

# Random matrices and applications

Marchal Olivier

Université Jean Monnet St-Etienne, France  
Institut Camille Jordan, Lyon, France

March 17<sup>th</sup> 2020

- 1 Random matrices
  - Introduction
  - Correlations between eigenvalues
  - Hermitian matrix integrals
  
- 2 Applications of random matrix theory
  - Laplacian growth
  - Cristal growth
  - Machine learning
  
- 3 A detailed example: Toeplitz determinants
  - Widom's result
  - Improvement of Widom's result
  
- 4 Conclusion



# Definition

## General problem

A random matrix is a  $N \times N$  matrix whose entries are random variables:

$$M_N = \begin{pmatrix} X_{1,1} & \dots & X_{1,N} \\ \vdots & & \vdots \\ X_{N,1} & \dots & X_{N,N} \end{pmatrix}$$

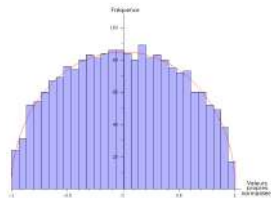
## Standard questions on random matrices

- Does  $M_N$  admit  $N$  simple eigenvalues almost surely?
- Can we characterize the eigenvalues distribution, at least in the large  $N$  limit?
- Are eigenvalues independent? Can we characterize the correlations between them?
- Can we control the “largest” or “lowest” eigenvalue?
- Are there some applications of random matrix theory?

# Answer

## Answer

Answers depend on the **assumptions on the randomness of the entries**: symmetry of the matrix, independence, existence of moments, etc. But some **universal results** arise under weak conditions...

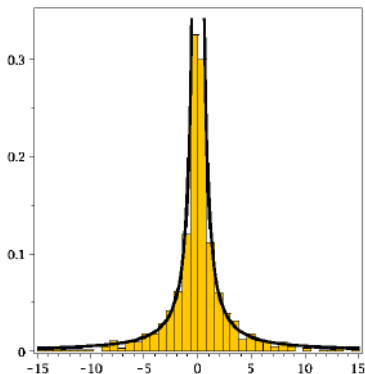


Histogram of the eigenvalues divided by  $\sqrt{N}$  of a  $100 \times 100$  Hermitian random matrix with i.i.d.  $\mathcal{N}(0, 1)$  entries.

## Semi-circle law

Semi-circle law holds for other distributions. But not all of them...

# Cauchy case



Histogram of the eigenvalues divided by  $N$  of a  $100 \times 100$  symmetric random matrix with i.i.d. entries drawn from the Cauchy distribution.

Black curve is  $x \mapsto \frac{1}{2\pi x^2}$  (correct large  $x$  asymptotics)

# A general result

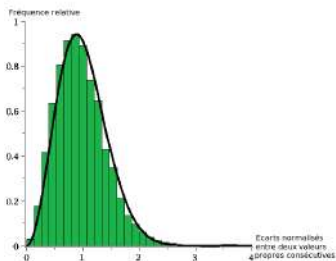
## A sufficient condition

An Hermitian random matrix  $M$  with upper triangular i.i.d. entries drawn from a probability distribution with **zero mean** and  $\mathbb{E}(|M_{i,j}|^{2+\epsilon}) < \infty$ , for some  $\epsilon > 0$ , gives rise to Wigner semi-circle law (Tao and Vu [2008]).

## Other results

Similar results are available for many other cases (relaxing the independence, not identically distributed entries, etc.). **Delocalization** results for **eigenvectors** are also available.

# Universality results



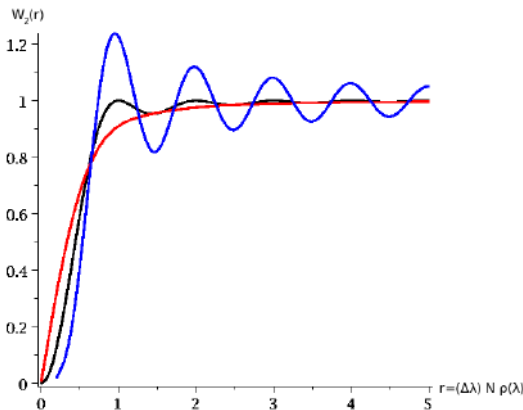
Histogram of gaps  $\sqrt{N}(\lambda_{i+1} - \lambda_i)$  between consecutive eigenvalues of a  $1000 \times 1000$  symmetric Gaussian random matrix with i.i.d. entries. Black curve is the Gaudin distribution.

## Universal limiting correlations

Eigenvalues of a random matrix are **not independent even in the large  $N$  limit**. **Limiting local correlations are universal** and only depends on the **symmetry** of the matrix and the **local position in the limiting distribution** (bulk, edge,...) (Dyson [1970])



# Universality in the bulk for the three classical ensembles



Two-points functions  $W_2(r)$  with  $r = N(\lambda_{i+1} - \lambda_i)\rho(\lambda_i)$  of the three classical ensembles around a bulk point. (Black: Hermitian, Red: Real-symmetric, Blue: Quaternionic self-dual)

# Hermitian matrix integrals

## Hermitian matrix integrals

Hermitian matrix integrals are drawn from partition functions:

$$Z_N(T) = \int_{\mathbb{E}_N} dM e^{-\frac{N}{T} \text{Tr}(V(M))}$$

where  $\mathbb{E}_N$  is a subset of Hermitian matrices.  $V$  is the “potential”.  $T$  is a “temperature” parameter.

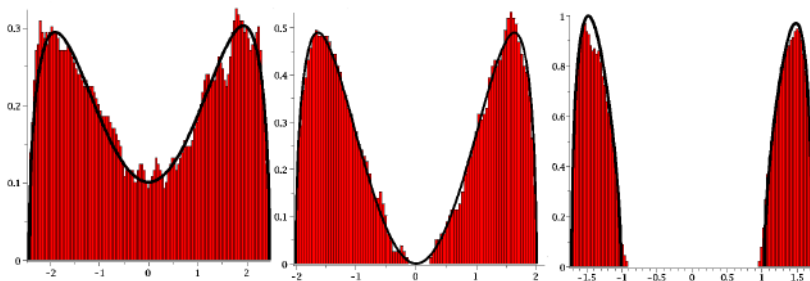
## Diagonalization $\Rightarrow$ Eigenvalues problem

$$Z_N = C_N \int_{E^N} d\lambda_1 \dots d\lambda_N \Delta(\lambda)^2 e^{-\frac{N}{T} \sum_{i=1}^N V(\lambda_i)}, \quad C_N = \text{Vol}(\mathcal{U}_N)$$

## Balance between localization and repulsion

Competition between the potential (**accumulation around minima**) and the **Coulomb repulsion**  $\Delta(\lambda)^2$ .

# Bigger diversity of the limiting eigenvalues distribution



Histogram of normalized eigenvalues of a  $200 \times 200$  random Hermitian matrix with potential  $V(x) = \left(\frac{x^4}{4} - x^2\right)$ .

Center picture is for the **critical case**  $T_c = 1$ .

Results obtained from Metropolis-Hastings algorithm.

# General results for the limiting eigenvalues distribution

## Potential theory

For polynomial potentials of even degree, **empirical eigenvalues distribution almost surely converges to an absolutely continuous measure** (relatively to the Lebesgue measure)  $\rho_\infty$  which is **supported on a finite number of intervals** (Mehta [2004]).

## Characterization

$\rho_\infty$  can be computed in most cases  $\Leftrightarrow$  Compute the limiting “**spectral curve**”, i.e. its Stieljes transform that satisfies an algebraic equation  $y^2 = Q(x)$ .

# New universality classes

## Correlation around critical points

$\rho_\infty$  may exhibit **critical points** where  $\rho_\infty(x) \stackrel{x \rightarrow x_c}{\sim} \alpha(x - x_c)^{\frac{p}{q}}$  with  $(p, q) \notin \{(0, 1), (1, 2)\}$ . Local correlations between eigenvalues obeys **new universality laws** (Mehta [2004]).

## Connection with integrable systems

Local correlations are characterized by **Fredholm determinants** whose kernel defines the universality class: **Sine kernel for bulk point**, **Airy kernel for the regular soft edge case**.

# Open questions

## Open questions

- Describe kernels for critical points and prove the Fredholm determinants representation
- Sine and Airy kernels: **integral representations** of the Fredholm determinants using **Painlevé transcendents** are available (Tracy and Widom [1994]):

$$F_{TW}(s) = \det(I - \chi_{[s, +\infty)} \mathbb{K}_{\text{Ai}} \chi_{[s, +\infty)}) = \exp \left( - \int_s^{+\infty} (x-s) q(x)^2 dx \right)$$

where  $q$  is the unique solution (Hasting-McLeod) of the Painlevé 2 equation:

$$q''(s) = 2q(s)^3 + sq(s), \quad q(s) \underset{s \rightarrow +\infty}{\sim} e^{-\frac{2}{3}s^{\frac{3}{2}}}$$

Are there similar integral representations using other Painlevé solutions for other critical points?

# Connection with integrable systems

- Random matrix integrals have **deep connections with integrable systems** (Bertola et al. [2003, 2006]).
- Complete study of the case  $(p, q) = (2m, 1)$  (Marchal and Cafasso [2011]).
- Partition functions of random matrix integrals are “**isomonodromic tau-function**” (Bertola and Marchal [2009])
- Personal recent results (Iwaki et al. [2018b], Marchal and Orantin [2019a,b]) are promising
  - ⇒ full understanding of the situation via the “topological recursion”
  - ⇒ **Reconstruction of the corresponding integrable systems** is on the way (“Quantum spectral curve”).
- Very involved algebraic geometry: Riemann surfaces, moduli spaces of meromorphic connections...
- Interests for string theory and enumerative geometry.

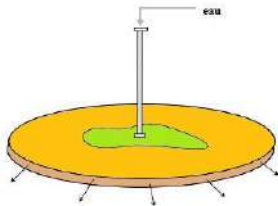
# Applications of random matrix theory



# (Too?) Many fields of applications

- Energy gaps for heavy nuclei (Wigner and Weinberg [1958])
- Laplacian growth (oil interface) (Saffman and Taylor [1958], Zabrodin [2009])
- Random permutations (Baik et al. [2000], Okunkov [2000])
- Pavings (Aztek diamants,...) (Johansson [2002])
- Self-avoiding random walks (TASEP,...) (Eynard [2009])
- Dyson Brownian motions (Joyner and Smilansky [2015])
- Enumerative geometry (counting triangulations/quadrangulations of Riemann surfaces) (Eynard [2016])
- Telecommunications: multiple input-multiple output (MIMO): e.g. 5G network (Heath and Lozano [2018])
- String theory, 2D gravity, Chern-Simons theory (Mariño [2005])
- Riemann hypothesis (Montgomery [1973])
- Fredholm determinants, integrable systems (Borodin and Okounkov [2000])
- Machine learning (Mai and Couillet [2018])
- **And many more...**

# Hele-Shaw cell



Hele-Shaw cell: insertion of a viscous fluid in a liquid one.

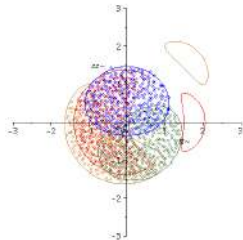
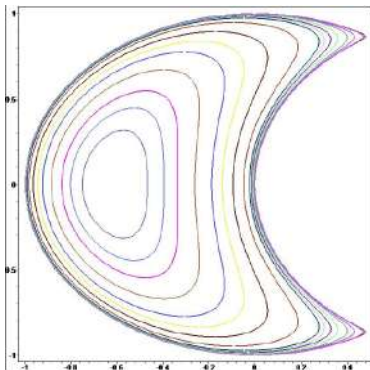
Theoretical model: **Normal matrix ensembles** ( $\Rightarrow$  **Complex eigenvalues**)

$$\mathbb{P}(z_1, \dots, z_n) = \frac{1}{Z_n} |\Delta(\mathbf{z})|^2 e^{-N \sum_{i=1}^N |z_i|^2 + V(z_j) + \bar{V}(\bar{z}_j)}$$

First result:  $\rho_{\text{emp.}}(z_1, \dots, z_N) \xrightarrow[N \rightarrow \infty]{\text{a.s.}} \frac{1}{\text{Area}(D)} \mathbb{1}_D$

$D \subset \mathbb{C}$ . Its edge  $\mathcal{C}$  represents the interface between the fluids.

# Laplacian growth

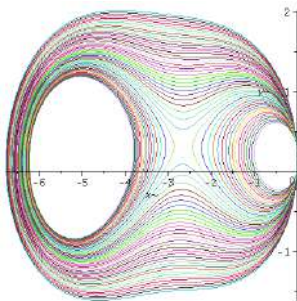


Growth of the interface for  $V(z) = c \ln(z - a)$ . (Personal talk at BIRS workshop 2011). Interface given by:

$$(-c - z(\bar{z} - a))(-c - \bar{z}(z - a)) - c^2 + \alpha = 0$$

$\alpha$  = Volume of fluid inserted.

# Laplacian growth 2

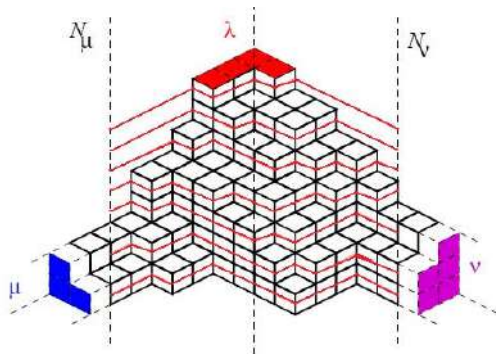


Another example of a Laplacian growth for  $V(z) = 3t_3z^2$

## Remark

These models exhibit singular domains in relation with universal classes...

# Self-avoiding walks and cristal growth



- Box stacking in the corner of a room (or cristal growth)
- Fixed edges described by three given 2D partitions  $\lambda, \mu, \nu$
- Partition function of the model:

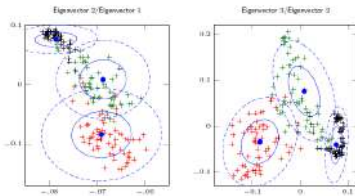
$$Z_{\lambda, \mu, \nu} = \sum_{\pi = \text{Config}} q^{|\pi|}, \quad |\pi| = \text{volume of } \pi$$





# Machine learning and RMT model

- Rand Matrix Theory (RMT) grasps and improves data processing (Couillet et al. [2018])
- RMT shows **good experimental results** for picture categorization problems: e.g.  $\{0, 1, 2\}$  problem (Mai and Couillet [2018])
  - 1 Model the unknown image as a reference image + noise (i.e. random matrix)
  - 2 Use RMT results to obtain control over the eigenvectors.
  - 3 Compare your data to the reference domains and select the best one.



2D representation of eigenvectors for the MNIST dataset. Theoretical means and 1 – 2 standard deviations in blue. 3 different classes in color (red, black, green). Picture extracted from a [R. Couillet talk \(2015\)](#).



# Machine learning 2

- Very recent application of RMT (less than 10 years)
- Very **in fashion** in the “Big Data” context
- Most theoretical results used depend on **Gaussian assumptions**. But real data may not always have perfect Gaussian noise
- Data are so far modeled with **very basic matrix models**: more complex RM models should be considered to fit a bigger range of data
- Still many steps to applications like neural networks, real-life applications,...
- But **literature and simulations are developing very fast...**

## A detailed example: Toeplitz determinants

# Description of the problem

## Statement of the problem

Let  $\epsilon \in (0, 1)$ . Compute the following integral ( $Z_n(\epsilon = 1) = 1$ ):

$$Z_n(\epsilon) = \frac{1}{(2\pi)^n n!} \int_{([-\pi\epsilon, \pi\epsilon])^n} d\theta_1 \dots d\theta_n \prod_{1 \leq p < q \leq n} |e^{i\theta_p} - e^{i\theta_q}|^2$$

## Various reformulations

Standard results give for  $a = \tan \frac{\pi\epsilon}{2}$ :

$$\begin{aligned} Z_n(\epsilon) &= \frac{1}{(2\pi)^n n!} \int_{([-\pi\epsilon, \pi\epsilon])^n} d\theta_1 \dots d\theta_n \prod_{1 \leq p < q \leq n} |e^{i\theta_p} - e^{i\theta_q}|^2 \\ &= \det(T_{p,q} = t_{p-q})_{1 \leq p, q \leq n} \text{ where } t_k = \epsilon \sin_c(k\pi\epsilon) \\ &= \frac{2^{n^2}}{(2\pi)^n n!} \int_{[-a, a]^n} dt_1 \dots dt_n \Delta(t_1, \dots, t_n)^2 e^{-n \sum_{k=1}^n \ln(1+t_k^2)} \end{aligned}$$

$(t_k)_{-(n-1) \leq k \leq n-1}$  are discrete Fourier coefficients of the symbol function  $f = \mathbb{1}_{\{e^{it}, t \in [-\pi\epsilon, \pi\epsilon]\}}$ .

# Some remarks

- Connections between **Toeplitz determinants**, **Hermitian matrix integral**, **integral over the unit circle** is very general and apply for any symbol function (Duits and Johansson [2010])
- Toeplitz determinants have **Fredholm determinant representations** (Borodin and Okounkov [2000])
- Toeplitz determinant reformulation allows **large  $n$  numerical simulations**
- Hermitian matrix integrals allows the use of **RMT results**.  
Potential is  $V(x) = \ln(1 + x^2)\mathbb{1}_{[-a,a]}(x)$ .

# Widom's result

## Widom's result

We have (Widom [1971]):

$$\begin{aligned} \ln Z_n(\epsilon) &= n^2 \ln \left( \sin \frac{\pi\epsilon}{2} \right) - \frac{1}{4} \ln n - \frac{1}{4} \ln \left( \cos \frac{\pi\epsilon}{2} \right) \\ &\quad + 3\zeta'(-1) + \frac{1}{12} \ln 2 + o(1) \end{aligned}$$

where  $\zeta$  denotes the Riemann zeta function.

## Comment

- Widom's method does not say anything about the  **$o(1)$  term**
- It does not generalize to other symbol functions

# How to improve Widom's result

- 1 Compute the **limiting eigenvalues density**  $\rho_\infty$  and the corresponding spectral curve.
- 2 Check that conditions for application of ([Borot and Guionnet \[2011\]](#), [Borot et al. \[2014\]](#)) results apply (conditions on  $\rho_\infty$  and potential  $V$ )

$$\Rightarrow \ln Z_n(\epsilon) = -\frac{1}{4} \ln n + \sum_{k=-2}^K F^{\{k\}}(\epsilon) n^{-k} + o(n^{-K}) \quad \forall K \geq -2$$

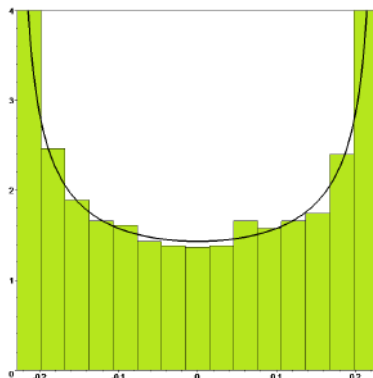
- 3 Coefficients  $(F^{\{k\}}(\epsilon))_{k \geq -2}$  can be computed by the **Eynard-Orantin topological recursion** ([Eynard and Orantin \[2007\]](#)) on the spectral curve up to some constants (independent of  $\epsilon$ )

$$F^{\{k\}}(\epsilon) - F^{\{k\}}(\epsilon_0) = F_{\text{EO}}^{\{k\}}(\epsilon) - F_{\text{EO}}^{\{k\}}(\epsilon_0)$$

# How to improve Widom's result 2

- ④ Carefully take the reference value  $\epsilon_0 \rightarrow 0$ :
  - $Z_n(\epsilon_0 = 0)$  is a known **Selberg integral** (Selberg [1944]) whose large  $n$  expansion is computable (Bernoulli numbers).
  - The spectral curve for  $\epsilon_0 = 0$  is equivalent to **Legendre's spectral curve**  $y = \frac{1}{\sqrt{1-x^2}}$ .  
 Results of (Iwaki et al. [2018a]) give all free energies  $(F_{\text{Leg.}}^{\{k\}})_{k \geq -2}$  in terms of Bernoulli numbers.
  - Turns out that both sets are identical except for  $k = 0$ .
- ⑤ **Compute the first terms** using Eynard-Orantin topological recursion and **compare with numerical simulations**.

# Limiting eigenvalues density



Empirical eigenvalues density obtained from 100 independent Monte-Carlo simulations for  $\epsilon = \frac{1}{7}$  and  $n = 20$ . Black curve is the theoretical density:

$$\rho_{\infty}(x) = \frac{1}{\pi \cos\left(\frac{\pi\epsilon}{2}\right)(1+x^2)\sqrt{\tan^2\left(\frac{\pi\epsilon}{2}\right) - x^2}} \mathbb{1}_{\left[-\tan\frac{\pi\epsilon}{2}, \tan\frac{\pi\epsilon}{2}\right]}(x)$$



# Remarks on $\rho_\infty$

- Support of  $\rho_\infty$  is a **single interval**  $[-\tan \frac{\pi\epsilon}{2}, \tan \frac{\pi\epsilon}{2}]$ .  $\Leftrightarrow$  **Genus 0 spectral curve**
- Single interval case is much simpler to deal with: **asymptotic expansion is purely “perturbative”**.  
No need to consider filling fractions (i.e. proportion of eigenvalues lying in each intervals of the support).
- Hard edges at  $\pm \tan \frac{\pi\epsilon}{2} \Rightarrow \rho_\infty$  diverges at the edges.
- **Hard edges are regular** because  $\rho_\infty(x) \sim \frac{c_\pm}{\sqrt{\tan(\frac{\pi\epsilon}{2}) \pm x}}$ .
- Potential is **confining** (null) at  $\pm\infty$ .
- $\Rightarrow$  Sufficient conditions to apply (Borot and Guionnet [2011], Borot et al. [2014]) results.

# Final result

## Improvement of Widom's result (Marchal [2019])

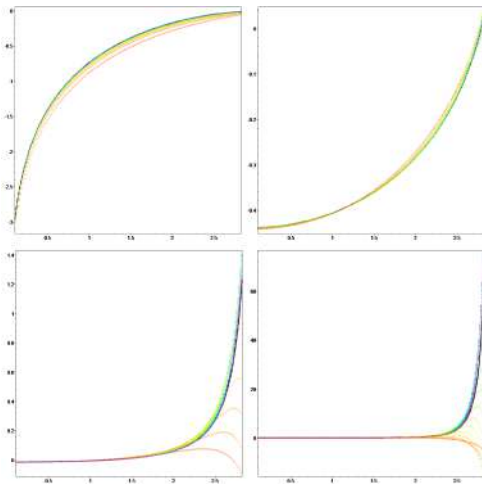
$$\ln Z_n(\epsilon) = n^2 \ln \left( \sin \left( \frac{\pi \epsilon}{2} \right) \right) - \frac{1}{4} \ln n - \frac{1}{4} \ln \left( \cos \left( \frac{\pi \epsilon}{2} \right) \right) \\ + 3 \zeta'(-1) + \frac{1}{12} \ln 2 - \sum_{g=2}^{\infty} F_{\text{EO}}^{(g)}(\epsilon) n^{2-2g}$$

where  $F_{\text{EO}}^{(g)}(\epsilon)$  are the Eynard-Orantin free energies associated to the spectral curve  $y^2(x) = \frac{1}{\cos^2(\frac{\pi \epsilon}{2})(1+x^2)^2(x^2 - \tan^2(\frac{\pi \epsilon}{2}))}$

## Computation of the first terms

$$\ln Z_n(\epsilon) = n^2 \ln \left( \sin \left( \frac{\pi \epsilon}{2} \right) \right) - \frac{1}{4} \ln n - \frac{1}{4} \ln \left( \cos \left( \frac{\pi \epsilon}{2} \right) \right) \\ + 3 \zeta'(-1) + \frac{1}{12} \ln 2 + \frac{1}{64n^2} \left( 2 \tan^2 \left( \frac{\pi \epsilon}{2} \right) - 1 \right) \\ + \frac{1}{256n^4} \left( 1 + 2 \tan^2 \left( \frac{\pi \epsilon}{2} \right) + 10 \tan^4 \left( \frac{\pi \epsilon}{2} \right) \right) + O \left( \frac{1}{n^6} \right)$$

# Numerical study



Computation of  $\epsilon \mapsto \ln Z_n(\epsilon)$  with  $0 < \epsilon < 1$  for  $2 \leq n \leq 35$  with subtraction of the first coefficients of the large  $n$  expansion.

# Possible generalizations

- Strategy applies to any symbol function supported on a subset of  $\{e^{it}, t \in [a, b]\}$  with  $-\pi < a < b < \pi$ .
- $\rho_\infty$  supported on several intervals  $\Rightarrow$  Additional terms in the expansion involving  $\Theta$  functions. Usually hard to compute analytically.
- Symbol function supported on the whole unit circle  $\Rightarrow$  **Drastic changes expected:**
  - ① Szegő theorem applies:  $\ln Z_n \propto n$  and no longer  $\ln Z_n \propto n^2$ .
  - ② Potential  $V$  is not sufficiently confining at  $\pm\infty$  to apply Borot-Guionnet-Koslowski results.
  - ③ Does the Eynard-Orantin recursion still reconstruct the asymptotic expansion?
- What about Hankel determinants, Fredholm determinants, Toeplitz operators?

# Conclusion



# References I

- M. Adler, P. Ferrari, and P. Van-Moerbeke. Airy processes with wanderers and new universality classes. *The Annals of Probability*, 38, 2010.
- M. Adler, P. Ferrari, and P. Van-Moerbeke. A PDE for non-intersecting Brownian motions and applications. *Advances in Mathematics*, 226, 2011.
- M. Adler, P. Ferrari, and P. Van-Moerbeke. Nonintersecting random walks in the neighborhood of a symmetric tacnode. *The Annals of Probability*, 40, 2013.
- J. Baik, P. Deift, and K. Johansson. On the distribution of the length of the second row of a Young diagram under Plancherel measure. *Geometric and Functional Analysis*, 10, 2000.
- M. Bertola and O. Marchal. The partition function of the two-matrix model as an isomonodromic tau-function. *Journal of Mathematical Physics*, 50, 2009.
- M. Bertola, B. Eynard, and H. John. Partition functions for matrix models and isomonodromic tau functions. *Journal of Physics A*, 36:3067–3083, 2003.
- M. Bertola, B. Eynard, and J. Harnad. Semiclassical orthogonal polynomials, matrix models and isomonodromic tau functions. *Communications in Mathematical Physics*, 263:401–437, 2006.

# References II

- A. Borodin and A. Okounkov. A Fredholm determinant formula for Toeplitz determinants. *Integral Equations and Operator Theory*, 37, 2000.
- G. Borot and A. Guionnet. Asymptotic Expansion of  $\beta$  Matrix Models in the One-cut Regime. *Communications in Mathematical Physics*, 317, 2011.
- G. Borot, A. Guionnet, and K. Kozłowski. Large-N asymptotic expansion for mean field models with Coulomb gas interaction. *International Mathematics Research Notices*, 20, 2014.
- R. Couillet, M. Tiomoko, S. Zozor, and E. Moisan. Random matrix-improved estimation of covariance matrix distances. *arXiv preprint: arXiv:1810.04534*, 2018.
- M. Duits and K. Johansson. Powers of large random unitary matrices and Toeplitz determinants. *Transactions of the American Mathematical Society*, 3, 2010.
- F. Dyson. Correlations between the eigenvalues of a random matrix. *Communications in Mathematical Physics*, 19, 1970.
- B. Eynard. A Matrix model for plane partitions. *Journal of Statistical Mechanics*, 2009.
- B. Eynard. Counting Surfaces. *Progress in Mathematical Physics*, 70, 2016.



## References III

- B. Eynard and N. Orantin. Invariants of algebraic curves and topological recursion. *Communications in Number Theory and Physics*, 1:347–452, 2007.
- R. Heath and A. Lozano. Foundations of MIMO Communication. *Cambridge University Press*, 2018.
- K. Iwaki, T. Koike, and Y. Takei. Voros Coefficients for the Hypergeometric Differential Equations and Eynard-Orantin's Topological Recursion - Part II : For the Confluent Family of Hypergeometric Equations. *arXiv preprint: arXiv:1810.02946*, 2018a.
- K. Iwaki, O. Marchal, and A. Saenz. Painlevé equations, topological type property and reconstruction by the topological recursion. *Journal of Geometry and Physics*, 124, 2018b.
- K. Johansson. Non-intersecting paths, random tilings and random matrices. *Probability theory and related fields*, 2002.
- C. Joyner and U. Smilansky. Dyson's Brownian-motion model for random matrix theory - revisited. *arXiv preprint: arXiv:1503.06417*, 2015.
- X. Mai and R. Couillet. A Random Matrix Analysis and Improvement of Semi-Supervised Learning for Large Dimensional Data. *Journal of Machine Learning Research*, 19, 2018.

# References IV

- O. Marchal. Asymptotic expansions of some Toeplitz determinants via the topological recursion. *Letters in Mathematical Physics*, 2019.
- O. Marchal and M. Cafasso. Double-scaling limits of random matrices and minimal  $(2m, 1)$  models: the merging of two cuts in a degenerate case. *Journal of Statistical Mechanics*, 2011, 2011.
- O. Marchal and N. Orantin. Isomonodromic deformations of a rational differential system and reconstruction with the topological recursion: the  $s/2$  case. *arXiv preprint: arXiv:1901.04344*, 2019a.
- O. Marchal and N. Orantin. Quantization of hyper-elliptic curves from isomonodromic systems and topological recursion. *arXiv preprint: arXiv:1911.07739*, 2019b.
- M. Mariño. Chern-Simons Theory, Matrix Models, and Topological Strings. *International Series of Monographs on Physics*, 2005.
- M. Mehta. *Random matrices*, volume 142. Elsevier academic press, 2004.
- H. Montgomery. The pair correlation of zeros of zeta function. *Proceedings of Symposia in Pure Mathematics*, 24, 1973.
- A. Okunkov. Random Matrices and Random Permutations. *International Mathematics Research Notices*, 2000, 2000.

# References V

- P. Saffman and G. Taylor. The penetration of a fluid into a porous medium or Hele-Shaw cell containing a more viscous liquid. *Proceedings of the Royal Society A*, 245, 1958.
- A. Selberg. Remarks on a multiple integral. *Norsk. Mat. Tidsskr.*, 26, 1944.
- T. Tao and V. Vu. Random matrices: the circular law. *Communications in Contemporary Mathematics*, 10, 2008.
- C. Tracy and H. Widom. Level-Spacing Distributions and the Airy Kernel. *Communications in Mathematical Physics*, 159, 1994.
- H. Widom. Strong Szegő limit theorem on circular arcs. *Indiana University Mathematics Journal*, 21, 1971.
- E. Wigner and A. Weinberg. Physical Theory of Neutron Chain Reactors. *University of Chicago Press*, 1958.
- A. Zabrodin. Random matrices and Laplacian growth. *Oxford Handbook of Random Matrix Theory*, 2009.