Extreme value statistics in a gas of 2*d* charged particles Large deviation theory in statistical physics

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Introduction

- Extreme value statistics for i.i.d. random variables
- Matrices of real eigenvalues
- Matrices of complex eigenvalues

2 Results

Oerivation of the Ginibre results

- Determinantal process
- Analysis of the CDF
- Matching



Extreme value statistics for i.i.d. random variables Matrices of real eigenvalues Matrices of complex eigenvalues

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EVS for i.i.d.

For i.i.d. random variables (x_1, \dots, x_N) drawn from a PDF p(x), only 3 classes of universality for the Extreme Value Statistics:

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• $p(x) \ll x^{-\alpha}$, $\forall \alpha$

EVS for i.i.d.

$$Q_N(w) = \left[\int_0^w p(x) dx\right]^N \to G(a_N(w - b_N)), \quad G(x) = e^{-e^{-x}}$$
(1)

Gumbel distribution

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Gumbel distribution

• $p(x) \sim x^{-\alpha-1}$, $\alpha > 0$

$$Q_N(w) = \left[\int_0^w p(x)dx\right]^N \to F_\alpha(a_N(w-b_N)), \ F_\alpha(x) = e^{-x^{-\alpha}}$$
(2)

Fréchet distribution

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(2)

Fréchet distribution

• $p(x) \sim (x^* - x)^{\nu}$, $\nu \ge 0$, $x \le x^*$

$$Q_N(w) = \left[\int_0^w p(x) dx\right]^N \to W_\nu(a_N(w - b_N)), \ W_\nu(x) = e^{-x^{\nu+1}}$$
(3)

Weibull distribution

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Gaussian Unitary matrices

See Satya Majumdar's lecture on Random Matrix Theory

For M a matrix belonging in the Gaussian Unitary Ensemble (GUE),

$$M = \begin{pmatrix} m_{11} & m_{12} & \cdots & m_{1N} \\ m_{12}^* & m_{22} & \cdots & m_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ m_{1N}^* & m_{2N}^* & \cdots & m_{NN} \end{pmatrix}, \quad m_{ij} = m_{ji}^* \sim \mathcal{N}(0, \frac{1}{\sqrt{2N}}) + i\mathcal{N}(0, \frac{1}{\sqrt{2N}}), \quad m_{ii} \sim \mathcal{N}(0, \frac{1}{\sqrt{N}})$$

the probability weight is $P(M) \propto e^{-\frac{1}{2} \operatorname{Tr}(M^{\dagger}M)}$.

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the probability weight is $P(M) \propto e^{-\frac{1}{2} \operatorname{Tr}(M^{\dagger}M)}$. The joint PDF of the (real) eigenvalues is

$$P(\lambda_1, \cdots, \lambda_N) = \frac{1}{Z_N} \prod_{i < j} |\lambda_i - \lambda_j|^2 e^{-N \sum_k \lambda_k^2} = \frac{1}{Z_N} \exp\left(-N \sum_k \lambda_k^2 + \sum_{i \neq j} \ln |\lambda_i - \lambda_j|\right)$$

The variables are identically distributed but correlated!

Introduction

Results

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Average density

Semi-circle law

$$ho_N(\lambda) = rac{1}{N} \langle \sum_k \delta(\lambda - \lambda_k)
angle \ o \
ho(\lambda) = rac{1}{\pi} \sqrt{2 - \lambda^2}$$



Introduction

Results tion of the Ginibre results

Results ibre results Conclusion Matrices of real eigenvalues Matrices of complex eigenvalues

Average density

Semi-circle law



This must imply for EVS of $\lambda_{max} = \max \lambda_k$, $\lambda_{max} \to \sqrt{2}$. Fluctuations $|\lambda_{max} - \sqrt{2}| \sim w_N \ll \sqrt{2}$

$$\int_{\sqrt{2}-w_N}^{\sqrt{2}}\rho(\lambda)d\lambda \propto w_N^{\frac{3}{2}} \sim N^{-1} \;, \;\; w_N \sim N^{-\frac{2}{3}}$$

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Extreme Value Statistics in GUE

The CDF, $\Pr(\lambda_{\max} \le x)$ is described in its typical regime $|\lambda_{\max} - \sqrt{2}| \sim w_N$ by the Tracy-Widom distribution

$$\Pr(\lambda_{\max} \le x) = \mathcal{F}_2\left(\sqrt{2}N^{2/3}(x-\sqrt{2})\right)$$

This distribution has two tails of the form



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This CDF $Pr(\lambda_{max} \leq x)$ takes large deviation forms on both sides

$$\Pr(\lambda_{\max} \le x) \sim \begin{cases} e^{-N^2 \Phi_{-}(x)} , \text{ for } 0 < (\sqrt{2} - x) = O(1) \\\\ \mathcal{F}_2\left(\sqrt{2}N^{2/3}(x - \sqrt{2})\right) , \text{ for } x - \sqrt{2} = O(N^{-2/3}) \\\\ 1 - e^{-N\Phi_{+}(x)} , \text{ for } 0 < (x - \sqrt{2}) = O(1) . \end{cases}$$

Majumdar and Schehr, J. Stat. Mech. P01012 (2014)

Large deviations

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Majumdar and Schehr, J. Stat. Mech. P01012 (2014) The tails behave as

Large deviations

$$\begin{split} \Phi_{-}(x) &\sim \frac{\sqrt{2}}{6} (\sqrt{2} - x)^3 \ , \ x \to \sqrt{2}_{-} \ , \\ \Phi_{+}(x) &\sim \frac{2^{11/4}}{3} (x - \sqrt{2})^{\frac{3}{2}} \ , \ x \to \sqrt{2}_{+} \ , \end{split}$$

allowing a smooth matching with the central part.



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Obtaining the LD rate functions

To compute the CDF $Pr(\lambda_{max} \le w)$, one imposes a wall at w. The LD functions can be evaluated as the change in the energy with and without the wall

$$\mathsf{E}_{\mathsf{N}}(\lambda_1,\cdots,\lambda_{\mathsf{N}})=\mathsf{N}\sum_k\lambda_k^2-\sum_{i
eq j}\ln|\lambda_i-\lambda_j|$$

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$$\overline{E}_N(\lambda_1, \cdots, \lambda_N) = N \sum_k \lambda_k^2 - \sum_{i \neq j} \ln |\lambda_i - \lambda_j|$$



• For $w < \sqrt{2}$, all eigenvalues move $\Delta E \sim N^2$, different $ho(\lambda)$

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For w < √2, all eigenvalues move ΔE ~ N², different ρ(λ)
For w > √2, only one eigenvalue moves ΔE ~ N, same ρ(λ)

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To evaluate $\Phi_{-}(w)$, we use

Case of $\Phi_{-}(w)$

$$E_N(\lambda_1, \cdots, \lambda_N) \to N^2 E[\rho, w],$$

with $E[\rho, w] = \int_0^w d\lambda \rho(\lambda) \lambda^2 - \iint_0^w d\lambda d\lambda' \rho(\lambda) \rho(\lambda') \ln |\lambda - \lambda'| + \mu(w) \left(\int_0^w d\lambda \rho(\lambda) - 1 \right)$

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The functional is then minimize with respect to $\rho(\lambda)$,

$$\frac{\delta E[\rho, w]}{\delta \rho(\lambda)} \bigg|_{\rho = \rho_{w}} = 0 = \lambda^{2} - 2 \int_{0}^{w} d\lambda' \rho_{w}(\lambda') \ln |\lambda - \lambda'| + \mu(w)$$

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Then, we evaluate (with $ho_\infty(\lambda) = rac{1}{\pi}\sqrt{2-\lambda^2}$)

 $\Phi_{-}(w) = E[\rho_w, w] - E[\rho_{\infty}, \infty]$

Case of Φ_+

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To evaluate $\Phi_+(w)$, we compute the energy for one charge in the semi-cirle

$$E_{in}(w) = w^2 - \int
ho(\lambda) \ln |\lambda - w| d\lambda \ , \ -\sqrt{2} < w < \sqrt{2}$$

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$$E_{in}(w) = w^2 - \int
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and the energy out of the semi-cirle

Case of Φ_+

$$E_{out}(w) = w^2 - \int
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Case of Φ_+

$$E_{out}(w) = w^2 - \int
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and the LD rate function is just the energy difference

 $\Phi_+(w) = E_{out}(w) - E_{in}(w)$

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Different classes of universality

If we consider the joint PDF of eigenvalues

$$P(\lambda_1, \cdots, \lambda_N) = \frac{1}{Z_N} \exp\left(-\frac{\beta}{2} \left[\sum_{\substack{k \text{ Potential } v(\lambda)}} \lambda_k^2 - \sum_{\substack{i \neq j \\ \text{Interaction}}} \left| \frac{\ln |\lambda_i - \lambda_j|}{\ln |\lambda_i - \lambda_j|} \right| \right)$$

The CDF for λ_{\max} can be changed in different ways

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The CDF for λ_{\max} can be changed in different ways

• Changing the potential $v(\lambda)$, large class of universality with same typical regime given by \mathcal{F}_2 but the large deviations are different

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The CDF for λ_{\max} can be changed in different ways

- Changing the potential $v(\lambda)$, large class of universality with same typical regime given by \mathcal{F}_2 but the large deviations are different
- Changing the inverse temperature $\beta,$ the typical regime given by \mathcal{F}_β but the large deviations are the same

Majumdar and Schehr, J. Stat. Mech. P01012 (2014)

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The CDF for λ_{max} can be changed in different ways

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- Changing the inverse temperature β , the typical regime given by \mathcal{F}_{β} but the large deviations are the same

Majumdar and Schehr, J. Stat. Mech. P01012 (2014)

• Changing the interaction, everything is different

See for instance Dahr et al. Phys. Rev. Lett. 119, 060601 (2017) (talk by A. Kundu last week)

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Different classes of universality

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• Changing the dimension?

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Complex Ginibre matrices

 ${\boldsymbol{G}}$ is a Complex Ginbre matrices for

$$G = \frac{1}{\sqrt{N}} \begin{pmatrix} g_{11} & g_{12} & \cdots & g_{1N} \\ g_{21} & g_{22} & \cdots & g_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ g_{N1} & g_{N2} & \cdots & g_{NN} \end{pmatrix}$$

$$g_{ij}, g_{ii} \sim \mathcal{N}(0,1) + i \mathcal{N}(0,1)$$

,

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Joint PDF of (complex) eigenvalues

$$P_{\text{joint}}(z_1, \cdots, z_N) = \frac{1}{Z_N} \prod_{i < j} |z_i - z_j|^2 e^{-N \sum_k |z_k|^2} = \frac{1}{Z_N} \exp\left(-\frac{N \sum_k |z_k|^2}{\sum_{\text{Potential}} |z_i - z_j|} + \sum_{\substack{i \neq j \\ \text{Interaction}}} \ln |z_i - z_j|\right)$$

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Only difference with GUE: eigenvalues live in 2d space

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Girko's law

Average density

$$ho_N(z) = rac{1}{N} \langle \sum_k \delta(z-z_k) \rangle
ightarrow
ho(z) = rac{\Theta(1-|z|)}{\pi}$$

Girko, Theory Probab. Appl. 29, 694 (1984)



For the EVS of $r_{\max} = \max_k |z_k|$, $r_{\max} \to 1$.

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Extreme value statistics

We are interested in the CDF $Q_N(w) = \text{Prob.}[r_{\max} \le w]$ with $r_{\max} = \max_{1 \le i \le N} |z_i|$

$$Q_N(w) = \int_{|z| \leq w} dz_1 dz_1^* \cdots \int_{|z| \leq w} dz_N dz_N^* P_{\text{joint}}(z_1, \cdots, z_N) .$$

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$$Q_N(w) = \int_{|z| \leq w} dz_1 dz_1^* \cdots \int_{|z| \leq w} dz_N dz_N^* P_{\mathrm{joint}}(z_1, \cdots, z_N) \, dz_N dz_N^* dz_N^*$$

In the typical regime $|w-1|\ll 1,$ the distribution is a Gumbel as for EVS of i.i.d. variables

 $Q_N(w) \sim G(a_N(w-b_N))$, with $G(y) = \exp(-\exp(-y))$

 $a_N \sim \sqrt{4Nc_N}$, $b_N - 1 \sim \sqrt{c_N/(4N)}$ and $c_N = \ln N - 2\ln \ln N - \ln 2\pi$. Rider, J. Phys. A 36(12), 3401, (2003).



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This CDF $Q_N(w)$ takes large deviation forms on both sides

$$Q_N(w) \sim \begin{cases} e^{-N^2 \Psi_-(w)}, \text{ for } 0 < (1-w) = O(1) \\ G(a_N(w-b_N)), \text{ for } (w-b_N) = O(a_N^{-1}) \\ 1 - e^{-N \Psi_+(w)}, \text{ for } 0 < (w-b_N) = O(1) \end{cases}$$

Cunden et al., J. Stat. Mech. 053303 (2017).

Large deviations

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Cunden et al., J. Stat. Mech. 053303 (2017).

The rate functions are

Large deviations

$$\begin{split} \Psi_{-}(w) &= \frac{1}{4}(4w^2 - w^4 - 4\ln w - 3) \ , \ \text{for} \ \ 0 < w < 1 \\ \Psi_{+}(w) &= w^2 - 2\ln w - 1 \ , \ \ \text{for} \ \ w > 1 \end{split}$$

To obtain Ψ_{\pm} , one can use the same method as for Φ_{\pm} (GUE case)
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If one wants to check the right matching:

Right matching

• From the inside, $G'(x)
ightarrow exp(-x) \;,\; x
ightarrow \infty$

$$Q_N'(w) \sim \exp\left[-\sqrt{4Nc_N}(w-b_N)
ight] \;,\;\; 0 < w-b_N \gg a_N$$

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• From the outside, $\Psi_+(w) o \Psi_+(b_N) + (w-b_N) \Psi_+'(b_N) \ , \ w o b_{N+1}$

$$egin{aligned} & \mathcal{N}\Psi_+'(1+\sqrt{rac{c_N}{4\mathcal{N}}}) = 2\mathcal{N}(1+\sqrt{rac{c_N}{4\mathcal{N}}}-(1+\sqrt{rac{c_N}{4\mathcal{N}}})^{-1})\sim\sqrt{4\mathcal{N}c_N} \ & \mathcal{Q}_N'(w)\sim \exp\left[-\sqrt{4\mathcal{N}c_N}(w-b_N)
ight] \ , \ & |w-b_N|\ll 1 \end{aligned}$$

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Left matching

• From the inside, $G(y) \rightarrow exp(-exp(-y))$, $y \rightarrow -\infty$

 $Q_N(w) \sim \exp\left[-\exp\left(-a_N(w-b_N)
ight)
ight], \ 0 < b_N - w \gg a_N$

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ight)
ight], \ 0 < b_N - w \gg a_N$$

• From the outside, $\Psi_-(w) o rac{4}{3}(1-w)^3 \ , \ w o 1_-$

$$Q_N(w) \sim \exp\left[-\frac{4N^2}{3}(1-w)^3
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Extreme value statistics for i.i.d. random variables Matrices of real eigenvalues Matrices of complex eigenvalues

Left matching

• From the inside,
$$G(y) \rightarrow exp(-exp(-y))$$
, $y \rightarrow -\infty$

$$Q_N(w) \sim \exp\left[-\exp(-a_N(w-b_N))
ight], \ 0 < b_N - w \gg a_N$$

• From the outside, $\Psi_-(w) o rac{4}{3}(1-w)^3 \ , \ w o 1_-$

$$Q_N(w) \sim \exp\left[-rac{4N^2}{3}(1-w)^3
ight] \ , \ \ 0 < 1-w \ll 1$$

No matching!



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2d One Component Plasma

Gas of charged particles in 2d

Competition between

- Coulomb repulsion $V_C(|r_i r_j| = r) = -\ln r$
- External symmetric potential v(r)



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 $E(\mathbf{r}_1,\cdots,\mathbf{r}_N)=N\sum_i v(|\mathbf{r}_j|)-\sum_{k\neq l} \ln|\mathbf{r}_k-\mathbf{r}_l|$

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$$E(\mathbf{r}_1, \dots, \mathbf{r}_N) = N \sum_j v(|\mathbf{r}_j|) - \sum_{k \neq l} \ln |\mathbf{r}_k - \mathbf{r}_l|$$

For $\mathbf{r} = (x, y) \leftrightarrow z = x + iy = re^{i\theta}$
For $v(r) = r^2$ this gives Ginibre

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Conclusion

There is an intermediate deviation regime for the CDF $Q_N(w)$ close to the edge $r_{edge} = 1$ on a scale $|w - r_{edge}| \sim w_N = (2N)^{-1/2}$



Figure: Numerics by diagonalization of 10^6 complex Ginibre matrices of rank N = 200

There is an intermediate deviation regime for the CDF $Q_N(w)$ close to the edge $r_{\rm edge} = 1$ on a scale $|w - r_{\rm edge}| \sim w_N = (2N)^{-1/2}$



Universal for all symmetric potentials $v(r) \gg \ln r^2$ for $r \to \infty$. In this case $r_{edge}v'(r_{edge}) = 2$ and $w_N = [2\pi N\rho(r_{edge})]^{-1/2}$

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Orthogonal polynomials

We introduce orthogonal polynomials $\pi_k(z) = z^{k-1}$ for $k = 1, \cdots, N$ which verify

$$\int dz dz^* \pi_k(z) \pi_l^*(z) e^{-N|z|^2} = \underbrace{\int_0^{2\pi} e^{i(k-l)\theta} d\theta}_{2\pi\delta_{k,l}} \int_0^{\infty} r^{k+l-1} e^{-Nr^2} dr = \pi N^{-k} \Gamma(k) \delta_{k,l}$$

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Computing the following quantity

$$\frac{1}{N!} \det_{1 \le i, j \le N} \frac{N^{j/2} \pi_j(z_i)}{\sqrt{\pi \Gamma(j)}} e^{-\frac{N|z_i|^2}{2}} \det_{1 \le k, l \le N} \frac{N^{k/2} \pi_k(z_l)}{\sqrt{\pi \Gamma(k)}} e^{-\frac{N|z_l|^2}{2}} = \underbrace{\frac{1}{Z_N} \prod_{i < j} |z_i - z_j|^2 e^{-N \sum_k |z_k|^2}}_{P_{\text{joint}}(z_1, \cdots, z_N)}$$

Chafaï and Péché, J. Stat. Phys., 156(2), 368-383, (2014)

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Chafaï and Péché, J. Stat. Phys., 156(2), 368-383, (2014)

This system of charges (or eigenvalues) is determinantal

CDF of r_{max}

Determinantal process Analysis of the CDF Matching

Using Cauchy-Binet-Andreiev the CDF $Q_N(w)$ is now obtained as

$$Q_{N}(w) = \int_{|z| \le w} dz_{1} dz_{1}^{*} \cdots \int_{|z| \le w} dz_{N} dz_{N}^{*} \frac{1}{N!} \left| \det_{1 \le i, j \le N} \frac{N^{j/2} \pi_{j}(z_{i})}{\sqrt{\pi \Gamma(j)}} e^{-\frac{N|z_{i}|^{2}}{2}} \right|^{2}$$
$$Q_{N}(w) = \det_{1 \le i, j \le N} \left(\frac{2N^{j}}{\Gamma(j)} \int_{0}^{w} r^{2j-1} e^{-Nr^{2}} dr \delta_{i,j} \right) = \prod_{k=1}^{N} \left[\frac{\gamma(k, Nw^{2})}{\Gamma(k)} \right]$$

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 r_{\max} is the maximum of independent but non-identically distributed random variables x_k such that $q_k(w) = \Pr[x_k \le w] = \frac{\gamma(k, Nw^2)}{\Gamma(k)}$

Determinantal process Analysis of the CDF Matching

Regime of interest

The average density can be obtained for finite N as

$$ho_N(r) = rac{1}{N} \langle \sum_{k=1}^N \delta(r-z_k)
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$$ho_N(r) = rac{1}{N} \langle \sum_{k=1}^N \delta(r-z_k)
angle = rac{\Gamma(N, Nr^2)}{\pi \Gamma(N)}$$

• For infinite N, the average density follows the Girko's law $\rho_{\rm b}(r) = \frac{\Theta(1-r)}{r}$

• For large but finite N, there is a scaling form on a scale $w_N = (2N)^{-1/2}$

$$ho_N(r)
ightarrow rac{1}{\pi} ilde{
ho} \left(rac{r-r_{
m edge}}{w_N}
ight) \hspace{0.5cm} {
m with} \hspace{0.5cm} \left[ilde{
ho}(u) = rac{1}{2} \, {
m erfc}(u)
ight.$$

Forrester and Honner, J. Phys. A 32, 2961 (1999)

This scale matches the unknown regime for the CDF!



Analysis of the CDF Matching

Individual CDF

By setting u = k/N, the individual CDF q_k reads

$$q_{Nu}(w) = \frac{\int_0^w e^{-N(r^2 - 2u \ln r)} \frac{dr}{r}}{\int_0^\infty e^{-N(r^2 - 2u \ln r)} \frac{dr}{r}}$$

The function $\varphi_u(r) = r^2 - 2u \ln r$ has a single minimum at $r_u = \sqrt{u}$

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The function $\varphi_u(r) = r^2 - 2u \ln r$ has a single minimum at $r_u = \sqrt{u}$ This integral is evaluated by a saddle point approximation,

$$q_{Nu}(w) \approx \begin{cases} \frac{1}{2} \operatorname{erfc} \left[\sqrt{2N} (\sqrt{u} - w) \right] , & w > \sqrt{u} \\ \sqrt{\frac{u}{2\pi N}} \frac{e^{\left[u - w^2 - \ln\left(\frac{u}{w^2}\right) \right]}}{u - w^2} , & w < \sqrt{u} . \end{cases}$$

Determinantal process Analysis of the CDF Matching

Intermediate regime

The full CDF takes the following form

$$Q_N(w) pprox \exp\left[N\int_0^1 du \ln rac{1}{2} \operatorname{erfc}\left[\sqrt{2N}(\sqrt{u}-w)
ight] - \int_0^1 du \Theta(u-w^2)f(u,w)
ight] \;.$$

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For $|w-1| \sim w_N = (2N)^{-1/2}$, the second integral vanishes and introducing $p = \sqrt{N/2}(1-u)$

$$Q_N(w) \approx \exp\left[-\sqrt{2N}\int_0^\infty dp\ln\frac{1}{2}\operatorname{erfc}\left[\sqrt{2N}(1-w)-p
ight]
ight]$$

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For $|w-1| \sim w_N = (2N)^{-1/2}$, the second integral vanishes and introducing $p = \sqrt{N/2}(1-u)$

$$Q_N(w) \approx \exp\left[-\sqrt{2N}\int_0^\infty dp \ln \frac{1}{2} \operatorname{erfc}\left[\sqrt{2N}(1-w) - p\right]\right]$$

The intermediate deviation rate function is

$$\phi_I(y) = -\int_y^\infty dp \ln \frac{1}{2} \operatorname{erfc}(-p)$$

Determinantal process Analysis of the CDF Matching

Matching with the typical regime

For
$$p \gg 1$$
, $erfc(-p) \rightarrow 2 - e^{-p^2}/(\sqrt{\pi}p)$,

$$\phi_I(y) = -\int_y^\infty dp \ln(1 - \frac{e^{-p^2}}{2\sqrt{\pi}p}) \approx \int_y^\infty dp \frac{e^{-p^2}}{2\sqrt{\pi}p} = \frac{e^{-y^2}}{4\sqrt{\pi}y^2}$$

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Then we may use from the outside part of the distribution

$$y = \sqrt{2N}(w-1) = \sqrt{2N}(b_N - 1 + x/a_N) = \sqrt{c_N/2} + x/\sqrt{2c_N},$$

$$Q_N(x = a_N(w - b_N)) = \exp\left[-\sqrt{2N}\phi_I(\sqrt{c_N/2} + \frac{x}{\sqrt{2c_N}})\right] \approx \exp\left[-\sqrt{2N}\frac{e^{-\frac{c_N}{2}-x}}{2\sqrt{\pi}c_N}\right] = e^{-e^{-x}}$$

Determinantal process Analysis of the CDF Matching

Matching with the left LD

For
$$0 < -p \gg 1$$
, $erfc(-p) \rightarrow e^{-|p|^2}/(\sqrt{\pi}|p|)\Theta(-p)$,
 $\phi_I(y) \approx -\int_y^0 dp \ln(\frac{e^{-p^2}}{2\sqrt{\pi}p}) \approx \frac{|y|^3}{3} + o(|y|^3)$

Determinantal process Analysis of the CDF Matching

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• From the inside of the distribution

$$Q_N(w) = e^{-\sqrt{2N}\phi_I(\sqrt{2N}(w-1))} \approx e^{-\frac{4N^2}{3}(1-w)^3 + o(N^2)} , \ 0 < 1-w \gg (2N)^{-1/2}$$

Determinantal process Analysis of the CDF Matching

Matching with the left LD

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, $erfc(-p) \rightarrow e^{-|p|^2}/(\sqrt{\pi}|p|)\Theta(-p)$,
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• From the inside of the distribution

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• From the outside of the distribution

$$Q_N(w) = e^{-N^2 \Psi_-(w)} pprox e^{-rac{4N^2}{3}(1-w)^3} \;, \;\; 0 < 1-w \ll 1$$

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Ginibre results

All regimes match smoothly!



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Universality				

If $v(r) \gg \ln r^2$ for $r \to \infty$,

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Universality

- If $v(r) \gg \ln r^2$ for $r \to \infty$,
 - $\bullet\,$ There is a finite edge $\mathit{r}_{\rm edge}$ at which the density drops to zero

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If $v(r) \gg \ln r^2$ for $r \to \infty$,

- There is a finite edge $r_{\rm edge}$ at which the density drops to zero
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Universality

If $v(r) \gg \ln r^2$ for $r \to \infty$,

- There is a finite edge $r_{\rm edge}$ at which the density drops to zero
- The typical regime is still Gumbel
- The left large deviation rate function vanishes as a power cube

$$\Psi_-(w)\sim (r_{
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 $\Psi_-(w)\sim (r_{\rm edge}-w)^3\;,\;\;w\to r_{\rm edge}$

• The polynomials $\pi_k(z) = z^{k-1}$ are still orthogonal

$$\int dz dz^* \pi_k(z) \pi_l^*(z) e^{-N_V(|z|)} = 2\pi \delta_{k,l} \int_0^\infty r^{2k-1} e^{-N_V(r)} dr$$

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The intermediate rate function ϕ_I is universal w.r.t. v(r)

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We found a Universal intermediate deviation regime solving a puzzle in the matching of typical regimes and large deviations

$$Q_{N}(w) \sim \begin{cases} e^{-N^{2}\Psi_{-}(w)}, \text{ for } 0 < (r_{edge} - w) = O(1) \\ e^{-\frac{r_{edge}}{w_{N}}\phi_{I}\left(\frac{w - r_{edge}}{w_{N}}\right)}, \text{ for } (r_{edge} - w) = O(N^{-1/2}) \\ G(a_{N}(w - b_{N})), \text{ for } (w - b_{N}) = O(a_{N}^{-1}) \\ 1 - e^{-N\Psi_{+}(w)}, \text{ for } 0 < (w - b_{N}) = O(1). \end{cases}$$

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These 4 regimes match smoothly A similar result was observed for fermions in a hard box See LACT et al. arXiv. 1706.03598 and talk by G. Schehr tomorow

Other classes of universality

We have seen that for i.i.d. random variables, there are three classes for the EVS. What about the case of independent NON identically distributed variables?

Other classes of universality

We have seen that for i.i.d. random variables, there are three classes for the EVS. What about the case of independent NON identically distributed variables?

• Large tail joint PDF $v_{\alpha}(r) = (1 + \alpha/N) \ln(1 + r^2)$ with $\alpha > 0$

For $\alpha = 1$, this is realized by computing the jPDF of eigenvalues of $M = A^{-1}B$ with A, B independent Ginibre matrices

Hough, Krishnapur, Peres, Virag, American Mathematical Society (Vol. 51) (2009).

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• Joint PDF with hard edge $v_{
u}(r) = u/N \ln(1-r^2)$ with $u \geq 0$

For any positive integer ν , this is realized computing the jPDF of a sub-block of a random unitary matrix.

Zyczkowski and Sommers, J. Phys. A, 33, 2045 (2000)

Thank you for your attention!