

Walking with Fabrice among large deviations and sum rules

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Le Croisic - MASCOT 2023

Plan

- 1 Introduction
- 2 MEM
- 3 Random moment problem
- 4 Spectral measures

Introduction

Fabrice is a statistician

How to estimate a (probability) measure ?

1) Knowing independent observations \rightarrow sampling i.i.d.

2) Knowing stationary observations \rightarrow periodogram.

3) Knowing some moments

Let $E = [0, 1]$ or \mathbb{T} (the unit circle). Let μ be a probability measure on E . Its k -th moment is

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Data : $m_1(\mu), \dots, m_n(\mu)$

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Common threads :

- discrete random measures

$$\mu^{(n)} = \frac{1}{n} \sum_{i=1}^n Z_i^{(n)} \delta_{X_i^{(n)}} \text{ with } \mathbb{E}X_i^{(n)} = 1.$$

- large deviations

$$\mathbb{P}(\mu^{(n)} \cong \mu) \cong \exp -a_n I(\mu) \quad (a_n \uparrow \infty)$$

- role played by the Kullback-Leibler information

$$I(\mathbb{P} \ll \mathbb{Q}) = \begin{cases} \int \log \frac{d\mathbb{P}}{d\mathbb{Q}} d\mathbb{P} & \text{if } \mathbb{P} \ll \mathbb{Q} \text{ and } \log \frac{d\mathbb{P}}{d\mathbb{Q}} \in L^1(\mathbb{P}), \\ \infty & \text{otherwise,} \end{cases} \quad (1)$$

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- 1) Maximum Entropy for the Mean
+ D. Dacunha-Castelle, + E. Gassiat (Orsay)
- 2) Random moment problems
(+ L-V. Lozada-Chang (La Habana), + H. Dette (Bochum))
- 3) Empirical spectral measures of stationary Gaussian processes
+ B. Bercu (Bordeaux), + M. Lavielle (INRIA), + AR, + M. Zani (Orléans)
- 4) Spectral measures, Random matrices and Sum rules
+ J. Nagel (Dortmund), + AR

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MEM

Estimate μ from noisy observations of some moments.

- ▶ A reference probability P
- ▶ Build a sequence

$$\frac{1}{n} \sum_1^n \delta_{x_k^{(n)}} \Rightarrow_{n \rightarrow \infty} P.$$

- ▶ Choose a law F and Z_k i.i.d. with law F and consider

$$v_n = \frac{1}{n} \sum_1^n Z_k \delta_{x_k}$$

- ▶ Compute

$$P_n^{\text{MEM}} = \text{Argmin}\{\mathcal{K}(R; F^{\otimes n})\}$$

among the laws R such that the mean moments of v_n under R satisfy the constraint.

- ▶ Define the estimator $\hat{v}_n^{\text{MEM}} = \mathbb{E}_{P_n^{\text{MEM}}} v_n$.

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Random moment problem

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The sets of moments are

$$M_k = \{\mathbf{m}_k(\mu); \mu \in \mathcal{M}_1(E)\} \quad (k \geq 1)$$

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They are compact convex sets.

If $E = [0, 1] \setminus M_k$ and if $(m_1, \dots, m_k) \in \text{Int } M_k$ then we can define

$$m_{k+1}^+ = \sup\{m_{k+1}(\mu); \mu \text{ s.t. } \mathbf{m}_k(\mu) = (m_1, \dots, m_k)\}$$

$$m_{k+1}^- = \inf\{m_{k+1}(\mu); \mu \text{ s.t. } \mathbf{m}_k(\mu) = (m_1, \dots, m_k)\}$$

There exists two discrete measures μ_k^\pm corresponding to

$$(m_1, \dots, m_k, m_k^\pm).$$

We can equip M_k with the uniform measure and consider the above (random) measures.

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Spectral measures

Let \mathcal{H} be an Hilbert space, A a bounded self-adjoint operator and e a cyclic unitary vector. From the spectral theorem, there exists a unique p.m. μ compactly supported such that

$$\langle e, A^k e \rangle_{\mathcal{H}} = \int_{\mathbb{R}} x^k d\mu(x), \quad k \geq 0.$$

If we define the equivalence relation

$$(\mathcal{H}, A, e) \sim (\mathcal{K}, B, f)$$

iff there exists an isometry $V : \mathcal{H} \rightarrow \mathcal{K}$ such that $B = VAV^{-1}$ and $f = Ve$ then μ is an invariant of the class.

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2 remarkable elements in each class :

$$\blacktriangleright (L^2(d\mu), h \mapsto (x \mapsto xh(x)), \mathbf{1})$$

where J is a tridiagonal matrix and $e_1 = (1, 0, 0, \dots)$.

Finite dimension

Let A_n be a $n \times n$ self-adjoint matrix, with eigenvalues $(\lambda_j)_{j=1}^n$ and (unitary) eigenvectors $(\psi_j)_{j=1}^n$. Assume that $e = e_1$ is cyclic. Then the sequence

$$((A_n)^k)_{11} \quad k \geq 1$$

is the sequence of moments of

$$\mu_w^{(n)} := \sum_{j=1}^n w_j \delta_{\lambda_j}, \quad w_j := |\langle \psi_j, e_1 \rangle|^2. \quad (2)$$

We can encode $\mu_w^{(n)}$ by two n -uplets (w_1, \dots, w_n) (weights) and $(\lambda_1, \dots, \lambda_n)$.

There is another encoding based on orthogonal polynomials. In the basis (e_1, \dots, e_n) obtained by the Gram-Schmidt procedure applied to $(e, A_n e, \dots, A_n^{n-1} e)$, the matrix A_n becomes

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In the basis (e_1, \dots, e_n) obtained by the Gram-Schmidt procedure applied to $(e, A_n e, \dots, A_n^{n-1} e)$, the matrix A_N becomes

$$J_n = \begin{pmatrix} b_1 & a_1 & 0 & \dots & 0 \\ a_1 & b_2 & a_2 & \dots & 0 \\ 0 & a_2 & b_3 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & a_{n-1} & b_n \end{pmatrix}$$

with $a_j > 0$ for all j .

If

$$(e, Ae, \dots, A^{n-1}e) \longleftrightarrow (1, x, \dots, x^{n-1})$$

then, by Gram-Schmidt

$$(\epsilon_1, \dots, \epsilon_n) \longleftrightarrow (1, p_1(x), \dots, p_{n-1}(x))$$

These polynomials satisfy the recursion :

$$xp_j(x) = a_{j+1}p_{j+1}(x) + b_{j+1}p_j(x) + a_jp_{j-1}(x).$$

Summarizing, we have two remarkable random measures :

$$\mu_u^{(n)} = \frac{1}{n} \sum_{j=1}^n \delta_{\lambda_j}$$

(empirical spectral distribution), whose moments are

$$m_k(\mu_u^{(n)}) = \frac{1}{n} \text{tr}(\mathcal{A}_n)^k$$

and

$$\mu_w^{(n)} = \sum_{j=1}^n w_j \delta_{\lambda_j}$$

(spectral measure of (\mathcal{A}_n, e_1)), whose moments are

$$m_k(\mu_w^{(n)}) = ((\mathcal{A}_n)^k)_{11}$$

Randomization

- ▶ Suppose the distribution of M_n has the GUE-density

$$Z_n^{-1} \exp -\frac{n}{2} \text{tr} (M^2)$$

- ▶ Dumitriu-Edelman ('02) proved that the Jacobi parameters are independent and

$$b_k^{(n)} \sim \mathcal{N}(0; n^{-1}) \quad (1 \leq k \leq n),$$

$$(a_k^{(n)})^2 \sim \text{Gamma} (n - k; n^{-1}) \quad (1 \leq k \leq n - 1).$$

Note that $b_k^{(n)} \rightarrow 0$, $a_k^{(n)} \rightarrow 1$, the Jacobi coefficients of SC :

$$\text{SC}(dx) = \frac{1}{2\pi} \sqrt{(4 - x^2)_+} dx.$$

Theorem (GR '11)

$\mu_w^{(n)}$ satisfies the LDP *with speed n* with rate function

$$J_{\text{coeff}} = \sum_1^{\infty} \frac{1}{2} b_k^2 + \sum_1^{\infty} G(a_k^2), \quad G(x) = x - 1 - \log x.$$

LDP for the "measure side", general potential (no gap)

- ▶ M_n random complex Hermitian $n \times n$ matrix with density

$$(\mathcal{Z}_n^V)^{-1} \exp(-n \operatorname{tr} V(M))$$

- ▶ Potential $V: \mathbb{R} \rightarrow (-\infty, \infty]$ smooth, e.g. $V(x) = x^2/2$, (GUE).

$$\mu_w^{(n)} = \sum_{i=1}^n w_i \delta_{\lambda_i}$$

- ▶ with $w_i = |U_{1,i}|^2$ for U unitary matrix of eigenvectors.

- ▶ The joint density of eigenvalues is

$$(\mathcal{Z}_n^V)^{-1} \prod_{i < j} (\lambda_i - \lambda_j)^2 \prod_{i=1}^n \exp(-nV(\lambda_i))$$

- ▶ and (w_1, \dots, w_n) is uniformly distributed on the simplex, and independent of the eigenvalues.

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$$(Z_n^V)^{-1} \prod_{i < j} (\lambda_i - \lambda_j)^2 \prod_i^n \exp(-nV(\lambda_i))$$

and (w_1, \dots, w_n) is uniformly distributed on the simplex, and independent of the eigenvalues.

Question : how to get LDP for

$$\mu_w^{(n)} = \sum_{k=1}^n w_i \delta_{\lambda_i}$$

directly ?

First point : Asymptotics of the ESD

$$\mu_u^{(n)} := \frac{1}{n} \sum_{j=1}^n \delta_{\lambda_j}$$

satisfies :

- ▶ $\lim_N \mu_u^{(n)} = \mu_V$ in probability with μ_V compactly supported by $[\alpha_V, b_V]$ (equilibrium measure a.k.a. density of states)
- ▶ Ben Arous, Guionnet ('97) : $(\mu_u^{(n)})$ satisfies the LDP with speed n^2 and rate function

$$J^{\text{ESD}}(\mu) = \int V(x) d\mu(x) - \iint \log|x-y| d\mu(x) d\mu(y) - c_V$$

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Second point : decoupling

At scale n , the measure $\mu_u^{(n)}$ is quasi-deterministic, and the randomness comes essentially from the weights w_k 's.

The weights w_k are not independent but

$$(w_1, \dots, w_n) \stackrel{(d)}{=} \left(\frac{\gamma_1}{\gamma_1 + \dots + \gamma_n}, \dots, \frac{\gamma_n}{\gamma_1 + \dots + \gamma_n} \right)$$

where the γ_k 's are independent, $\exp(1)$. So, we can write

$$\mu^{(n)} \stackrel{(d)}{=} \frac{\mu_n}{\int d\tilde{\mu}_n} \text{ with } \tilde{\mu}_n = \sum_{k=1}^n \gamma_k \delta_{\lambda_k}$$

study first μ_n and then make the "contraction".

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$\mu \sim \left\{ \int f d\mu; f \in \mathcal{C}_b \right\}$ (Gärtner-Ellis approach)

$$\begin{aligned} \mathbb{E} \left[\exp \left(n \int f d\tilde{\mu}_n \right) \right] &= \mathbb{E} \left[\prod_{k=1}^n \exp(\gamma_k f(\lambda_k)) \right] \\ &= \mathbb{E} \left[\prod_{k=1}^n \exp(L \circ f(\lambda_k)) \right] = \mathbb{E} \left[\exp \left(n \int (L \circ f) d\mu_u^{(n)} \right) \right] \end{aligned}$$

with $L(x) = -\log(1-x)$. Then, it could be expected that

$$\frac{1}{n} \log \mathbb{E} \left[\exp \left(n \int f d\tilde{\mu}_n \right) \right] \rightarrow \int (L \circ f) d\mu_{\mathcal{V}}$$

and then the LDP for $\tilde{\mu}_n$ would be

$$\tilde{I}(\mu) = \sup_f \left\{ \int f d\mu - \int (L \circ f) d\mu_{\mathcal{V}} \right\} = \mathcal{H}(\mu_{\mathcal{V}} | \mu) + \int \mu - 1.$$

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But there are contributions of the outliers, due to their LDP **with speed n** with rate function \mathcal{F}_V^\pm . This function is the effective potential (up to a constant). When the potential is quadratic, it is

$$\mathcal{F}_H^\pm(x) = \int_2^{|x|} \sqrt{t^2 - 4} dt,$$

i.e. if $\lambda_1^{(n)} > \lambda_2^{(n)} > \dots > \lambda_r^{(n)}$, then

$$\mathbb{P}\left(\lambda_1^{(n)} \cong E_1^+, \dots, \lambda_r^{(n)} \cong E_r^+\right) = \exp -n \left[\sum_1^r \mathcal{F}_H^+(E_i^+) + o(1) \right]$$

Theorem (GNR '16)

Under assumptions on V , $(\mu_w^{(n)})$ satisfies the LDP in the scale N with good rate function

$$\mathcal{J}_{\text{meas}}(\mu) = \mathcal{K}(\mu_V | \mu) + \sum_k \mathcal{F}_V(E_k^+) + \sum_k \mathcal{F}_V(E_k^-)$$

for probability measures μ on \mathbb{R} satisfying

$$\text{Supp}(\Sigma) = [a_V, b_V] \cup \{E_k^-\}_{k=1}^{K^-} \cup \{E_k^+\}_{j=1}^{K^+}$$

where K^+ (resp. K^-) is 0, finite or infinite and $E_k^- \uparrow a_V$ and $E_k^+ \downarrow b_V$ are isolated points of the support, μ_V is the equilibrium measure and $[a_V, b_V]$ is its support.

First sum rule

We have 2 LDPs for the same object under two different encodings

I_{coeff} via the coefficients encoding and I_{meas} via the weight + support encoding. By uniqueness we obtain $I_{\text{coeff}}(\mu) = I_{\text{meas}}(\mu)$. We recover the

Killip-Simon sum rule (2003)

$$\mathcal{K}(\text{SC} | \mu) + \sum_{\mathbf{k}} \mathcal{F}(E_{\mathbf{k}}^+) + \sum_{\mathbf{k}} \mathcal{F}(E_{\mathbf{k}}^-) = \sum_{\mathbf{j}} G(a_{\mathbf{j}}^2) + \frac{b_{\mathbf{j}}^2}{2},$$

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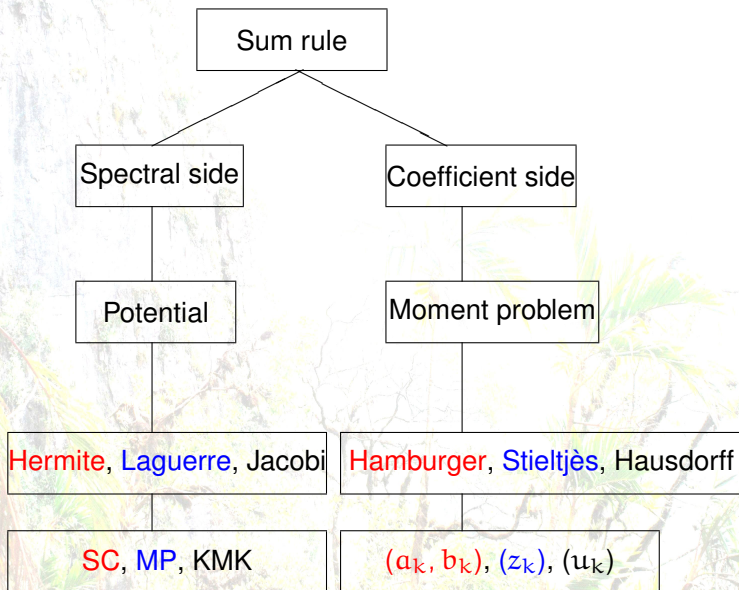
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Recovering

Szegő-Verblunsky formula (1915-1936)

$$\mathcal{K}(\text{UNIF} \mid \mu) = \sum_j -\log(1 - |\alpha_j|^2)$$

New sum rules

Gross-Witten, with potential $\mathcal{V}(e^{i\theta}) = g \cos \theta$.

Hua-Pickrell, with potential $\mathcal{V}(e^{i\theta}) = d \log |1 - e^{i\theta}|^2$.

Conclusion: Fabrice is also a spectral analyst!

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Merci pour votre attention!
Thanks for your attention!

and

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