

## 5) Extended determinantal point processes.

### 5.1) Karlin-McGregor Theorem.

The original work of Karlin and McGregor was in continuous time but discrete space. Here we present the analogue for Brownian Motions.

Consider  $N$  Brownian Motions starting from  $X_i(0) = Y_i$  and arriving at  $X_i(t) = x_i$ ,  $1 \leq i \leq N$ .

Let  $x_1 > x_2 > \dots > x_N$  and  $y_1 > y_2 > \dots > y_N$ . Denote by  $P_{\text{non-int}}(A)$  the probability of  $A$  and that the Brownian Motions do not intersect.

#### Theorem 17:

$$(5.1) \quad P_{\text{non-int}}(X_1(t) = x_1, \dots, X_N(t) = x_N \mid X_i(0) = y_i, \dots, X_N(0) = y_N) = \\ = \det \left[ P(X(t) = x_i \mid X(0) = y_j) \right]_{1 \leq i, j \leq N}.$$

where  $P(X(t) = x_i \mid X(0) = y_j)$  is the transition density for a single Brownian Motion.

Proof: Ingredients: (a) Continuity of paths  
(b) Reflection principle.

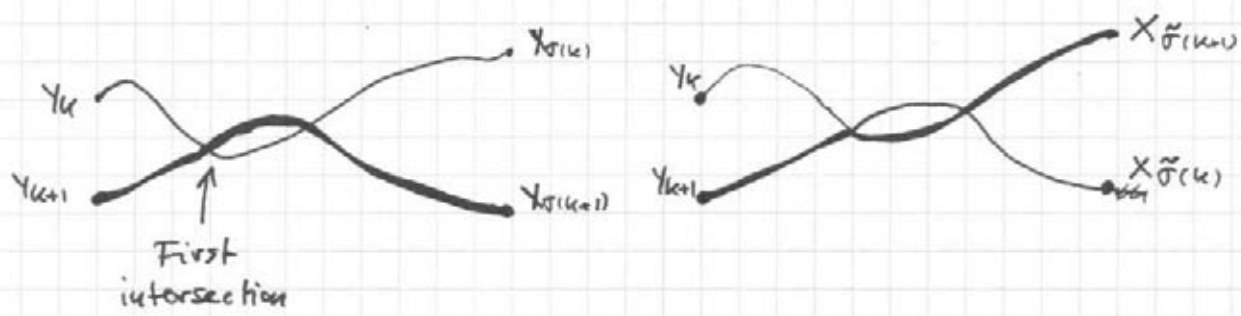
Consider the R.H.S. of (5.1): let  $p(x_i, y_j) \doteq P(X(t) = x_i \mid X(0) = y_j)$ .

$$\Rightarrow \det(p(x_i, y_j))_{1 \leq i, j \leq N} = \sum_{\sigma \in S_N} (-1)^{|\sigma|} \prod_{k=1}^N p(x_k, y_{\sigma(k)}).$$

Transition density from  $\begin{matrix} x_1 \\ \vdots \\ x_N \end{matrix}$  to  $\begin{matrix} y_{\sigma(1)} \\ \vdots \\ y_{\sigma(N)} \end{matrix}$   
with intersections.

We have to see that the contributions of the paths with intersections is exactly cancelled.

• Consider paths with intersections. let us focus at the first intersection.



Prefactor:

$$(-1)^{|\sigma|} \quad (-1)^{|\tilde{\sigma}|} = (-1)^{|\sigma|} \cdot (-1)^{|\sigma|}$$

The contributions cancel, since have the same weight. #

• A first generalisation is known on Graphs. It is called the Lindström-Gessel-Viennot theorem (LGV).

5.2) LGV Theorem.

- Consider a directed graph  $(V, E)$  of vertices  $V$  and edges  $E$ .
- A path  $\pi$  is a sequence of consecutive vertices joined by directed edges. We denote by  $\mathcal{P}(u, v)$  = set of all paths from  $u$  to  $v$ ,  $u, v \in V$ .

• Two paths  $\pi$  and  $\pi'$  intersects if they have a common vertex.

• Weights: To every edge  $e \in E$  assign a weight  $w(e)$ .

• The weight of a path  $\pi$  is then  $w(\pi) = \prod_{e \in \pi} w(e)$ .

• The total weights of paths from  $u$  to  $v$  is

$$h(u, v) = \sum_{\pi \in \mathcal{P}(u, v)} w(\pi)$$

- Assumption: Given points  $(u_1, \dots, u_m)$  and  $(v_1, \dots, v_m)$ ,  $\exists$  at most one  $\sigma \in S_m$  st. one can connect  $u_i$  to  $v_{\sigma(i)}$ ,  $i=1, \dots, m$ , without intersections.
- If such  $\sigma$  exists,  $(u_1, \dots, u_m)$  and  $(v_1, \dots, v_m)$  are compatible, and we can relabel them to have  $\sigma = \mathbb{1}$ .

Theorem (LGV) 18: Denote by  $\mathcal{P}_{\text{non-int}}(\vec{u}, \vec{v})$  the set of non-intersecting  $m$ -tuples of paths from  $\vec{u} = (u_1, \dots, u_m)$  to  $\vec{v} = (v_1, \dots, v_m)$ . Then,

$$(5.2) \quad W(\mathcal{P}_{\text{non-int}}(\vec{u}, \vec{v})) = \sum_{\substack{(\pi_1, \dots, \pi_m) \\ \in \mathcal{P}_{\text{non-int}}(\vec{u}, \vec{v})}} w(\pi_1) \dots w(\pi_m) = \det(h(u_i, v_j))_{1 \leq i, j \leq m}$$

Remark: The proof uses the same ingredients of Karlin-McGregor theorem, namely weight = product of local weights (Markov) and the fact that to exchange their position they first have to intersect.

5.3) Non-intersecting Brownian Motions.

Consider  $N$  Brownian motions with fixed initial and final positions.

Focus at  $m$  intermediate times:  $0 < \tau_1 < \tau_2 < \dots < \tau_m < T$   
 $\uparrow$   $\tau_0$   $\uparrow$   $\tau_{m+1}$

Denote  $x_k^n := X_k(\tau_n), 0 \leq n \leq m+1, 1 \leq k \leq N$

Let  $\phi_{n, n+1}(x, y) = \mathbb{P}(X_n(\tau_{n+1}) = y | X_n(\tau_n) = x)$ , the transition density from time  $\tau_n$  to time  $\tau_{n+1}$ .

Then, by Theorem 17, the measure on  $\{x_k^n, 1 \leq k \leq N, 1 \leq n \leq m\}$  is given by

$$(5.3) \quad \frac{1}{Z_{N,m}} \cdot \det(\phi_{0,1}(x_i^0, x_j^1))_{1 \leq i, j \leq N} \cdot \left( \prod_{n=1}^{m-1} \det(\phi_{n, n+1}(x_i^n, x_j^{n+1}))_{1 \leq i, j \leq N} \right) \cdot \det(\phi_{m, m+1}(x_i^m, x_j^{m+1}))_{1 \leq i, j \leq N}$$

where  $Z_{N,m}$  is the normalisation constant.

Assume that we have a measure of the form (5.3) with  $Z_{N,m} \neq 0$ .

Then, the space-time correlation functions have determinantal form.

Rem.:  $x_i^0$ 's and  $x_i^{m+1}$ 's are fixed.

Proposition 19: The space-time correlation functions of (5.3) are given by:

(5.4)  $S^{(n)}(x_1, t_1; \dots; x_n, t_n) = \det \left( K(x_i, t_i; x_j, t_j) \right)_{i, j \in \{1, \dots, n\}}$ , where

$x_i \in \mathbb{R}$ ,  $t_i \in \{\tau_1, \dots, \tau_m\}$  and the kernel is given by

(5.5)  $K(x, \tau_r; y, \tau_s) = -\phi_{r,s}(x, y) + \sum_{i,j=1}^m \phi_{r,i+1}(x, x_i^{m+1}) \cdot [A^{-1}]_{ij} \cdot \phi_{j,s}(x_j^0, y)$

with  $\phi_{r,s}(x, y) = \begin{cases} (\phi_{r,r+1} \times \dots \times \phi_{s-1,s})(x, y), & \text{if } r < s, \\ 0, & \text{if } r \geq s. \end{cases}$

and  $A_{ij} = \phi_{i,m+1}(x_i^0, x_j^{m+1})$ . Notation:  $(\phi_{r,m+1} \times \phi_{r,m+2})(x, y) \equiv \int dz \phi_{r,m+1}(x, z) \phi_{r,m+2}(z, y)$

Remark: Applying Cauchy-Binet  $m$  times one obtains  $Z_{N,m} = \det(A)$ , so since by assumption  $Z_{N,m} \neq 0$ ,  $A$  is invertible.

Proof of Proposition 19: We prove it for  $m=2$ . The proof for any  $m$  can be made on the same line.

First a small Lemma; Lemma 20: let  $(x_1, \dots, x_n; y_1, \dots, y_n) \equiv (x, y)$  and consider the matrix  $M$  with blocs  $\begin{pmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{pmatrix}$  and entries.

$\langle x, y | M | x, y \rangle \equiv \begin{pmatrix} \langle x, M_{11} x \rangle & \langle x, M_{12} y \rangle \\ \langle y, M_{21} x \rangle & \langle y, M_{22} y \rangle \end{pmatrix}$ . Then,

(5.6)  $\det \left( \langle x, y | M | x, y \rangle \right) = \det \left( \langle x, y | M \cdot Q | x, y \rangle \right)$  for any  $Q$  of the form  $\begin{pmatrix} \mathbb{1} & 0 \\ A & \mathbb{1} \end{pmatrix}$ .

Proof:  $\det \left( \langle x, y | M | x, y \rangle \right) = \det \begin{pmatrix} \langle x, M_{11} x \rangle & \langle x, M_{12} y \rangle \\ \langle y, M_{21} x \rangle & \langle y, M_{22} y \rangle \end{pmatrix} \cdot \int dz dw \begin{pmatrix} \langle z, \mathbb{1} x \rangle & \langle w, \mathbb{1} y \rangle \\ \langle z, A x \rangle & \langle w, \mathbb{1} y \rangle \end{pmatrix}$   
 $= \int dz dw \det \begin{pmatrix} \langle x, M_{11} z \rangle & \langle x, M_{12} w \rangle \\ \langle y, M_{21} z \rangle & \langle y, M_{22} w \rangle \end{pmatrix} \cdot \det \begin{pmatrix} \langle z, \mathbb{1} x \rangle & 0 \\ \langle z, A x \rangle & \langle w, \mathbb{1} y \rangle \end{pmatrix}$   
 $= \det \left( \langle x, y | M \cdot Q | x, y \rangle \right) \neq$

For  $m=2$ , (5.3) becomes:

$$(5.7) \quad \frac{1}{Z} \cdot \det(\phi_{01}(x_i^0, x_i^1)) \det(\phi_{12}(x_i^1, x_i^2)) \det(\phi_{23}(x_i^2, x_i^3)).$$

Let  $A_{ij} = (\phi_{01} * \phi_{12} * \phi_{23})(x_i^0, x_i^3)$ . Then,  $Z = \det A \neq 0$ .

Notations:

$$\begin{aligned} \cdot \Psi_j^2(x) &\equiv \phi_{23}(x, x_j^3) \\ \cdot \Psi_j^1(x) &\equiv (\phi_{12} * \Psi_j^2)(x) \end{aligned}$$

Define :  $\Phi_j^1(x) = \sum_{k=1}^N A_{jk}^{-1} \cdot \phi_{01}(x_k^0, x)$  and set  $\Phi_j^2(x) = (\Phi_j^1 * \phi_{12})(x)$ .

Then, (5.7) becomes:

$$(5.7) = \frac{1}{\det A} \det A \det(\Phi_j^1(x_j^0)) \det(\Psi_j^2(x_j^2)) \det(\phi_{12}(x_i^1, x_i^2)).$$

$$(5.8) = \det \begin{pmatrix} 0 & -\phi_{12}(x_i^1, x_i^2) \\ \sum_{k=1}^N \Psi_k^2(x_i^2) \Phi_k^1(x_j^0) & 0 \end{pmatrix}$$

In operator form:  $\det \langle x^1, x^2 | M | x^1, x^2 \rangle$  with

$$M = \begin{pmatrix} 0 & -\phi_{12} \\ \sum_{k=1}^N |\Psi_k^2\rangle \langle \Phi_k^1| & 0 \end{pmatrix}$$

Consider  $\tilde{M} = \begin{pmatrix} \mathbb{1} & \phi_{12} \\ 0 & \mathbb{1} \end{pmatrix} \cdot M \cdot \begin{pmatrix} \mathbb{1} & \phi_{12} \\ 0 & \mathbb{1} \end{pmatrix} = \begin{pmatrix} \sum_{k=1}^N |\phi_{12} * \Psi_k^2\rangle \langle \Phi_k^1| & -\phi_{12} + \sum_{k=1}^N |\phi_{12} * \Psi_k^2\rangle \langle \Phi_k^1 * \phi_{12}| \\ \sum_{k=1}^N |\Psi_k^2\rangle \langle \Phi_k^1| & \sum_{k=1}^N |\Psi_k^2\rangle \langle \Phi_k^1 * \phi_{12}| \end{pmatrix}$

By Lemma 20,

$$(5.8) = \det \langle x^1, x^2 | \tilde{M} | x^1, x^2 \rangle.$$

So, we have obtained:

$$P(x_{11}^1 \dots x_{1N}^1; x_{11}^2 \dots x_{1N}^2) = \det \begin{pmatrix} K_{11}(x_{i1}^1, x_{i1}^1) & K_{12}(x_{i1}^1, x_{i1}^2) \\ K_{21}(x_{i1}^2, x_{i1}^1) & K_{22}(x_{i1}^2, x_{i1}^2) \end{pmatrix}$$

• Replacing the definitions of  $\Psi$  and  $\Phi$  we get:

$$(5.9) \begin{cases} K_{11}(x, y) = \sum_{i_0=1}^N \phi_{113}(x, x_{i_0}^3) \bar{A}_{i_0}^{-1} \phi_{01}(x_{i_0}^0, y), \\ K_{12}(x, y) = -\phi_{12}(x, y) + \sum_{i_0=1}^N \phi_{113}(x, x_{i_0}^3) \bar{A}_{i_0}^{-1} \phi_{02}(x_{i_0}^0, y), \\ K_{21}(x, y) = \sum_{i_0=1}^N \phi_{213}(x, x_{i_0}^3) \bar{A}_{i_0}^{-1} \phi_{01}(x_{i_0}^0, y), \\ K_{22}(x, y) = \sum_{i_0=1}^N \phi_{213}(x, x_{i_0}^3) \bar{A}_{i_0}^{-1} \phi_{02}(x_{i_0}^0, y). \end{cases}$$

• What remains to do is to integrate over some of the variable and see that the form for the correlations is maintained.

• An orthogonal relation:

$$\Phi_k^n * \Psi_e^n = \delta_{ke}, \quad 1 \leq k, e \leq N, \quad n=1, 2.$$

Let us verify for  $n=1$ :

$$\begin{aligned} \Phi_k^1 * \Psi_e^1 &= \sum_{j=1}^N \bar{A}_{kj}^{-1} \phi_{01}(x_{i_0}^0, \cdot) * \phi_{112} * \phi_{213}(\cdot, x_e^3) \\ &= \sum_{j=1}^N \bar{A}_{kj}^{-1} \bar{A}_{je} = \delta_{ke}. \quad \# \end{aligned}$$

$= \phi_{013}(x_{i_0}^0, x_e^3) = \bar{A}_{je}$

• The correlation function for  $n_1$  points at time  $\tau_1$  and  $n_2$  points at time  $\tau_2$  is then given by:

$$S^{(n_1, n_2)}(x_{i_1}^1, \dots, x_{i_{n_1}}^1; x_{i_1}^2, \dots, x_{i_{n_2}}^2) = \frac{N}{(N-n_1)!} \cdot \frac{N}{(N-n_2)!} \int dx_{n_1+1}^1 \dots dx_{n_1}^1 dx_{n_1+1}^2 \dots dx_{n_1}^2 \cdot \det \begin{pmatrix} K_{11}(x_{i_1}^1, x_{i_1}^1) & K_{12}(x_{i_1}^1, x_{i_1}^2) \\ K_{21}(x_{i_1}^2, x_{i_1}^1) & K_{22}(x_{i_1}^2, x_{i_1}^2) \end{pmatrix}$$

• Using the orthogonal relation it is very easy to verify that:

$$\left. \begin{aligned} & \bullet K_{22} * K_{21} = K_{21} \quad ; \quad K_{22} * K_{22} = K_{22} \\ & \bullet K_{12} * K_{21} = 0 \quad ; \quad K_{12} * K_{22} = 0 \\ & \bullet K_{11} * K_{11} = K_{11} \quad ; \quad K_{11} * K_{12} = 0 \\ & \bullet K_{21} * K_{12} = 0 \quad ; \quad K_{21} * K_{11} = K_{21}. \end{aligned} \right\} \begin{array}{l} \text{The analogues of (2.9),} \\ \text{see page (12).} \end{array}$$

and:  $\int dx K_{ii}(x, x) = N$  : Analogous of (2.8).

Remark:

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The generalisation to any  $n$  is made using the following matrix multiplication: (ex. for  $n=4$ )

$$M = \begin{pmatrix} 0 & -\phi_{12} & 0 & 0 \\ 0 & 0 & -\phi_{23} & 0 \\ 0 & 0 & 0 & -\phi_{34} \\ \sum_k |\Psi_k^4\rangle \langle \Phi_k^1| & 0 & 0 & 0 \end{pmatrix}$$

$$\tilde{M} = \begin{pmatrix} \mathbb{1} & 0 & 0 & \phi_{14} \\ 0 & \mathbb{1} & 0 & \phi_{24} \\ 0 & 0 & \mathbb{1} & \phi_{34} \\ 0 & 0 & 0 & 0 \end{pmatrix} \cdot M = \begin{pmatrix} \mathbb{1} & \phi_{12} & \phi_{13} & \phi_{14} \\ 0 & \mathbb{1} & \phi_{23} & \phi_{24} \\ 0 & 0 & \mathbb{1} & \phi_{34} \\ 0 & 0 & 0 & \mathbb{1} \end{pmatrix}$$

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- The final step is to use these relations and develop the determinant along the column with the variable to integrate out, exactly like in the proof of Proposition 6 (see page (13)) and one gets the result. #

#### 5.4) Application to Brownian Bridges.

- From Brownian Motions to Brownian Bridges one does the usual limit procedure:  $x_i^0 = x_i^{N+1} = -\varepsilon \cdot i$  and send  $\varepsilon \rightarrow 0$ .

- First term:  $\det(\phi_{0,1}(x_i^0, x_j^1))$ :

$$\phi_{0,1}(-\varepsilon k, x) = \text{const} \cdot e^{-\frac{x^2}{2\varepsilon}} \cdot e^{-\frac{\varepsilon^2 k^2}{2\varepsilon}} \cdot e^{-\frac{\varepsilon k x}{\varepsilon}}$$

$\xrightarrow{\varepsilon \rightarrow 0} 1$ 
 $\downarrow$ 
 $\downarrow$

$$= 1 - \frac{k \varepsilon x}{\varepsilon} + \dots + \frac{(-k \varepsilon x)^{N-1}}{(N-1)! \varepsilon^{N-1}} + \mathcal{O}(\varepsilon^N).$$

Linear combinations

$$\Rightarrow \det(\phi_{0,1}(x_i^0, x_j^1)) = \text{const} \cdot \det \begin{pmatrix} 1 + \mathcal{O}(\varepsilon^N) \\ \varepsilon x_j^1 + \mathcal{O}(\varepsilon^N) \\ \vdots \\ (\varepsilon x_j^1)^{N+1} + \mathcal{O}(\varepsilon^N) \end{pmatrix}$$

$$= \varepsilon^{\frac{N(N-1)}{2}} \cdot \text{cte} \cdot \det \begin{pmatrix} 1 + \mathcal{O}(\varepsilon^N) \\ x_j^1 + \mathcal{O}(\varepsilon^{N-1}) \\ \vdots \\ (x_j^1)^{N+1} + \mathcal{O}(\varepsilon) \end{pmatrix}$$

$\xrightarrow{\varepsilon \rightarrow 0} \Delta_N(x_1^1, \dots, x_N^1)$

- The last term is analogous and the factors  $\varepsilon^{\frac{N(N-1)}{2}}$  enters in the normalization.
- Also, we can freely choose two sets of polynomials  $\{\Phi_{i-1}^1(x), i=1, \dots, N\}$  and  $\{\Psi_{i-1}^N(x), i=1, \dots, N\}$  with  $\Phi_{i-1}^1(x), \Psi_{i-1}^N(x)$  of degree  $i-1$ , instead of the monomials in the Vandermonde determinant.



Notations:

$$(5.10) \begin{cases} \cdot \phi_{n,m}(x,y) = \frac{\exp\left(-\frac{(y-x)^2}{2(\tau_m - \tau_n)}\right)}{\sqrt{2\pi(\tau_m - \tau_n)}} \cdot \mathbb{1}_{[\tau_m > \tau_n]} \\ \cdot \Phi_i^r(x) = \frac{\sqrt{2\pi\tau}}{\sqrt{i!2^i}} \cdot \left(\frac{\tau - \tau_r}{\tau_r}\right)^{i/2} \cdot H_i\left(\frac{x}{\sqrt{2\tau_r(\tau - \tau_r)/\tau}}\right) \cdot \frac{e^{-\frac{x^2}{2\tau_r}}}{\sqrt{2\pi\tau_r}} \\ \cdot \Psi_j^s(x) = \frac{\sqrt{2\pi\tau}}{\sqrt{j!2^j}} \cdot \left(\frac{\tau_s}{\tau - \tau_s}\right)^{j/2} \cdot H_j\left(\frac{x}{\sqrt{2\tau_s(\tau - \tau_s)/\tau}}\right) \cdot \frac{e^{-\frac{x^2}{2(\tau - \tau_s)}}}{\sqrt{2\pi(\tau - \tau_s)}} \end{cases}$$

with  $H_i(x)$  the standard Hermite polynomial of degree  $i$ .

• These functions satisfy:

$$(5.11) \begin{cases} \int_{\mathbb{R}} dx \Phi_i^r(x) \phi_{r,s}(x,y) = \Phi_i^s(y), \text{ for } s > r. \\ \int_{\mathbb{R}} dx \phi_{r,s}(x,y) \Psi_j^s(y) = \Psi_j^r(x), \text{ for } r < s. \end{cases}$$

• Moreover,  $\begin{cases} \text{vect} \{ \Phi_i^r(x), i=0, \dots, N-1 \} = \text{vect} \{ e^{-\frac{x^2}{2\tau_r}} \cdot x^i, i=0, \dots, N-1 \} \\ \text{vect} \{ \Psi_j^s(x), i=0, \dots, N-1 \} = \text{vect} \{ e^{-\frac{x^2}{2(\tau - \tau_s)}} \cdot x^i, i=0, \dots, N-1 \}. \end{cases}$

• Therefore, as  $\varepsilon \rightarrow 0$ , the measure on  $\{x_k^u, 1 \leq k \leq N, u=1, \dots, M\}$  for Brownian Bridges from 0 at time 0 to 0 at time  $T$ , is given by:

$$(5.12) \quad \frac{1}{Z} \cdot \det(\Phi_i^r(x_j^0)) \left( \prod_{k=1}^{M-1} \det(\phi_{k,k+1}(x_k^k, x_{k+1}^{k+1})) \right) \cdot \det(\Psi_i^m(x_k^M)).$$

This measure is exactly of the form (5.3). Therefore, the space-time correlations are determinantal (extended determinantal point process),

with kernel:

$$(5.13) \quad \underline{K_N(x, \tau_r; y, \tau_s) = -\phi_{r,s}(x,y) + \sum_{k=0}^{N-1} \Psi_k^r(x) \Phi_k^s(y).}$$

Remark: This for  $\tau_r = \tau_s$  is also the GUE kernel!

5.5) Edge scaling and Airy process.

We consider the following edge scaling:

$T = 4N \implies$  at  $t \approx 2N$ , the top B.B. is around  $2N$ .

(5.14) 
$$\begin{cases} \tau_i = 2N + 2u_i N^{2/3}, & u_1, u_2, \dots, u_M \text{ fixed.} \\ x_i = 2N - u_i^2 \cdot N^{1/3} + s_i N^{1/3} \left( \equiv H_N(\tau_i) + s_i N^{1/3} + O(1) \right). \end{cases}$$

Position from the limit shape:  $\text{Limit shape: } X_i(t) \equiv \sqrt{Z(4N-t)} =: H_N(\tau)$

Fluctuations:  $\frac{1}{3}$  exponent as in R.M.!

Rescaled kernel:  $K_N^{\text{edge}}(u_1, s_1; u_2, s_2) \doteq N^{1/3} \cdot K_N(x_1, \tau_1; x_2, \tau_2)$ .

One uses the asymptotics for  $\Psi$  and  $\Phi$ , setting  $k = N - 2N^{2/3}$ ,  $\lambda \in \frac{N}{N^{1/3}}$ .

(5.15) 
$$\begin{cases} \Psi_{N-2N^{2/3}}^{\tau_i}(x_i) \cong N^{-1/3} \cdot Ai(s_i + \lambda) \cdot e^{\lambda u_i} \cdot \underbrace{\varphi(s_i, u_i)}_{= \exp(-\frac{u_i^3}{3} + s_i u_i)} \\ \Phi_{N-2N^{2/3}}^{\tau_i}(x_i) \cong N^{-1/3} \cdot Ai(s_i + \lambda) \cdot e^{-\lambda u_i} \cdot \varphi(s_i, u_i) \end{cases}$$

For  $\tau_j > \tau_i$ :  $\Phi_{\tau_j, \tau_i}(x_i, y) \cong N^{-1/3} \cdot \frac{\varphi(s_i, u_i)}{\varphi(s_j, u_i)} \cdot \frac{1}{\sqrt{4\pi(u_j - u_i)}} \cdot \exp\left(-\frac{(s_j - s_i)^2}{4(u_j - u_i)} + \frac{1}{12} \cdot \frac{(u_j - u_i)^3}{2} - \frac{(u_j - u_i)(s_i + s_j)}{2}\right)$

$$\sum_{k=0}^{N-1} \implies \frac{1}{N^{1/3}} \sum_{\lambda \in \frac{N}{N^{1/3}}} \rightarrow \int_0^\infty d\lambda$$

Final result: **Theorem 21:** Let  $N$  Brownian Bridges from  $t=0$  to  $t=4N$  be conditioned on non-intersecting (excepts at  $t=0, t=4N$ ).

Let 
$$\begin{cases} \tau = 2N + 2u N^{2/3}, \\ x = 2N - u^2 N^{1/3} + s N^{1/3} \end{cases}$$

Then, in the  $N \rightarrow \infty$  limit, the extended determinantal point process has kernel given by:

$$(5.16) \quad K_{\mathcal{A}_2}(u, s; u', s') = \begin{cases} \int_0^\infty d\lambda \mathcal{A}_i(s+\lambda) \mathcal{A}_i(s'+\lambda) \cdot e^{(u'-u)\lambda} & , \text{ if } u' \leq u, \\ - \int_{-\infty}^0 d\lambda \mathcal{A}_i(s+\lambda) \mathcal{A}_i(s'+\lambda) \cdot e^{(u'-u)\lambda} & , \text{ if } u' > u. \end{cases}$$

. This is called the extended Airy kernel.

Remark:  $\int_{\mathbb{R}} d\lambda \mathcal{A}_i(s+\lambda) \mathcal{A}_i(s'+\lambda) e^{\lambda u} \stackrel{u \gg 0}{=} \frac{1}{\sqrt{4\pi u}} \cdot \exp\left(-\frac{(s'-s)^2}{4u} + \frac{1}{12} u^3 - u \frac{(s'+s)}{2}\right).$

Corollary 22: Let  $x_1(t)$  be trajectory of the top Brownian Bridge. Define the rescaled process:

$$(5.17) \quad Y_N(u) := \frac{x_1(2N + 2uN^{2/3}) - (2N - u^2N^{1/3})}{N^{1/3}}.$$

Then,  $\lim_{N \rightarrow \infty} Y_N(u) = \mathcal{A}_2(u)$

in the sense of finite-dimensional distributions, where  $\mathcal{A}_2(u)$  is called the Airy<sub>2</sub> process.

Definition 23: The Airy<sub>2</sub> process is defined via the finite-dimensional distributions given by:

$$(5.18) \quad \mathbb{P}\left(\bigcap_{k=1}^m \mathcal{A}_2(u_k) \leq s_k\right) = \det(\mathbb{1} - \chi_s K_{\mathcal{A}_2} \chi_s)_{L^2(\mathbb{R}^2_{\geq u_1, \dots, u_m} \times \mathbb{R})}$$

with  $\chi_s(u, x) = \mathbb{1}[x > s]$  and  $K_{\mathcal{A}_2}$  is the extended Airy kernel given above.

Compact formula:

$$K_{\mathcal{A}_2}(u, s; u', s') = -\left(e^{-(s'-s)H_{\mathcal{A}_i}}\right)(u, u') \cdot \mathbb{1}[s' > s] + \left(e^{sH_{\mathcal{A}_i}} \bar{K}_{\mathcal{A}_2} \cdot e^{-s'H_{\mathcal{A}_i}}\right)(u, u'), \text{ with}$$

$\bar{K}_{\mathcal{A}_2}(s, s') = \int_0^\infty d\lambda \mathcal{A}_i(\lambda+s) \mathcal{A}_i(\lambda+s')$ , and  $H_{\mathcal{A}_i}$  is the Airy operator:  $(H_{\mathcal{A}_i} \psi)(x) = -\frac{d^2}{dx^2} \psi(x) + x \psi(x).$

Eigenfunctions:  $H_{\mathcal{A}_i} \mathcal{A}_i(x-\lambda) = \lambda \mathcal{A}_i(x-\lambda).$

## 5.6) Dyson's Brownian Motion.

• It is a Brownian Motion on space of Matrices.

• let us denote by  $H_\mu$ ,  $\mu = 1, \dots, \frac{N(N+1)}{2} = p$ , for GOE, the  
 $\mu = 1, \dots, N^2 = p$ , for GUE

independent entries of the symmetric/hermitian  $N \times N$  matrices.

• let these  $H_\mu$  perform independent Brownian Motion in a quadratic potential:  $dH_\mu = -\gamma \cdot H_\mu dt + \sigma_\mu dB_\mu$ , with  $\sigma_\mu = \begin{cases} 1, & \mu = (i,i) \\ \frac{1}{2}, & \text{otherwise.} \end{cases}$   
 $\uparrow$   
 standard B.M.  
 $(\text{Var}(B_\mu(t)) = t)$ .

• Then,  $P(H_1, \dots, H_p | t)$  be the probability density of  $H$  at time  $t$ , it satisfies the Smoluchowski equation:

$$(5.19) \quad \frac{\partial P}{\partial t} = \sum_{\mu=1}^p \left[ \frac{1}{2} \sigma_\mu \frac{\partial^2}{\partial H_\mu^2} P + \gamma \cdot \frac{\partial}{\partial H_\mu} (H_\mu P) \right].$$

• Its stationary solution is the GOE/GUE measure:

$$(5.20) \quad P^{\text{stat}}(H) = \frac{1}{Z} \cdot e^{-\gamma \text{Tr}(H^2)}$$

• The stationary process is called Dyson's Brownian Motion, and has transition probability density

$$(5.21) \quad P(H(t) | H(0)) = \frac{c t e}{(1 - q_t^2)^{p/2}} \cdot \exp\left(-\frac{\gamma \cdot \text{Tr}(H(t) - q_t \cdot H(0))^2}{1 - q_t^2}\right)$$

where  $q_t = \exp(-\gamma \cdot t)$ .

• The evolution of the eigenvalues satisfy then (one need some computations):

$$d\lambda_i = \left[ -\gamma \lambda_i + \frac{\beta}{2} \sum_{j \neq i} \frac{1}{\lambda_i - \lambda_j} \right] dt + db_i, \quad i = 1, \dots, N$$

where  $db_i$  are standard independent B.M.

5.6.1)  $\beta=2$  Dyson's Brownian Motion.

• Consider GUE ( $\beta=2$ ) case and set  $\gamma = \frac{1}{2N}$ .

Let  $P(H(t=0)) = P^{stat}(H(t=0))$ .

• Consider  $m$  times  $0 < t_1 < t_2 < \dots < t_m$ .

Then, the multi-time measure is, with  $H_i \doteq H(t_i)$ , given by

(5.22)  $\frac{1}{Z} \cdot e^{-\frac{\text{Tr}(H_0^2)}{2N}} \cdot \prod_{j=0}^{m-1} e^{-\frac{\text{Tr}(H_{j+1} - q_j H_j)^2}{2N(1-q_j^2)}} dH_0 \dots dH_m$

where  $q_j \doteq \exp\left(-\frac{t_{j+1} - t_j}{2N}\right)$ .

• Denote by  $\alpha_k \doteq \frac{1}{2N(1-q_k^2)}$ ,  $\gamma_k = \frac{1 - q_{k-1}^2 q_k^2}{2N(1-q_{k-1}^2)(1-q_k^2)}$ ,  $\beta_k = \frac{q_k}{N(1-q_k^2)}$ .

Then, one verifies that (5.22) can be rewritten as

(5.23)  $\frac{1}{Z} \cdot e^{-\alpha_0 \cdot \text{Tr}(H_0^2)} \left( \prod_{k=1}^{m-1} e^{-\gamma_k \cdot \text{Tr}(H_k^2)} \right) e^{-\alpha_{m-1} \cdot \text{Tr}(H_m^2)} \cdot \prod_{k=0}^{m-1} e^{\beta_k \cdot \text{Tr}(H_k \cdot H_{k+1})} dH_0 \dots dH_m$

• What about the measure on their eigenvalues?

For GUE we have seen that  $dH_k = \Delta_N^2(\lambda^k) d\lambda^k \cdot dU_k$  with  $\lambda^k = (\lambda_1^k, \dots, \lambda_N^k)$ , and  $H_k = U_k \Lambda_k U_k^{-1}$ , with  $\Lambda_k = \begin{pmatrix} \lambda_1^k & & 0 \\ & \ddots & \\ 0 & & \lambda_N^k \end{pmatrix}$ .   
  $\Delta_N^2$  Haar measure on  $U(N)$ .

• Thus,  $\prod_{k=0}^{m-1} \beta_k \text{Tr}(H_k H_{k+1}) dH_0 \dots dH_m = \prod_{k=0}^{m-1} e^{\beta_k \text{Tr}(U_k \Lambda_k U_k^{-1} U_{k+1} \Lambda_{k+1} U_{k+1}^{-1})} \cdot \Delta_N^2(\lambda^0) \dots \Delta_N^2(\lambda^m) d\lambda^0 \dots d\lambda^m dU_0 \dots dU_m$

• Defining  $U_k^{-1} U_{k+1} \doteq V_k$ , we get the terms of type

(5.24)  $\int_{U(N)^m} \prod_{k=0}^{m-1} e^{\beta_k \text{Tr}(\Lambda_k V_k \Lambda_{k+1} V_k^{-1})} dV_k$

to evaluate.

Lemma 24 [Harish-Chandra / Itzykson-Zeiger formula]:

$$(5.25) \quad \int_{U(N)} dU e^{\gamma \text{Tr}(U_1 U_2 U^{-1})} = \frac{1}{\gamma^{N(N-1)/2}} \cdot \frac{\left(\prod_{p=1}^{N-1} p!\right) \cdot \det(e^{\gamma \lambda_i^1 \lambda_j^2})_{1 \leq i, j \leq N}}{\Delta_N(\lambda_1) \Delta_N(\lambda_2)}$$

Using this, the measure on the eigenvalues  $\{\lambda_i^k, i=1, \dots, N, k=0, \dots, m\}$  is given by

$$(5.26) \quad \frac{1}{Z} \cdot \left(\prod_{i=1}^N e^{-\alpha_0 (\lambda_i^0)^2}\right) \cdot \left(\prod_{k=1}^{m-1} \prod_{i=1}^N e^{-\gamma_k (\lambda_i^k)^2}\right) \cdot \prod_{i=1}^N e^{-\alpha_{m-1} (\lambda_i^m)^2} d\lambda^0 \dots d\lambda^m$$

$$\cdot \Delta_N(\lambda^0) \left(\prod_{k=0}^{m-1} \det(e^{\beta_k \lambda_i^k \lambda_j^{k+1}})_{1 \leq i, j \leq N}\right) \cdot \Delta_N(\lambda^m)$$

This measure has the form (5.3), so one can apply Proposition 19, and finds:

The  $p=2$  Dyson's Brownian Motion's eigenvalues form an extended determinantal point process with kernel (Extended Hermite):

$$(5.27) \quad K_N(x_1, t_1; x_2, t_2) = \begin{cases} \sum_{k=0}^{N-1} e^{-\frac{k(t_2-t_1)}{2N}} \cdot P_k(x) P_k(y) e^{-\frac{x^2+y^2}{4N}}, & \text{for } t_1 \leq t_2, \\ -\sum_{k=N}^{\infty} e^{-\frac{k(t_2-t_1)}{2N}} \cdot P_k(x) P_k(y) \cdot e^{-\frac{x^2+y^2}{4N}}, & \text{for } t_1 > t_2, \end{cases}$$

where  $P_k(x) = \frac{1}{\sqrt{2\pi N} \sqrt{2^k k!}} \cdot H_k\left(\frac{x}{\sqrt{2N}}\right)$

Edge scaling:  $\lambda_i(t)$  be the  $i$ th largest e.v.

$$\lambda_{i,N}^{\text{edge}}(s) := \frac{\lambda_i(2.5 \cdot N^{2/3}) - 2N}{N^{1/3}}$$

The rescaled kernel converges to the Airy<sub>2</sub> kernel as  $N \rightarrow \infty$ .

$$\Rightarrow \lim_{N \rightarrow \infty} \lambda_{N,N}^{\text{edge}}(s) = \text{Ai}_2(s) : \text{the Airy}_2 \text{ process.}$$