

More generally let  $X$  and  $Y$  be Banach spaces and let  $A: X \rightarrow Y$ ,  $B: Y \rightarrow X$  be bounded linear operators. Then the following commutator formula is true:

$$(75.1) \quad \frac{\lambda}{\lambda + AB} + A \frac{1}{\lambda + BA} B = 1_Y$$

in the sense that if  $0 \neq -\lambda \in \rho(BA)$  = resolvent set of  $BA$ , then  $-\lambda \in \rho(AB)$  and

$$\frac{1}{\lambda} \left( 1_Y - A \frac{1}{\lambda + BA} B \right)$$

is the resolvent of  $AB$ , and vice versa. In

particular we see that (75.1) is true for general bounded operators in Banach spaces. (75.1) is also true,

suitably interpreted, for certain classes of unbounded operators (see Deift [DnJ, 1978]).

We now prove (7.2). Let  $\mu$  and  $f_i, g_i \in L^2(\mu)$

be given. Then

$$\int \dots \left| \det \left( f_j(x_k) \right)_{j,k=1,\dots,N} \det \left( g_j(x_k) \right)_{j,k=1,\dots,N} \right| d\mu(x_1) \dots d\mu(x_N)$$

$$= \sum_{\sigma, \tau} \text{sgn } \sigma \text{sgn } \tau \int f_{\sigma(1)}(x_1) \dots f_{\sigma(N)}(x_N) \times g_{\tau(1)}(x_1) \dots g_{\tau(N)}(x_N) d\mu(x_1) \dots d\mu(x_N)$$

$$= \sum_{\sigma, \tau} \text{sgn } \sigma \text{sgn } \tau \left[ \int f_{\sigma(1)}(x_1) g_{\tau(1)}(x_1) d\mu(x_1) \right] \dots \left[ \int f_{\sigma(N)}(x_N) g_{\tau(N)}(x_N) d\mu(x_N) \right]$$

$$= \sum_{\sigma, \tau} \text{sgn } \sigma \tau^{-1} \left[ \int f_{\sigma\tau^{-1}(1)}(x_1) g_{\tau(1)}(x_1) d\mu(x_1) \right]$$

$$\times \dots \times \left[ \int f_{\sigma\tau^{-1}(N)}(x_N) g_{\tau(N)}(x_N) d\mu(x_N) \right]$$

$$= \sum_{\sigma} \sum_{\sigma\tau^{-1}: \tau \in S_N} \text{sgn } \sigma \tau^{-1} \left[ \int f_{\sigma\tau^{-1}(1)}(x_1) g_{\tau(1)}(x_1) d\mu(x_1) \right]$$

$$\times \dots \times \left[ \int f_{\sigma\tau^{-1}(N)}(x_N) g_{\tau(N)}(x_N) d\mu(x_N) \right]$$

$$= \sum_{\sigma} \sum_{\sigma\tau^{-1}: \tau \in S_N} \text{sgn } \sigma \tau^{-1} \left[ \int f_{\sigma\tau^{-1}(1)}(x_1) g_{\tau(1)}(x_1) d\mu(x_1) \right]$$

$$\times \dots \times \left[ \int f_{\sigma\tau^{-1}(N)}(x_N) g_{\tau(N)}(x_N) d\mu(x_N) \right]$$

$$= \sum_{\sigma} \sum_{\tau \in S_N} \text{sgn } \tau^{-1} \left[ \int f_{\tau^{-1}(1)}(x_1) g_{\tau(1)}(x_1) d\mu(x_1) \right] \dots \left[ \int f_{\tau^{-1}(N)}(x_N) g_{\tau(N)}(x_N) d\mu(x_N) \right]$$



$$= \sum_{\sigma} \det \left( \int f_j(x) g_h(x) d\mu(x) \right)_{j,h=1,\dots,N}$$

$$= N! \det \left( \int f_j(x) g_h(x) d\mu(x) \right)_{j,h=1,\dots,N}$$

as desired.

The particular case

$$d\mu(x) = \sum_{k=1}^M \delta_{\lambda_k}(x)$$

for a given set of numbers  $\lambda_1, \dots, \lambda_M$ . Then the LHS

of (71.2) becomes

$$\sum_{k_1=1}^M \dots \sum_{k_N=1}^M \int \det \begin{pmatrix} f_1(x_1) & \dots & f_1(x_N) \\ \vdots & & \vdots \\ f_N(x_1) & \dots & f_N(x_N) \end{pmatrix} \det \begin{pmatrix} g_1(x_1) & \dots & g_1(x_N) \\ \vdots & & \vdots \\ g_N(x_1) & \dots & g_N(x_N) \end{pmatrix}$$

$$\delta_{\lambda_{k_1}}(x_1) \dots \delta_{\lambda_{k_N}}(x_N)$$

$$= \sum_{k_1=1}^M \dots \sum_{k_N=1}^M \det \begin{pmatrix} f_1(\lambda_{k_1}) & \dots & f_1(\lambda_{k_N}) \\ \vdots & & \vdots \\ f_N(\lambda_{k_1}) & \dots & f_N(\lambda_{k_N}) \end{pmatrix} \det \begin{pmatrix} g_1(\lambda_{k_1}) & \dots & g_1(\lambda_{k_N}) \\ \vdots & & \vdots \\ g_N(\lambda_{k_1}) & \dots & g_N(\lambda_{k_N}) \end{pmatrix}$$

$$\begin{aligned}
 &= N! \sum_{1 \leq k_1 < k_2 < \dots < k_N \leq M} \det \begin{pmatrix} f_1(\lambda_{k_1}) & \dots & f_1(\lambda_{k_N}) \\ \vdots & & \vdots \\ f_N(\lambda_{k_1}) & \dots & f_N(\lambda_{k_N}) \end{pmatrix} \\
 &\quad \times \det \begin{pmatrix} g_1(\lambda_{k_1}) & \dots & g_M(\lambda_{k_1}) \\ \vdots & & \vdots \\ g_1(\lambda_{k_N}) & \dots & g_M(\lambda_{k_N}) \end{pmatrix}
 \end{aligned}$$

On the other hand, the RHS of (71.2) gives

$$N! \det \left( \sum_{i=1}^M f_j(\lambda_i) g_k(\lambda_i) \right)_{j,k=1, \dots, N}.$$

Equating these expressions we see that

$$\begin{aligned}
 \text{if } F &= (F_{ij}) = \{f_i(\lambda_j)\} = \begin{pmatrix} f_1(\lambda_1) & \dots & f_1(\lambda_M) \\ \vdots & & \vdots \\ f_N(\lambda_1) & \dots & f_N(\lambda_M) \end{pmatrix} \\
 &= N \times M
 \end{aligned}$$

$$\begin{aligned}
 \text{and } G &= (G_{ij}) = \{g_j(\lambda_i)\} = \begin{pmatrix} g_1(\lambda_1) & \dots & g_M(\lambda_1) \\ \vdots & & \vdots \\ g_1(\lambda_M) & \dots & g_M(\lambda_M) \end{pmatrix} \\
 &= M \times N
 \end{aligned}$$



we obtain the classical Cauchy-Binet formula

(79)

$$(79.1) \quad \det FG = \sum_{1 \leq j_1 < \dots < j_N \leq M} \det \begin{pmatrix} F_{j_1 1} & F_{j_1 2} & \dots & F_{j_1 N} \\ \vdots & \vdots & \ddots & \vdots \\ F_{j_N 1} & F_{j_N 2} & \dots & F_{j_N N} \end{pmatrix} \det \begin{pmatrix} G_{j_1 1} & \dots & G_{j_1 N} \\ \vdots & \ddots & \vdots \\ G_{j_N 1} & \dots & G_{j_N N} \end{pmatrix}$$

eg if  $F = \begin{pmatrix} a_1 & a_2 & a_3 \\ b_1 & b_2 & b_3 \end{pmatrix}$ ,  $G = \begin{pmatrix} c_1 & d_1 \\ c_2 & d_2 \\ c_3 & d_3 \end{pmatrix}$

then

$$\det \begin{pmatrix} a_1 & a_2 & a_3 \\ b_1 & b_2 & b_3 \end{pmatrix} \begin{pmatrix} c_1 & d_1 \\ c_2 & d_2 \\ c_3 & d_3 \end{pmatrix}$$

$$= \det \begin{pmatrix} a_1 & a_2 \\ b_1 & b_2 \end{pmatrix} \det \begin{pmatrix} c_1 & d_1 \\ c_2 & d_2 \end{pmatrix} + \det \begin{pmatrix} a_1 & a_3 \\ b_1 & b_3 \end{pmatrix} \det \begin{pmatrix} c_1 & d_1 \\ c_3 & d_3 \end{pmatrix}$$

$$+ \det \begin{pmatrix} a_2 & a_3 \\ b_2 & b_3 \end{pmatrix} \det \begin{pmatrix} c_2 & d_2 \\ c_3 & d_3 \end{pmatrix}$$

Of course if  $N \geq M$ , (79.1) is just the familiar

fact that

$$\det FG = \det F \det G$$

and for  $N > M$  both LHS and RHS are 0 (why?)

We will also need the following basic definition

Let  $q_n(x)$  be a Borel measure on  $\mathbb{R}$

with all moments finite,

$$(80.1) \quad \int_{\mathbb{R}} |x|^m q_n(x) < \infty, \quad m = 0, 1, 2, \dots$$

Suppose that the support of  $q_n$  is infinite i.e.

$q_n$  is not a finite linear combination of delta

functions. Then by the Gram-Schmidt procedure

there exist unique monic polynomials

$$\pi_k(x) = x^k + \dots, \quad k \geq 0$$

which are orthogonal with respect to  $q_n$  i.e.

$$\int_{\mathbb{R}} \pi_k(x) \pi_j(x) q_n(x) = 0 \quad \text{for } j \neq k.$$

For

$$\delta_k = \left( \int_{\mathbb{R}} \pi_k^2(x) q_n(x) \right)^{-\frac{1}{2}} > 0, \quad k = 0, 1, 2, \dots$$

set



$$P_k(x) = \delta_k \Pi_k(x), \quad k \geq 0.$$

The polynomials  $\{P_k\}$  are the orthonormal <sup>polynomials</sup> with respect to  $q_n$ , i.e.

$$\int_{\mathbb{R}} P_k(x) P_j(x) q_n(x) dx = \delta_{kj}, \quad j, k = 0, 1, 2, \dots$$

The  $P_k$ 's are called the orthonormal polynomials (wrt  $q_n$ ) and the  $\Pi_k$ 's are called the monic orthogonal polynomials (wrt  $q_n$ ). Exercise: what happens if  $q_n$  has finite support?

As we will see, the  $P_k$ 's and  $\Pi_k$ 's play a central role in RMT.

We now show how to compute <sup>certain basic</sup>  $\Lambda$  statistics for invariant unitary ensembles with probability distributions

$$P_N(\mathbf{M}) d\mathbf{M} = \frac{e^{-\text{tr} Q(\mathbf{M})} d\mathbf{M}}{Z_N}$$

where  $Q(x) \rightarrow +\infty$  sufficiently rapidly as  $|x| \rightarrow \infty$ . (see pp 84, 85 below)



In particular we will compute

$$\langle f \rangle = \int f(m) P_N(m) dm$$

for  $f(m)$  of the form

$$(82.0) \quad f(m) = \det(I + g(m))$$

for bounded functions  $g: \mathbb{R} \rightarrow \mathbb{R}$ ,

From the Hermitian analog of (68.1) we have

$$(82.1) \quad \langle f \rangle = C_N^{-1} \int_{\lambda_1 < \dots < \lambda_N} \prod_{i=1}^N (1 + g(\lambda_i)) \prod_{1 \leq i < j \leq N} (\lambda_i - \lambda_j)^2 \prod_{i=1}^N w(\lambda_i) d^N \lambda$$
  
$$= C_N^{-1} \int_{\lambda_1 < \dots < \lambda_N} \prod_{i=1}^N (1 + g(\lambda_i)) V(\lambda)^2 \prod_{i=1}^N w(\lambda_i) d^N \lambda$$

where

$$(82.2) \quad w(x) = e^{-Q(x)}$$

$$(82.3) \quad V(\lambda) = \text{ Vandermonde } = \det(\lambda_i^{j-1})_{1 \leq i, j \leq N}$$

and

$$(82.4) \quad C_N^{-1} = \left( \int_{\lambda_1 < \dots < \lambda_N} V(\lambda)^2 \prod_{i=1}^N w(\lambda_i) d^N \lambda \right)^{-1}$$

As the integrands in (82.1) and (82.4) are



invariant under all permutation  $\sigma$

$$(\lambda_1, \dots, \lambda_N) \rightarrow (\lambda_{\sigma_1}, \dots, \lambda_{\sigma_N})$$

we may rewrite (82.1) (82.4) in the following symmetrized form

$$(83.1) \quad \langle f \rangle = C_N \int_{\mathbb{R}^N} \prod_{i=1}^N (1+g(\lambda_i)) V(\lambda) \prod_{i=1}^N w(\lambda_i) d^N \lambda$$

where

$$(83.2) \quad C_N = C_N^1 (N!)^{-1}$$

Now define

$$(83.3) \quad f_i(x) = g_i(x) = x^{i-1}, \quad 1 \leq i \leq N$$

Then

$$V(\lambda)^2 = \det(f_i(\lambda_j))_{1 \leq i, j \leq N} \det(g_i(\lambda_j))_{1 \leq i, j \leq N}$$

Hence we can apply the generalized Cauchy-Binet formula to (83.1) with measure  $d\mu(x) \leftarrow w(x) (1+g(x))$

(the fact that  $d\mu$  <sup>maybe</sup> a signed measure, as opposed

to a pos. measure, clearly does not affect the proof



of (83.11). We obtain

$$\langle \mathcal{F} \rangle = C_N \det \left( \int \mathcal{F}_j(\lambda) g_k(\lambda) q_\mu(\lambda) \right)_{j,k=1}^N$$

where we note from (82.4) that  $C_N$  depends only on  $N$  and  $w$ , but not on  $g(x)$ .

We have

$$(84.1) \quad \int \mathcal{F}_j(\lambda) g_k(\lambda) q_\mu(\lambda) = \int \mathcal{F}_j(\lambda) g_k(\lambda) (1+g(\lambda)) w(\lambda) d\lambda \\ = \int \lambda^{j+k-2} (1+g(\lambda)) w(\lambda) d\lambda$$

Let  $p_j(\lambda)$ ,  $j \geq 0$ , be the orthogonal polynomials with respect to the measure  $w(\lambda) d\lambda$  i.e.

$$\int_{\mathbb{R}} p_k(\lambda) p_j(\lambda) w(\lambda) d\lambda = \delta_{jk}, \quad j, k \geq 0.$$

(Note that  $w(\lambda) d\lambda = e^{-Q(\lambda)} d\lambda$  does not have

finite support: also by "sufficient decay" we

are assuming, at least, that  $e^{-Q(\lambda)} d\lambda$  has

finite moments: not that this implies

$$\int (V(\lambda))^k \frac{1}{\lambda} w(\lambda) d\lambda < \infty$$



so that  $P_N(x) dx$  is a normalized prob. measure with finite moments).

Now as we can add rows and columns without changing a determinant, we have (recall  $p_j(x) = \delta_j, \pi_j(x)$ )

$$\begin{aligned}
 (85.1) \quad \langle f \rangle &= C'_N \det \left( \int \pi_j(x) \pi_k(x) (1+g(x)) w(x) dx \right)_{0 \leq j, k \leq N-1} \\
 &= \frac{C'_N}{\prod_{j=0}^{N-1} \delta_j^2} \det \left( \int p_j(x) p_k(x) (1+g(x)) w(x) dx \right)_{0 \leq j, k \leq N-1}
 \end{aligned}$$

Set

$$(85.2) \quad \phi_j(x) = p_j(x) w(x)^{\frac{1}{2}}, \quad j \geq 0$$

Have  $\int \phi_j(x) \phi_k(x) dx = \delta_{jk}, \quad j, k \geq 0.$

Then (85.1) takes the form.

$$\begin{aligned}
 (85.3) \quad \langle f \rangle &= \frac{C''_N}{\prod_{j=0}^{N-1} \delta_j^2} \det \left( \int \phi_j(x) \phi_k(x) (1+g(x)) dx \right)_{0 \leq j, k \leq N-1} \\
 &= C''_N \det \left( \delta_{j,k} + \int g(x) \phi_j(x) \phi_k(x) dx \right)_{j, k=0}^{N-1}
 \end{aligned}$$

where again  $C''_N$  does not depend on  $g(x)$ . Setting  $g=0$ ,



we have  $f(N) = 1$  and no LHS of (85.3) = 1

But  $RHS = C_N'' \times \det(\delta_{j,h}) = C_N''$ , so  $C_N'' = 1$ .

Thus

$$(86.1) \quad \langle F \rangle = \det \left( \delta_{j,h} + \int_{\mathbb{R}} \phi_j(x) \phi_h(x) g(x) dx \right)_{j,h=0}^{N-1}.$$

Now we are primarily interested in the situation where the size  $N$  of the matrices become large. We see from (86.1) that  $\langle F \rangle$  is expressed in terms of determinants of larger and larger size. Limits of this kind are generally very difficult to control.

Fortunately we can use (71.1)  $\det(I_x + AB) = \det(I_y + BA)$  to reduce (86.1) to the (Fredholm) determinant on a fixed space (see below). Such limits are, generally speaking, easier to control: in



particular if  $k_N$  is a trace class operator on  
 a (fixed) Hilbert space  $\mathcal{H}$ , and  $k_N \rightarrow K$  in trace norm,

then

$$\det(I + k_N) \rightarrow \det(I + K)$$

It is just a matter of continuity of the determinant  
 in the trace norm.

Now let  $A: L^2(\mathbb{R}) \rightarrow \mathbb{C}^N$  denote the bounded

operator

$$(87.1) \quad (Ah)_j = \int \phi_j(x) g(x) h(x) dx, \quad j=0, \dots, N-1, \\ h \in L^2(\mathbb{R})$$

and let  $B: \mathbb{C}^N \rightarrow L^2(\mathbb{R})$  denote the bounded

operator

$$(87.2) \quad (Ba)(x) = \sum_{j=0}^{N-1} \phi_j(x) a_j, \quad a = (a_0, \dots, a_{N-1})^T \in \mathbb{C}^N$$

Then  $AB$  maps  $\mathbb{C}^N \rightarrow \mathbb{C}^N$  and for  $a \in \mathbb{C}^N$

$$(87.3) \quad ((AB)a)_j = \left( A \left( \sum_{k=0}^{N-1} \phi_k(\cdot) a_k \right) \right)_j \\ = \sum_{k=0}^{N-1} a_k (A\phi_k)_j$$



$$= \sum_{h=0}^{N-1} a_h \left( \int \phi_j(x) g(x) \phi_h(x) dx \right)$$

and we see from (86.1) that

$$(88.1) \quad \langle \rho \rangle = \det (1_{\mathbb{R}^N} + AB)$$

On the other hand  $BA: L^2(\mathbb{R}) \rightarrow L^2(\mathbb{R})$  and

for  $h \in L^2(\mathbb{R})$

$$(BAh)(x) = \left( B \left( \left( \int \phi_j(y) g(y) h(y) dy \right)_{j=0}^{N-1} \right) \right) (x).$$

$$= \sum_{j=0}^{N-1} \phi_j(x) \int \phi_j(y) g(y) h(y) dy$$

$$= \int K(x, y) g(y) h(y) dy$$

where

$$(88.2) \quad K(x, y) = \sum_{j=0}^{N-1} \phi_j(x) \phi_j(y)$$

is the so-called correlation kernel for the

ensemble:  $K(x, y)$  plays a central role in RMT.

Thus

$$(88.3) \quad BA = K \chi_g$$

where  $\chi_g$  denotes multiplication by  $g(x)$  and  $K$  denotes



The operator with kernel  $k$  is.  $k_h(x) = \int k(x,y)h(y)dy$ . (89)

Assembling the above results we obtain the key formula

$$(89.1) \quad \langle f \rangle = \det (I_{L^2(\mathbb{R})} + k \chi_g)$$

Note that as  $A$  (and also  $B!$ ) is finite rank,

$A$  is trace class and the Fredholm determinant in

(89.1) is well-defined. There are analogous, but more complicated, formulae for  $\beta=1$  and  $\beta=4$  (see Ref (3)).

If  $\Omega$  is a Borel set in  $\mathbb{R}$  and

$$g(x) = -\chi_{\Omega}$$

then we see from (89.1) that the gap

probability considered before is given by

$$(89.2) \quad \text{Prob}(\text{no eigenvalues in } \Omega)$$

$$= \left\langle \prod_{i=1}^N (1 - \chi_{\Omega}(a_i)) \right\rangle$$

$\chi_{\Omega}$  = characteristic function of  $\Omega$

$$= \det (I_{L^2(\mathbb{R})} - k \chi_{\Omega})$$

Note that if  $\Omega = \emptyset$ , then RHS = 1 i.e.  $\boxed{X}$



(90)

Prob {no eigs in  $\emptyset$ } = 1, as it should be. On the other hand for  $\Omega = \mathbb{R}$ , Prob {no eigs in  $\mathbb{R}$ } = 0.

On the other hand for any  $k = 0, 1, \dots, N-1$ ,

$$\begin{aligned} k\phi_k(x) &= \int_0^{N-1} \sum_0^{N-1} \phi_j(x) \phi_j(y) \phi_k(y) dy \\ &= \sum_0^{N-1} \phi_j(x) \delta_{jk} \\ &= \phi_k(x) \end{aligned}$$

Thus 1 is an eigenvalue of  $k$  (of multiplicity  $N > 0$ ) and so  $\det(I - k) = 0$ , as it should be.

Now take  $\Omega = (a, \infty)$  for any  $a \in \mathbb{R}$ .

Then clearly

$$\text{Prob}(\text{no eigs in } (a, \infty)) = \text{Prob}(\lambda_{\max} \leq a)$$

where  $\lambda_{\max}$  is the largest eigenvalue of  $k_{\Omega}$ . Thus

$$(90.1) \quad \text{Prob}(\lambda_{\max} \leq a) = \det(I_{L^2(\mathbb{R})} - k_{(a, \infty)})$$

This is a key formula in RMT for unitary



ensembles,

### Exercise

qf  $\Omega = \Omega_1 \cup \dots \cup \Omega_k$  is a union of disjoint sets in  $\mathbb{R}$ ,  $\Omega_j \cap \Omega_h = \emptyset$  for  $j \neq h$ ,

then we have computed

$$\begin{aligned} & \text{Prob} (0 \text{ eigs in } \Omega_1, \dots, 0 \text{ eigs in } \Omega_k) \\ &= \text{Prob} (0 \text{ eigs in } \Omega = \bigcup_{i=1}^k \Omega_i) \end{aligned}$$

Derive an explicit formula for

$$\text{Prob} (n_1 \text{ eigs in } \Omega_1, \dots, n_k \text{ eigs in } \Omega_k)$$

for any non-negative integers  $n_1, \dots, n_k$ . (see ref (3)

pp 86-88)

We now show how to compute

correlation functions for unitary ensembles (recall

that 2-point correlation functions arose in the study

(92)

of the non-trivial zeros of the Riemann zeta function in the first lecture).

If  $P_N(x) dx$  is the probability distribution for a system of  $N$  identical random particles

$P_N(x_1, \dots, x_N)$  symmetric in the  $x_i$ 's

then the  $n$ -point correlation function

$$R_n = R_n(x_1, \dots, x_n), \quad 1 \leq n \leq N$$

for  $P_N(x) dx$  is defined by

$$(92.1) \quad R_n(x_1, \dots, x_n) = \frac{N!}{(N-n)!} \int \dots \int P_N(x_1, \dots, x_n, x_{n+1}, \dots, x_N) dx_{n+1} \dots dx_N$$

Note that  $\int R_n(x_1, \dots, x_n) dx_1 \dots dx_n \neq 1$   $\therefore$  hence

$R_n$  is not a prob. distrib (more later!).

Correlation functions are useful whenever we want to focus on  $n < N$  particles and "average out"