

IPAM Culminating Workshop

Hamilton Jacobi Equations

Dima Shlyakhtenko, UCLA

Large- N limit of random
matrices model

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Disclaimer: no HJ, barely any PDE
in this talk.

RMT

A_1, \dots, A_d random $N \times N$ self-adjoint matrices

Observables: unitarily invariant functions of
 A_1, \dots, A_d $\xrightarrow{A_1, \dots, A_d \mapsto U A_i U^*}, U A_d U^*$

These are trace polynomials

$$E(\tau_N(p_1(A_1, \dots, A_d))) \tau_N(p_2(A_1, \dots, A_d)) \dots \tau_N(p_k(A_1, \dots, A_d))$$

$$\tau_N = \frac{1}{N} \text{Tr} \xrightarrow{\text{e.g.}} A_1 A_3 + A_3 A_2 + A_2 A_3 + A_1 A_5 A_1$$

τ_N is trace normalized

$$\text{so } \tau_N(I) = 1.$$

$$p(t_1, t_2, t_3) = t_3 t_1 + t_1 t_3 + t_2^2$$

$$\underline{d=1} \quad A_1 / \text{unitary conjugation} = (\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_N)$$

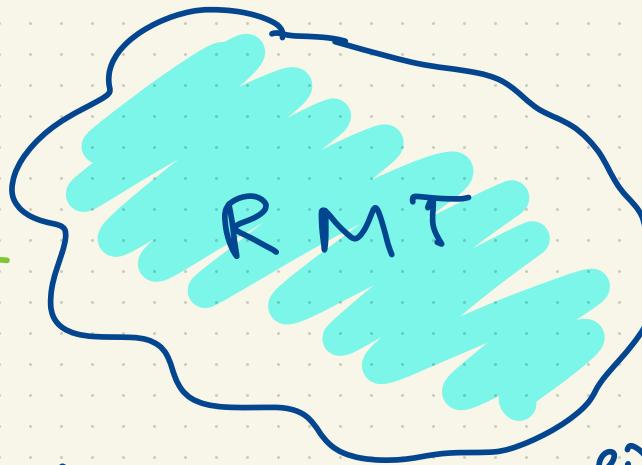
eigenvalues

$$= \text{random measure } \frac{1}{N} \sum_{j=1}^N \delta_{\lambda_j} = \nu_N$$

$$\tau_N(\rho_1(A)) \cdot \tau_N(\rho_2(A)) \dots \tau_N(\rho_k(A))$$

$$= \prod \int \rho_j(t) d\nu_N(t)$$

Mainly $d=1$



Especially $d > 1$

local eigenvalue
statistics

- eigenvalue spacing
- min/max eigenvalues
- Tracy-Widom law
- ...

eigenvalue distribution
[limits of $\frac{1}{N} \sum \delta_{x_j}$]

- limit laws
- semicircle, Marchenko-Pastur
- free probability



Examples of RM Models of interest to us

$$(A_1, \dots, A_d) \sim \mu_N = \frac{1}{Z_N} e^{-N^2 V(A_1, \dots, A_d)} dA_1 \dots dA_d$$

\$Z_N\$ ← normalization const.
\$dA_1 \dots dA_d\$ Lebesgue

$V(A_1, \dots, A_d)$ e.g. non-commutative

polynomial [or limit of]

$$V(A_1, \dots, A_d) = \frac{1}{2} \sum A_j^2 \quad \mu_N = \text{Gaussian measure}$$

$$V(A_1, \dots, A_d) = \left[\frac{1}{2} \sum A_j^2 + \varepsilon W \right] \times \begin{cases} +\infty & \text{if } \max \|A_j\| < R \\ 1 & \text{if } \max \|A_j\| \geq R \end{cases}$$

$V(A_1, \dots, A_d)$ "convex"

Under these assumptions

$$d\mu_N = \frac{1}{Z_N} e^{-N^2 \zeta_N(V(A_1 - A_d))} dA_1 \dots dA_d$$

concentrates

$$\hookrightarrow P(f - E(f) > \varepsilon) \sim e^{-N^2}$$

$$\text{if } \|f\|_{Lip} \leq 1 \quad f = \zeta_N(A_1^2 A_3 + A_3 A_1)$$

\hookrightarrow Trace-polynomials simplify ch. Lmkt:

$$\lim_{N \rightarrow \infty} E(\zeta_N(p_1(A_1, \dots, A_d)) \dots \zeta_N(p_k(A_1, \dots, A_d))) = \prod_j \lim_{N \rightarrow \infty} E(\zeta_N(p_j(A_1, \dots, A_d)))$$

Thus the $N=\infty$ limit is described:

- $d=1$: deterministic measure

$$\mathcal{V} = \text{a.sure} \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{j=1}^N S_{X_j}$$

- $d>1$: "non-commutative law"

$$\tau : \langle \langle t_1, \dots, t_d \rangle \rangle \rightarrow \mathbb{C}$$

$$\tau(p) = \lim_{N \rightarrow \infty} \cancel{\mathbb{E}}(\tau_N(p(A_1, \dots, A_d)))$$

(ordinary measures: $C_c(\mathbb{R})^*$)

\mathcal{C} is an algebraic object not suitable for analysis

Replace $\langle\langle t_1, \dots, t_j \rangle\rangle$ by a larger algebra

$$[\langle\langle t \rangle\rangle \rightarrow L^\infty(\mu)] \quad (t_{i_1 \dots i_k})^* = t_{i_k \dots i_1}$$

$$L^2(\mathcal{C}) = \overline{\langle\langle t_1, \dots, t_j \rangle\rangle}^{||\cdot||_2} \quad ||x||_2 = \mathcal{C}(x^*x)^{1/2}$$

\hat{A}_j = extension of left mult by t_j on $L^2(\mathcal{C})$

Get a Von Neumann algebra of operators
on a Hilbert space

(def: $L^\infty(\mu)$ acting on $L^2(\mu)$)

With this it is possible to do analysis at $N = \infty$
→ free probability.

Some examples:

1°

Notion of independence. (Voiculescu)

(M, τ) von Neumann algebra, $1 \in M$, $j \subseteq M$
subalgebra

M_j freely independent if $x_1 \in M_1, x_2 \in M_2, x_3 \in M_3$

$\tau(x_1 \dots x_k) = 0$ if $\tau(x_j) = 0, x_j \in M_{i(j)}, i(1) \neq i(2)$
 $i(k-1) \neq i(k)$

[analogy of $E(X_1 X_2) = E(X_1) E(X_2)$ for $X_1 \perp\!\!\! \perp X_2$]

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Free Probability versions of SDEs

$$\left(\left[dW_{i;j,s}^t \right]_{i,j=1}^N, \dots, \left[dW_{i;j,d}^t \right]_{i,j=1}^N \right) \xrightarrow[N \rightarrow \infty]{} \begin{array}{l} [\text{Biane-Speicher}] \\ [\text{Guionnet et al.}] \\ (\int \Sigma_i^t, \dots, \int \Sigma_d^t) \end{array}$$

It's formula [Biane-Speicher]

$$\begin{aligned} \tau(\rho(A_1 + \sqrt{t}\Sigma_1, \dots, A_d + \sqrt{t}\Sigma_d)) &= \tau(\rho(A_1, \dots, A_d)) \\ &+ t \sum_{j=1}^d \tau \otimes \tau(\partial_j P) \end{aligned}$$

$$\partial_j : C\langle t_1, \dots, t_d \rangle \xrightarrow{j} C\langle t_1, \dots, t_d \rangle \otimes C\langle t_1, \dots, t_d \rangle$$

$$\partial_j(ab) = a \partial_j(b) + \partial_j(a) b ; \quad \partial_j t_k = \delta_{j=k} \underline{101}$$

∂_j is a "replacement" for $\frac{\partial}{\partial x_j}$.

$d=1: \quad \partial(p) = \frac{p(x) - p(y)}{x - y} \text{ if identify } C\langle t \rangle \otimes C\langle t \rangle \text{ with } C[x, y]$

Fact: limit law of RM model
[Guionnet et al] under convexity assumptions

$$(A_{1,} \rightarrow A_1) \sim \frac{1}{Z_N} e^{-N^2 Z_N(V(A_{1,} \rightarrow A_1))}$$

is the unique stationary solution to

$$dX_j^{(t)} = dS_j^t - \overbrace{D.V(X_{1,}^{(t)} \rightarrow X_2^{(t)})}^{\text{cyclic partial derivative}} dt$$

3.

Free versions of Fokker-Planck equation

$$\mathrm{d}y_j^{(t)} = \mathrm{d}S_j^t - \mathcal{D}_j V(y_1^t, \dots, y_d^t) \mathrm{d}t$$

$$\hookrightarrow \partial_t \tau(f(y_t)) = \tau(\mathbb{L} f)$$

$$\mathbb{L} f = \frac{1}{2} \sum_i ((1 \otimes \tau) \partial_i \circ (1 \otimes \tau) \partial_i) f - \sum_i \mathcal{D}_i f \mathcal{D}_i^* V$$

\mathbb{L} $\mathbb{L} f = \frac{1}{2} D^2 f - f' V'$

$$Df(t) = \int \frac{f(s) - f(t)}{s - t} d\mu(s)$$

4° Free independence in limit:

$$V(t_1, \rightarrow t_d) = V_1(t_1, \rightarrow t_k) + V_2(t_{k+1}, \rightarrow t_d)$$

\Rightarrow in the limit

$$A_1, \rightarrow A_k \quad \& \quad A_{k+1}, \dots, A_d$$

are freely independent.

5° $V(t_1, \rightarrow t_d) = \frac{1}{2} \sum t_j^2$

\Rightarrow in the limit $S_1, \rightarrow S_d$ are freely indep

& each $S_j \xrightarrow{\text{law}} \text{semicircle law}$



Summary so far:

- Free probability: $N \rightarrow \infty$ limit of certain matrix observables
 $(\tau_N(p, (A) \rightarrow A_\delta))$ [Voiculescu, Bratteli-Speicher, Guionnet et al]
- Some control of analysis at $N = \infty$
- MFG - like question: how well does analysis at $N = \infty$ control $N < \infty$?

Case study: monotone transport.

Theorem [Guionnet + D.S. '12]

τ_0 = law of free semicircular d-tuple $[V = \frac{1}{2} \sum t_j^2]$

τ_1 = limit law of d-tuple $[V = \frac{1}{2} \sum t_j^2 + \varepsilon W]$

For $|\varepsilon| \ll 1 \exists$ n.c. power series F_1, \dots, F_d ,

G_1, \dots, G_d o.t:

if $(X_1, \dots, X_d) \sim \tau_1 \Rightarrow (F_1(X_1, \dots, X_d), \dots, F_d(X_1, \dots, X_d)) \sim \tau_0$

and $F \circ G = \text{id.}$

" $F_{\#} \tau_1 = \tau_0$ "

Idea of pf:

look for $F = \text{id} + \varepsilon D\varphi$

where φ is an unknown function.

... get PDE for φ \leftarrow "log of Monge-Ampère"

... solve PDE.

Th2. As before, $F \leftarrow$ s.t. $(F)_{\#} \tau_1 = \tau_0$

when $\tau_0 = \text{free measure}$

$\tau_1 = \text{limit law of } V = \frac{1}{2} \sum_j t_j^2 + \varepsilon W.$

$$[V = \frac{1}{2} \sum_j t_j^2]$$

$$\underline{N=\infty}$$

$$\tau_1 \xrightarrow{F_{\#}} \tau_0$$

$F_{\#}^{(n)} = \text{optimal}$

transport map

$$\underline{N < \infty}$$

$$\mu_N^{(i)} = \frac{1}{Z_N} e^{-\frac{N}{2} \sum_j \tau_N(A_j^2) + \varepsilon W}$$

$$\mu_N^{(i)} = \frac{1}{Z_N} e^{-\frac{N}{2} \sum_j \tau_N(A_j^2)}$$

$\tilde{F}_{\#}^{(N)} = \text{apply } F_{\#}$

$N = \infty$

$N < \infty$

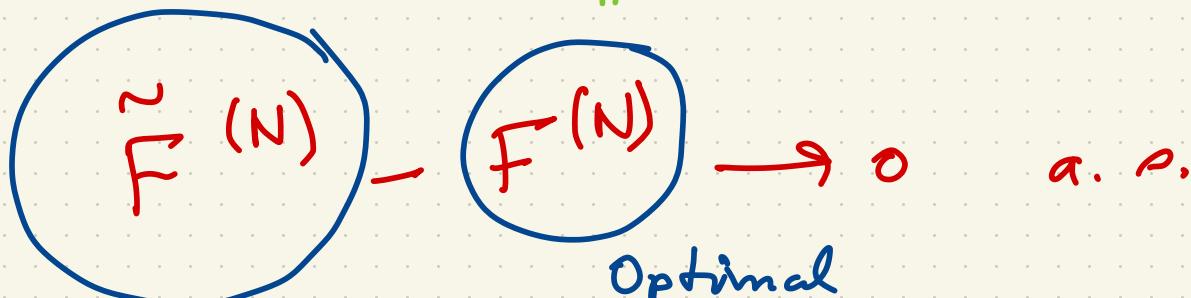
$$\mathcal{T}_1 \xrightarrow{F_{\#}} \mathcal{T}_0$$

$F_{\#}^{(N)} = \text{optimal transport map}$

$$\mu_N^{(1)} = \frac{1}{Z_N} e^{-\frac{N}{2} \sum \tau_N(A_j^2) + \sum w_j} dA_1 \dots dA_N$$
$$\mu_N^{(0)} = \frac{1}{Z_N} e^{-\frac{N}{2} \sum \tau_N(A_j^2)} dA_1 \dots dA_N$$

$\tilde{F}_{\#}^{(N)} = \text{apply } F_{\#}$

Then



$N = \infty$ prediction
evaluated at $N < \infty$

Optimal
solution
at $N < \infty$

Von Neumann's free entropy

$$\chi(\tau, \parallel \tau_0) \quad [\text{a kind of } H_{\infty}(\parallel)]$$

$$\chi(\parallel) = \lim \left(\frac{1}{N^2} H_N(\parallel) + \alpha_N \right)$$

$$\chi(\tau, \parallel \tau_0) \text{ maximal} \Leftrightarrow \tau_1 = \tau_0.$$

$N = \infty$

$$\tau_1 \xrightarrow{F^\#} \tau_0$$

$F^\# = \text{optimal}$

transport
map

$N < \infty$

$$\mu_N^{(1)} = \frac{1}{Z_N} e^{-\frac{N}{2} \sum \tau_N(A_j^1 + \varepsilon \omega)}$$
$$dA_1 - dA_N$$

$$\mu_N^{(0)} = \frac{1}{Z_N} e^{-\frac{N}{2} \sum \tau_N(A_j^2)}$$
$$dA_1 - dA_N$$

$\tilde{F}^\# = \text{apply } F^\#$

Then

$$\tilde{F}^\# - F^\# \rightarrow 0 \quad a.s.$$

$N = \infty$ prediction
evaluated at $N < \infty$

Optimal
solution
at $N < \infty$

$$\text{Pf: } (F_N)^\# \mu_N^{(0)} = \mu_N^{(1)} \quad \mu_N^{(0)} = \frac{1}{Z_N} e^{-\frac{N^2}{2} \zeta_N (\sum A_j^2)} \quad \mu_N^{(1)} = \frac{1}{Z_N} e^{\frac{N^2}{2} \zeta_N (\sum A_j^2 + b)}$$

$$\text{Let } \eta_N(f) = H_N(f^\# \mu_N^{(1)} \| \mu_N^{(0)}) \leftarrow \text{entropy/KL divergence}$$

Then $\eta_N(f)$ is concave in f & reaches max value of 0 $\Leftrightarrow f = F_N$. $f \Rightarrow g$ free entropy

$$\begin{aligned} \eta_N(\tilde{F}_N) &= H_N(\tilde{F}_N^\# \mu_N^{(1)} \| \mu_N^{(0)}) \approx H_\infty(F_\# \tau_0 \| \tau_0) \\ &= 0 \text{ because } F_\# \tau_0 = \tau_1 \end{aligned}$$

$$\text{Thus } \eta_N(\tilde{F}_N) \approx 0 \Rightarrow \|\tilde{F}_N - F_N\|_{L^2} \approx 0$$

+ concentration: $\tilde{F}_N - F_N \rightarrow 0$ a.e.

Summary:

$N = \infty$

free probability

of analysis on operators

$N < \infty$

RMT analysis on
matrices

Other much MFG-like examples ?

References

Anderson, Guionnet, Zeitouni

An Introduction to Random Matrices

PCMI Random Matrix Summer School

I have some notes on free probability
and RMT

Guionnet, Shlyakhtenko; Free Monotone

Transport, Inv. Math. 2014

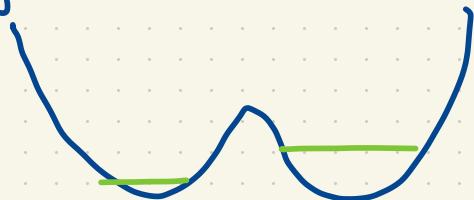
See talk by D. Jekel for PDF story

Open questions

1) Non-convex case ?

Nice analysis in double-well $d=1$

case



No analog when $d > 1$

$$\tau_0, \tau_1 : \mathbb{C} \langle t_1, \neg t_1 \rangle \rightarrow \mathbb{C}$$

$$\inf \sum_{i=1}^d \tau((t_i - s_i)^2)$$

$$\tau : \mathbb{C} \langle t_1, \neg t_d, s_1, \dots, s_d \rangle$$

law $\left\{ \begin{array}{l} \text{positive} \\ \tau(p^* p) \geq 0 \end{array} \right.$

s.t. $\tau|_{\mathbb{C} \langle t_1, \neg t_d \rangle} = \tau_0$

$$\tau|_{\mathbb{C} \langle s_1, \neg s_d \rangle} = \tau_1$$

limit laws
abstractly
Vidick et al.

laws at fusion