = D_N \prod_{i < j} |y_i - y_j| \prod_i e^{-\frac{\lambda_i^2}{2}}$$

## Relation with maximal eigenvalue of GOE



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# Number of Minima and GOE eigenvalues

$$\mathcal{H} = \frac{\mu}{2} \sum_{k=1}^N x_k^2 + V$$

Finally ,we get :

$$\langle \mathcal{N}_m \rangle = \frac{\mu_c}{\mu} B_N I_N(\mu/\mu_c)$$

$$\text{with } I_N(\mu/\mu_c) = \int_{-\infty}^{+\infty} dy e^{\frac{y^2}{2} - \frac{N}{2} \left( y \sqrt{\frac{2}{N}} - \frac{\mu}{\mu_c} \right)^2} \frac{d}{dy} [\mathbb{P}_{N+1}(\max \leq y)]$$



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# Number of Minima and GOE eigenvalues

$$\mathcal{H} = \frac{\mu}{2} \sum_{k=1}^N x_k^2 + V$$

$$\mu_c = \overline{f''(0)}$$

(V : random part)

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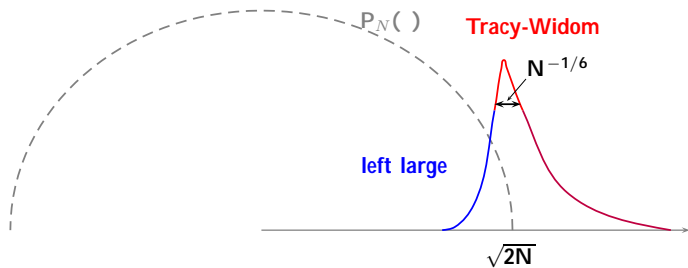


# Outline





# Maximal eigenvalue of GOE : large deviations as $N \rightarrow \infty$



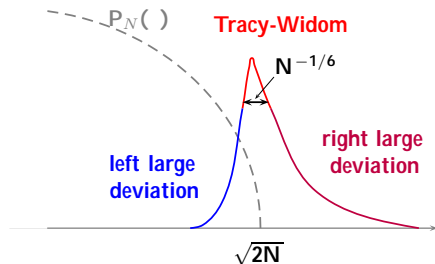
# Maximal eigenvalue of GOE : large deviations as $N \rightarrow \infty$

## Large deviations of pdf of $\lambda_{\max}$ for GOE

[Dean, Majumdar (2006)]

[Majumdar, Vergassola (2009)]

d



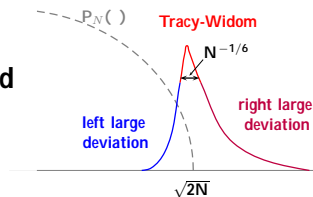


# Correspondance between $\lambda_{\max}$ and our glass transition

$$\langle \mathcal{N}_m \rangle = \frac{\mu_c}{\mu} B_N \int dy e^{\frac{y^2}{2} - \frac{N}{2} \left( y \sqrt{\frac{2}{N}} - \frac{\mu}{\mu_c} \right)^2} \frac{d}{dy} [\mathbb{P}_{N+1}(\max \leq y)]$$

Use large deviations of  $\max$  + saddle point method  
as  $N \rightarrow \infty$

d







# Correspondance between $\lambda_{\max}$ and our glass transition

$P_N(\ )$

---

$\sqrt{2N}$



# Glassy phase (logarithmic equivalent for $N \rightarrow \infty$ )

$$\langle \mathcal{N}_m \rangle = \frac{\mu_c^-}{\mu}^N B_N \int dy e^{\frac{y^2}{2} - \frac{N}{2} \left( y \sqrt{\frac{2}{N}} - \frac{\mu}{\mu_c} \right)^2} \frac{d}{dy} [\mathbb{P}_{N+1}(\max \leq y)]$$

Use large deviations of  $\max$  + saddle point method

$$\frac{d}{dy} [\mathbb{P}_N(\max \leq y)] \approx \begin{cases} e^{-N^2 \psi_-(s)} & \text{for } s < \sqrt{2} \\ e^{-N \psi_+(s)} & \text{for } s > \sqrt{2} \end{cases}$$

$\Rightarrow$  recover the result of [Fyodorov, Williams (2007)] :

$$\mu < \mu_c$$

$$\langle \mathcal{N}_m \rangle \approx e^N \left( \frac{\mu}{\mu_c} \right)$$

$$\psi(s) = -\ln(\psi(s)) - \frac{m^2}{2} + 2 - \frac{3}{2}$$

glassy phase : random part ( $V$ ) dominates

$$\mu > \mu_c$$

$$\langle \mathcal{N}_m \rangle \approx O(1)$$

harmonic part dominates

$$\text{critical point } \mu_c = \overline{f''(0)}$$

## A step further (1) : more detailed large deviation results

**Large deviations of  $\frac{d}{dy} [\mathbb{P}_N(\max \leq y)]$  for **GOE** :  $y = s\sqrt{N}$ , large**

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**Large deviations of  $\frac{d}{dy} [\mathbb{P}_N(\max \leq y)]$  for GOE :  $y = s\sqrt{N}$ , large  $N$**

- **Left tail** :  $y < \sqrt{2N}$ , ie  $s < \sqrt{2}$

$$\frac{d}{dy} [\mathbb{P}_N(\max \leq y)] \sim e^{-N^2\psi_-(s) + N^{-1}\phi_1(s) - \phi_2(s)}$$

cf [Borot, Eynard, Majumdar, Nadal (2011)] : left large deviations of  $\max$  for G E (here  $\beta = 1$ ) using loop equations.

- **Right tail** :  $y > \sqrt{2N}$ , ie  $s > \sqrt{2}$

$$\frac{d}{dy} [\mathbb{P}_N(\max \leq y)] \sim \frac{e^{-N\psi_+(s)}}{2\sqrt{-2 + s^2}^{1/4} (s + \sqrt{-2 + s^2})}$$

cf [Borot, Nadal (2012)] : right large deviations for G E (loop equations).



## A step further (2) : exact equivalent for both phases

Using previous results and saddle point method, get large  $N$  equivalents :

- **Phase where the harmonic potential dominates :  $\mu > \mu_c$**

$$\langle \mathcal{N}_m \rangle \sim 1$$

A step further (2) : exact equivalent for both phases



## A step further (2) : exact equivalent for both phases

Using previous results and saddle point method, get large  $N$  equivalents :



# Outline

1 Introduction : the model (random Gaussian surface)





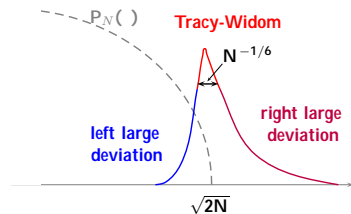


# Close to transition : Tracy-Widom (1)

GOE, fluctuations of  $\max$  close to mean value, ie

$$\max - \sqrt{2N} = O(N^{-1/6}) :$$

$$\mathbb{P}_N \left( \frac{\max - \sqrt{2N}}{N^{-1/6}/\sqrt{2}} \leq x \right) \sim \mathcal{F}_1(x)$$





## Close to transition : Tracy-Widom (2)

Correspondance between **GOE** and our **disordered system** :

	max for GOE	Curvature (disordered system)
Critical point	$y_c = \sqrt{2N}$	$\mu_c = \overline{f''(0)}$

## Close to transition : Tracy-Widom (2)

Correspondance between **GOE** and our **disordered system** :

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Critical point	$y_c = \sqrt{2N}$	$\mu_c = \overline{f''(0)}$
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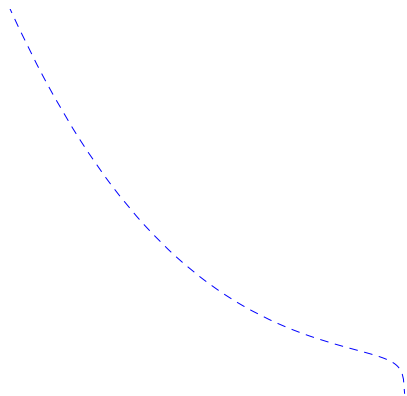
**Transition regime** :

$$\langle \mathcal{N}_m \rangle \sim \mathcal{N}(\ ) \quad \text{for} \quad \frac{\mu}{\mu_c} = 1 + N^{-1/3} + \dots$$



Phases in disordered system  $\mathcal{H}(\mathbf{x}) = \frac{\mu}{2}$

Phases in disordered system  $\mathcal{H}(\mathbf{x}) = \frac{\mu}{2} \sum_{\mathbf{k}=1}^N \mathbf{x}_{\mathbf{k}}^2 + \mathbf{V}$



Phases in disordered system  $\mathcal{H}(\mathbf{x}) =$





# Matching between different regimes

**Intermediate regime :**  $\langle \mathcal{N} \rangle$





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**Intermediate regime :**  $\langle \mathcal{N}_m \rangle \sim \mathcal{N}(\ )$  for  $\frac{\mu}{\mu_c} = 1 + N^{-1/3} + \dots$

- **Matching with the right tail :**  $\rightarrow \infty$

Right asymptotics of Tracy-Widom :  $1 - \mathcal{F}_1(x) \sim \frac{e^{-\frac{2}{3}x^{\frac{3}{2}}}}{4\sqrt{x}^3}$

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Right asymptotics of Tracy-Widom :  $1 - \mathcal{F}_1(x) \sim \frac{e^{-\frac{2}{3}x^{\frac{3}{2}}}}{4\sqrt{x^{\frac{3}{4}}}}$  as  $x \rightarrow \infty$

Find  $x^* \sim 2$  and recover phase  $\mu > \mu_c$  :  $\langle \mathcal{N}_m \rangle \sim 1$ .

- **Matching with the left tail :**  $\rightarrow -\infty$

Left asymptotics of TW :  $\mathcal{F}_1(x) \sim 1 - \frac{e^{-\frac{1}{24}|x|^3 - \frac{1}{3\sqrt{2}}|x|^{\frac{3}{2}}}}{|x|^{\frac{1}{16}}}$  as  $x \rightarrow -\infty$

Find  $x^* \sim -2\sqrt{-2}$  and

$$\langle \mathcal{N}_m \rangle \sim 2 \cdot 2^{\frac{21}{32}} \sqrt{|x|} \left| \frac{23}{32} - 1 \right| e^{\frac{|\delta|^3}{3} + \frac{4\sqrt{2}}{3}|\delta|^{\frac{3}{2}} - \frac{2^{7/4}}{3}|\delta|^{\frac{3}{4}} + \frac{1}{4}}$$

## Matching between different regimes

**Intermediate regime :**  $\langle \mathcal{N}_m \rangle \sim \mathcal{N}(\ )$  for  $\frac{\mu}{\mu_c} = 1 + N^{-1/3} + \dots$

- **Matching with the right tail :**  $\rightarrow \infty$

Right asymptotics of Tracy-Widom :  $1 - \mathcal{F}_1(x) \sim e$

# Conclusion

**Study of the**

Thank you !

Reference :

**Yan V. Fyodorov and Céline Nadal,**

**“Critical Behavior of the Number of Minima of a Random Landscape**