

Lecture 4 :

Determinantal calculus & Asymptotics

Play : Cauchy - Binet identity

Sylvester's identity

From determinants to Fredholm determinants

Steepest descent method & Tracy-Widom

Proposition (Cauchy-Binet or Andreief identity)

Let $\phi_i, \psi_i \in L^2(X, \mu)$ for $i=1, \dots, N$

then

$$\frac{1}{N!} \int_{X^N} \det(\phi_i(x_j))_{i,j \leq N} \det(\psi_i(x_j))_{i,j \leq N} \mu(dx_1) \cdots \mu(dx_N)$$

$$= \det\left(\int_X \phi_i(x) \psi_j(x) \mu(dx)\right)_{i,j \leq N}$$

Proof: $\det(\phi_i(x_j)) = \sum_{\sigma \in S_N} (-1)^\sigma \prod_{i=1}^N \phi_i(x_{\sigma(i)})$

& same for $\psi_i(x_j)$

$$\Rightarrow \frac{1}{N!} \int_{X^N} \det(\phi_i(x_j)) \det(\psi_i(x_j)) \mu(dx_1) \cdots \mu(dx_N)$$

$$= \frac{1}{N!} \sum_{\sigma, \tau} (-1)^{\sigma+\tau} \int_{X^N} \prod_{i=1}^N \phi_i(x_{\sigma(i)}) \cdot \prod_{i=1}^N \psi_i(x_{\tau(i)}) \mu(dx_1) \cdots \mu(dx_N)$$

Golden rule: Before proceeding look at special examples!

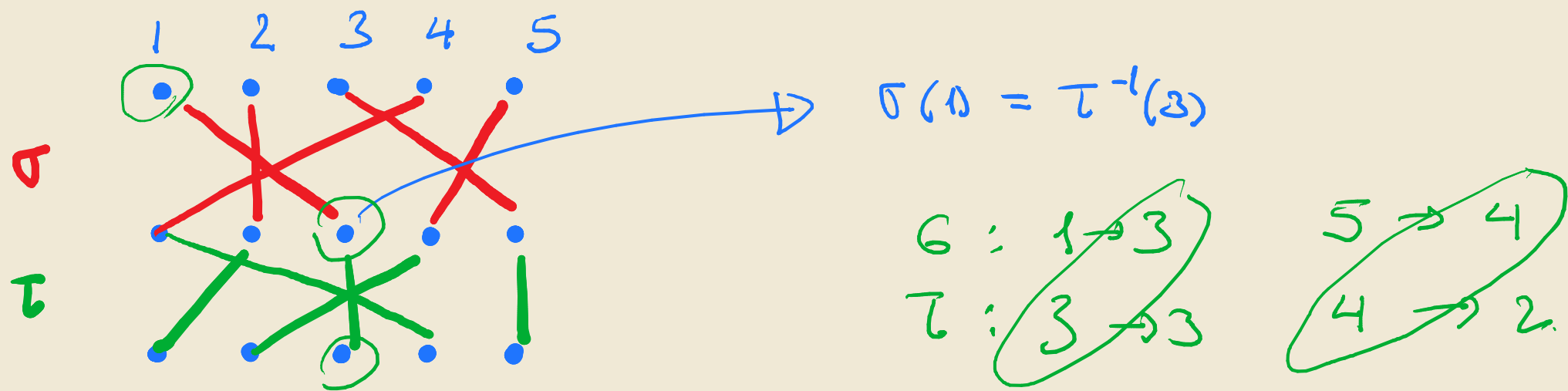
$$\text{So, } N=2 \text{ \& say } \sigma = \begin{pmatrix} 1 & 2 \\ 2 & 1 \end{pmatrix}, \tau = \begin{pmatrix} 1 & 2 \\ 1 & 2 \end{pmatrix}$$

then

$$\begin{aligned} & \iint \phi_1(x_2) \phi_2(x_1) \cdot \varphi_1(x_1) \varphi_2(x_2) dx_1 dx_2 \\ &= \int \phi_1(x_2) \varphi_2(x_2) \cdot \int \phi_2(x_1) \varphi_1(x_1) dx_1 \\ &= \int \phi_1(x) \varphi_2(x) dx \cdot \int \phi_2(x) \varphi_1(x) dx \end{aligned}$$

Observation: things will factorise & then it will be an issue of summing up all permutations σ, τ .

After example (s) ... details!



$$\int_{X^N} \phi_1(x_{\sigma(1)}) \cdots \phi_N(x_{\sigma(N)}) \cdot \psi_1(x_{\tau(1)}) \cdots \psi_N(x_{\tau(N)})$$

$$= \int_{X^N} \phi_1(x_{\sigma(1)}) \psi_{\tau^{-1}(\sigma(1))}(x_{\sigma(1)}) dx_{\sigma(1)}$$

$$\times \phi_2(x_{\sigma(2)}) \psi_{\tau^{-1}(\sigma(2))}(x_{\sigma(2)}) dx_{\sigma(2)}$$

$$\vdots$$

$$\times \phi_N(x_{\sigma(N)}) \psi_{\tau^{-1}(\sigma(N))}(x_{\sigma(N)}) dx_{\sigma(N)}$$

$$= \prod_{i=1}^N \int_X \phi_i(x) \psi_{\tau^{-1}(\sigma(i))}(x) dx$$

... So, we have that

$$\begin{aligned} & \frac{1}{N!} \int_{X^N} \det(\phi_i(x_j)) \det(\psi_i(x_j)) \prod_{i=1}^N \mu(dx_i) \\ &= \frac{1}{N!} \sum_{\sigma, \tau \in S_N} (-1)^{\sigma+\tau} \prod_{i=1}^N \int_X \phi_i(x) \psi_{\sigma(\tau^{-1}(i))}(x) \mu(dx) \end{aligned}$$

Set $\sigma \circ \tau^{-1} =: \rho$. Then $(-1)^{\sigma+\tau} = (-1)^\rho$

and

$$= \frac{1}{N!} \sum_{\rho} \sum_{\sigma} (-1)^\rho \prod_{i=1}^N \int_X \phi_i(x) \psi_{\sigma(i)}(x) \mu(dx)$$

$$= \frac{1}{N!} \sum_{\sigma \in S_N} \det \left(\int_X \phi_i(x) \psi_j(x) \mu(dx) \right)_{i,j \in N}$$

$$= \det \left(\int_X \phi_i(x) \psi_j(x) \mu(dx) \right)_{i,j \in N}$$

□

Proposition (Sylvester's identity)

$$\text{Let } A: L^2(Y, \nu) \rightarrow L^2(X, \mu)$$

$$B: L^2(X, \mu) \rightarrow L^2(Y, \nu)$$

be trace class operators. Then

$$\det(I + AB)_{L^2(X, \mu)} = \det(I + BA)_{L^2(Y, \nu)}$$

Proof Use the definition of Fredholm determinant

$$\det(I + AB) = 1 + \sum_{k \geq 1} \int_{X^k} \det(AB(x_{ij}))_{i,j \leq k} \prod_{i=1}^k dx_i$$

$$= 1 + \sum_{k \geq 1} \sum_{\sigma} (-1)^\sigma \int_{X^k} \prod_{j=1}^k AB(x_i, x_{\sigma(j)}) \prod_{i=1}^k dx_i$$

$$= 1 + \sum_{k \geq 1} \sum_{\sigma} (-1)^\sigma \int_{X^k} \prod_{i=1}^k \int_Y A(x_i, \gamma) B(\gamma, x_{\sigma(i)}) d\gamma \prod_{i=1}^k dx_i$$

$$= 1 + \sum_{k \geq 1} \sum_{\sigma} (-1)^\sigma \int_{X^k} \int_{Y^k} \prod_{i=1}^k A(x_i, \gamma_i) B(\gamma_i, x_{\sigma(i)}) \prod_{i=1}^k dx_i d\gamma_i$$

Fubini

$$= 1 + \sum_{k \geq 1} \sum_{\sigma} (-1)^\sigma \int_{Y^k} d\vec{\gamma} \int_{X^k} \prod_{i=1}^k dx_{\sigma(i)} A(x_{\sigma(i)}, \gamma_{\sigma(i)}) \cdot B(\gamma_i, x_{\sigma(i)})$$

$$= 1 + \sum_{k \geq 1} \sum_{\sigma} (-1)^\sigma \int_{Y^k} d\vec{\gamma} \prod_{i=1}^k \int_X dx B(\gamma_i, x) A(x, \gamma_{\sigma(i)})$$

$$= 1 + \sum_{k \geq 1} \int_{Y^k} d\vec{\gamma} \sum_{\sigma} (-1)^\sigma \prod_{i=1}^k (BA)(\gamma_i, \gamma_{\sigma(i)})$$

$$= 1 + \sum_{k \geq 1} \int_{Y^k} \det(BA(\gamma_i, \gamma_j))_{i,j \leq k} d\vec{\gamma}$$

$$= \det(I + BA)_{L^2(Y, \nu)}$$

□

Remark the significance of Sylvester's identity:

it reduces the determinant of a potentially huge matrix to the determinant of a small matrix.

Ex.

$$a = (a_1, a_2, \dots) \quad b = (b_1, b_2, \dots)$$

$$\det(I + a^T b) = \det(I + b a^T) = \det\left(1 + \sum_i a_i b_i\right)$$

$$a^T b = (a_i b_j)_{i,j \geq 1} \quad \left(\longrightarrow \right) \left(\right) \quad 1 + \sum_i a_i b_i$$

Proposition (the basic determinantal computation)

Consider a determinantal measure defined as

$$\mu_N(f) = \frac{Z_N(f)}{Z_N}$$

where

$$Z_N(f) = \int_{X^n} \det(\phi_i(x_j))_{i,j \leq n} \det(\psi_i(x_j))_{i,j \leq n} \prod_{i=1}^n f(x_i) dx_i$$

& $Z_N = Z_N(1)$ is the normalisation or partition function

$$\text{then } \mu_N(1+g) = \det(I + gK)_{L^2(X)}$$

$$\text{with } K(x, \gamma) = \sum_{i,j} \psi_i(x) [G^{-1}]_{ij} \phi_j(\gamma)$$

$$\text{\&} \quad G_{ij} = \int_X \phi_i(x) \psi_j(x) dx \quad (\text{Gram matrix})$$

Proof $\frac{Z_N(1+g)}{Z_N} =$

$$\int_{X^N} \det(\phi_i(x_j)) \det(\psi_i(x_j)) \prod (1+g(x))$$

$$= \frac{\int_{X^N} \det(\phi_i(x_j)) \det(\psi_i(x_j)) \prod (1+g(x))}{\det \left(\int \phi_i(x) \psi_j(x) (1+g(x)) \right)}$$

Causdy
Berez

$$\frac{\det \left(\int \phi_i(x) \psi_j(x) (1+g(x)) \right)}{\det \left(\int \phi_i(x) \psi_j(x) dx \right)}$$

$$= \frac{\det \left(G_{ij} + \int \phi_i(x) \psi_j(x) g(x) dx \right)}{\det(G_{ij})}$$

$$\frac{1}{\det G} = \det G^{-1}$$

$$\downarrow \det A \cdot \det B = \det(AB)$$

$$= \det \left(\delta_{ij} + \sum_{1 \leq k \leq n} [G^{-1}]_{ik} \int \underbrace{\phi_k(x)}_{A_i(x)} \underbrace{\psi_j(x)}_{B_j(x)} g(x) dx \right)_{i,j \leq n}$$

$$= \det \left(\delta_{ij} + \int \sum_{k \leq n} [G^{-1}]_{ik} \phi_k(x) \psi_j(x) g(x) dx \right)_{i,j \leq n}$$

$$= \det \left(\delta_{ij} + \int \underbrace{A(i,x) B(x,j)}_{dx} \right)_{i,j \leq n}$$

where $A(i,x) = \sum_k [G^{-1}]_{ik} \phi_k(x)$

$$B(x,j) = g(x) \psi_j(x)$$

Sylvester

$$\det \left(I + \sum_i \underbrace{B(x,i) A(i,\gamma)}_{L^2(x)} \right)_{L^2(x)}$$

$$= \det \left(I + g(x) \sum_{i,k} \psi_i(x) [G^{-1}]_{ij} \phi_j(\gamma) \right)_{L^2(x)}$$



Application : LPP

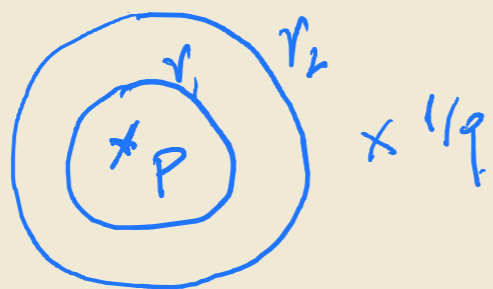
Prop. $W = (W_{ij})_{i,j \leq N}$ with independent entries &

$$\mathbb{P}(W_{ij} = w_{ij}) = (1 - p_i q_i) (p_i q_i)^{w_{ij}}, w_{ij} \in \mathbb{N}$$

then for $\tau_N = \max_{\pi} \sum_{ij \in \pi} (\text{zigzag})$

$$\mathbb{P}(\tau_N \leq x) = \det(I + K_N^{\text{LPP}}) e^2(x+N, x+N+1, \dots)$$

with
$$K_N^{\text{LPP}}(t,s) = \frac{1}{(2\pi i)^2} \int_{\gamma_1} dJ \int_{\gamma_2} d\eta \frac{\eta^s J^t}{1 - J\eta} \prod_{j=1}^N \left(\frac{1 - \eta q_j}{\eta - p_j} \right) \cdot \prod_{i=1}^N \left(\frac{1 - p_i J}{J - q_i} \right)$$



$$|\gamma_1| = 1 - \varepsilon < 1 + \varepsilon = |\gamma_2|$$

Proof Recall that via RSK we obtained

$$\mathbb{P}(T_N \leq x) = \prod_{i,j} (1 - p_i q_j) \sum_{\lambda: \lambda_1 \leq x} S_\lambda(p) S_\lambda(q)$$

Schur function

$$\lambda = \lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n$$

$$S_\lambda(p) = \frac{\det(p_i^{\lambda_j + N - j})}{\det(p_i^{N - j})} \Bigg| =$$

$$= \frac{1}{\Delta(p)} \det(p_i^{\lambda_j + N - j})$$

$$\Delta(p) = \det(p_i^{N - j}) = \prod_{i > j} (p_j - p_i)$$

Vandermonde determinant

So

$$P(\tau_N \leq x) = \frac{\prod_{i,j} (1 - p_i q_j)}{\Delta(p) \Delta(q)} \sum_{x \geq \lambda_1 \geq \dots \geq \lambda_N \geq 0} \det(p_i^{\lambda_j + N_j}) \cdot \det(q_i^{\lambda_j + N_j})$$

setting $Z^{-1} := \frac{\prod_{i,j} (1 - p_i q_j)}{\Delta(p) \Delta(q)} = \frac{1}{\det\left(\frac{1}{1 - p_i q_j}\right)}$ Cauchy determinant

& $t_j = \lambda_j + N_j$

they

$$P(\tau_N \leq x) = \frac{1}{Z} \sum_{\substack{x + N - 1 \geq t_1 > t_2 > \dots \\ \dots > t_N \geq 0}} \det(p_i^{t_j}) \det(q_i^{t_j})$$

$$= \frac{1}{N! Z} \sum_{t_1, \dots, t_N \in \mathbb{N}} \det(p_i^{t_j}) \det(q_i^{t_j}) \prod_{i=1}^N \mathbb{1}_{[0, x + N - 1]}(t_i)$$

Symmetry of determinant

this has now the form of a determinantal measure as before with

$$\phi_i(t) = p_i^t \quad \& \quad \psi_i(t) = q_i^t$$

$$\& \quad G_{ij} = \sum_{t \in \mathbb{N}} \phi_i(t) \psi_j(t)$$

$$= \sum_{t \in \mathbb{N}} (p_i q_j)^t$$

$$= \frac{1}{1 - p_i q_j}$$

← G_{ij} is the Cauchy matrix.

Applying the main determinantal proposition we have

$$\mathbb{P}(T_N \leq x) = \det \left(I + gK \right)_{\ell^2(N)}$$

where $g(t) = \mathbb{1}_{[0, x+N-1]}(t)$

$$\mathcal{L} \quad K(s, t) = \sum_{i, j} \psi_i(s) [G^{-1}]_{ij} \phi_j(t)$$

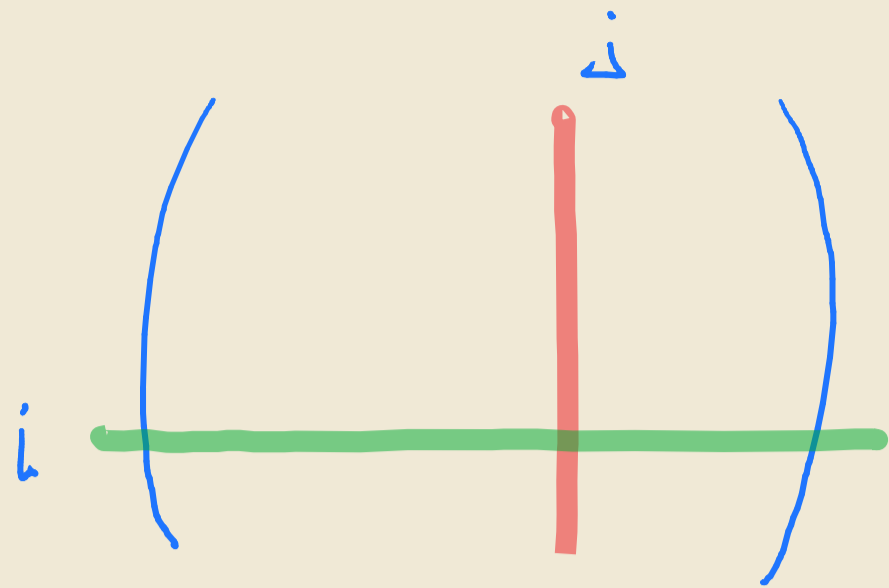
$$= \sum_{i, j} P_i^s [G^{-1}]_{ij} q_j^t$$

To proceed we need to compute G^{-1}

$$G_{ij} = \frac{1}{1 - p_i q_j}$$

Cramer's rule $[G^{-1}]_{ij} = \frac{(-1)^{i+j} \det G^{ij}}{\det G}$

Notice that the minor



is also a Cauchy matrix with i rows & j columns removed

So $\det G^{ij}$ can be computed with the same formula as $\det G$

After some cancellations:

$$[G^{-1}]_{ij} = \frac{\prod_{1 \leq l \leq N} (1 - p_j q_l) \prod_{1 \leq k \leq N} 1 - p_k q_i}{(1 - p_j q_i) \prod_{l \neq j} (p_j - p_l) \prod_{k \neq i} (q_i - q_k)}$$

and $K(s,t) = \sum_{i,j} q_i^t [G^{-1}]_{ij} p_j^s$

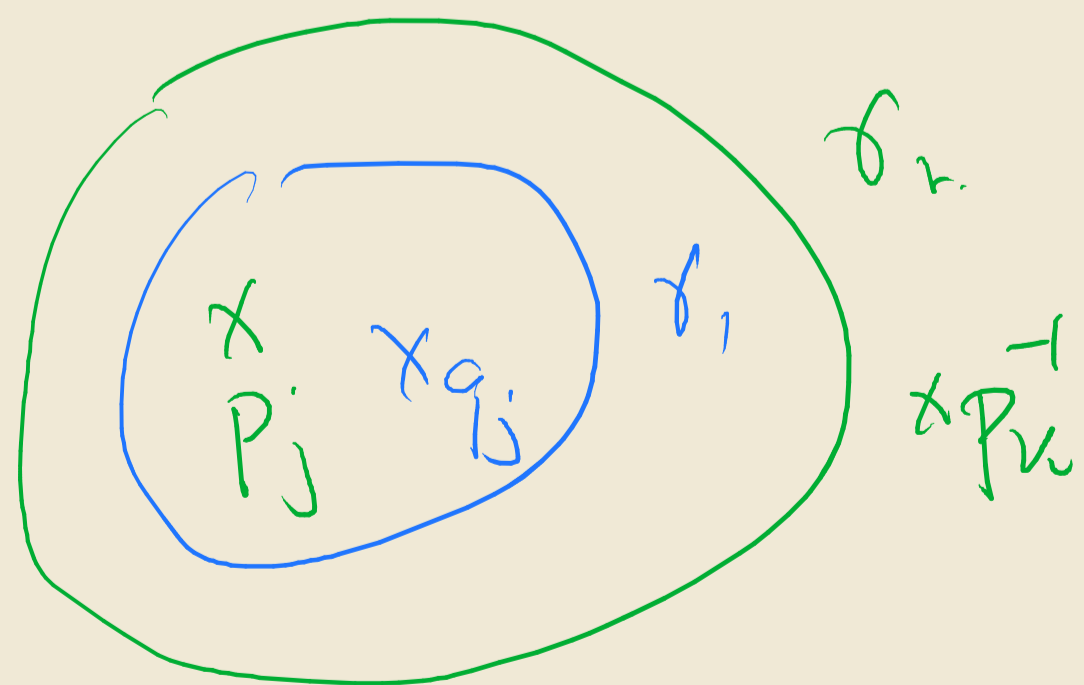
$$K(s,t) = \sum_{1 \leq i,j \leq N} q_i^t p_j^s \frac{\prod_{1 \leq l \leq N} (1 - p_j q_l) \prod_{1 \leq k \leq N} 1 - p_k q_i}{(1 - p_j q_i) \prod_{l \neq j} (p_j - p_l) \prod_{k \neq i} (q_i - q_k)}$$

Residue thm. $\frac{1}{(2\pi i)^2} \int_{\gamma_1} dz \int_{\gamma_2} d\eta \frac{z^s \eta^t}{1 - z\eta} \prod_{j=1}^N \frac{1 - q_j z}{1 - p_j z} \cdot \frac{1 - p_j \eta}{\eta - q_j}$

Extras

$$\int_{\gamma_1} dz \cdot z^t \sum_k \frac{p_k^s}{1 - z p_k} \prod_{j=1}^N \frac{1 - p_j z}{z - q_j} \cdot \frac{\prod_{j=1}^N (1 - p_k q_j)}{\prod_{j \neq k} (p_k - p_j)}$$

$$\sum_k p_k^s \frac{\prod_{j=1}^N 1 - p_k q_j}{\prod_{j \neq k} (p_k - p_j)} \int_{\gamma_1} dz \cdot z^t \frac{1 - z p_k}{1 - z p_k} \frac{\prod_{j=1}^N \frac{1 - p_j z}{z - q_j}}{1 - z p_k}$$



$$\sum_l \frac{q_l^t}{1 - q_l p_k} \frac{\prod_{j=1}^N 1 - p_j q_l}{\prod_{l \neq j} (q_l - q_j)}$$

pay attention to the potential pole

at $z = p_k^{-1}$. \Rightarrow there will be no residue if p_k^{-1} is outside the contours.

Example 2 (GUE matrices).

(Extras)

$$H = (h_{ij})_{i,j \leq N}$$

hermitian matrix
with h_{ij} i.i.d.

Complex normal variables

$$\frac{h_{ij} + h_{ji}^*}{\sqrt{2}} = N(0,1)$$

The law of ev's $\lambda_1, \dots, \lambda_N$ has density.

$$\frac{1}{Z} \prod_{1 \leq i < j \leq N} |\lambda_i - \lambda_j|^2 e^{-\frac{1}{2} \sum \lambda_j^2} \prod_{i=1}^N d\lambda_i$$

$$\frac{1}{Z} \Delta(\lambda) \Delta(\lambda) e^{-\sum \lambda_j^2 / 2}$$

$$\begin{vmatrix} 1 & \lambda_1 & \dots & \lambda_1^{N-1} \\ 1 & \lambda_2 & & \lambda_2^{N-1} \\ \vdots & \vdots & & \vdots \\ 1 & \lambda_N & & \lambda_N^{N-1} \end{vmatrix}$$

↑ ↑

$$= \det (H_j(\lambda_i))$$

Hermite polynomials

$$G_{ij} = \int H_j(t) H_i(t) e^{-x^2/2} dt = \delta_{ij}$$

$$G^{-1} = I.$$