# Lectures on Random Matrices (Spring 2025) Lecture 8: Cutting corners and loop equations

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## 1 Cutting corners: polynomial equation and distribution

### 1.1 Recap: polynomial equation

Recall the polynomial equation we proved in the last Lecture 7. Fix  $\lambda = (\lambda_1 \geq \ldots \geq \lambda_n)$ . Let  $H \in \text{Orbit}(\lambda)$  be a random Hermitian matrix defined as

$$H = U \operatorname{diag}(\lambda_1, \dots, \lambda_n) U^{\dagger},$$

<sup>\*</sup>Course webpage • Live simulations • TeX Source • Updated at 02:25, Friday 28<sup>th</sup> February, 2025

where U is Haar-distributed unitary matrix from U(n). This is the case  $\beta = 2$ , but the statement holds for the cases  $\beta = 1, 4$  with appropriate modifications. Let  $\mu_1, \ldots, \mu_{n-1}$  be the eigenvalues of the  $(n-1) \times (n-1)$  corner  $H^{(n-1)}$ .

**Lemma 1.1.** The distribution of  $\mu_1, \ldots, \mu_{n-1}$  is the same as the distribution of the roots of the polynomial equation

$$\sum_{i=1}^{n} \frac{\xi_i}{z - \lambda_i} = 0, \tag{1.1}$$

where  $\xi_i$  are i.i.d. random variables with the distribution  $\chi^2_{\beta}$ .

Recall also that this passage from  $\lambda$  to  $\mu$  works inductively, and the distribution of the next level eigenvalues  $\nu = (\nu_1 \geq \ldots \geq \nu_{n-2})$  is given by the same polynomial equation, but with  $\lambda$  replaced by  $\mu$ . In this way, we can define a *Markov map* from  $\lambda$  to  $\mu$ , which is then iterated to construct the full array of eigenvalues of the corners of H.

For  $\beta = \infty$ , this map is deterministic, and is equivalent to successive differentiating the characteristic polynomial of H.

#### 1.2 Extension to general $\beta$

We extend the polynomial equation to general  $\beta$ , by *declaring* (defining) that the general  $\beta$  corners distribution is powered by the passage from  $\lambda = (\lambda_1 \ge ... \ge \lambda_n)$  to  $\mu = (\mu_1 \ge ... \ge \mu_{n-1})$ , where  $\mu$  solves (1.1) with  $\xi_i$  i.i.d.  $\chi^2_{\beta}$ . In this way,  $\mu$  interlaces with  $\lambda$ . For  $\beta = 1, 2, 4$ , this definition reduces to the one with invariant ensembles with fixed eigenvalues  $\lambda$ .

### 1.3 Distribution of the eigenvalues of the corners

Let  $\mu$  be obtained from  $\lambda$  by the general  $\beta$  corners operation.

**Theorem 1.2.** The density of  $\mu$  with respect to the Lebesgue measure is given by

$$\frac{\Gamma(N\beta/2)}{\Gamma(\beta/2)^n} \prod_{1 \le i \le j \le n-1} (\mu_i - \mu_j) \prod_{i=1}^{n-1} \prod_{j=1}^n |\mu_i - \lambda_j|^{\beta/2-1} \prod_{1 \le i \le j \le n} (\lambda_i - \lambda_j)^{1-\beta}.$$

*Proof.* Let  $\varphi_i = \xi_i / \sum_{j=1}^n \xi_j$ . It is well-known<sup>1</sup> the joint density of  $(\varphi_1, \dots, \varphi_n)$  is the (symmetric) Dirichlet density

$$\frac{\Gamma(N\beta/2)}{\Gamma(\beta/2)^n} w_1^{\beta/2-1} \dots w_n^{\beta/2-1} dw_1 \dots dw_{n-1}$$

(note that the density is (n-1)-dimensional).

We need to compute the Jacobian of the transformation from  $\varphi$  to  $\mu$ , if we write

$$\sum_{i=1}^{n} \frac{\varphi_i}{z - \lambda_i} = \frac{\prod_{i=1}^{n-1} (z - \mu_i)}{\prod_{i=1}^{n} (z - \lambda_i)},$$

<sup>&</sup>lt;sup>1</sup>See Problem H.3.

and compute (as a decomposition into partial fractions):

$$\varphi_a = \frac{\prod_{i=1}^{n-1} (\lambda_a - \mu_i)}{\prod_{i \neq a} (\lambda_a - \lambda_i)}.$$

Therefore,

$$\frac{\partial \varphi_a}{\partial \mu_b} = \frac{\prod_{i=1}^{n-1} (\lambda_a - \mu_i)}{\prod_{i \neq a} (\lambda_a - \lambda_i)} \frac{1}{\mu_b - \lambda_a}, \qquad a = 1, \dots, n, \quad b = 1, \dots, n-1.$$
 (1.2)

The Jacobian is essentially the determinant of the matrix  $1/(\mu_b - \lambda_a)$ , which is the Cauchy determinant (Problems H.1 and ??). The final density is obtained from the symmetric Dirichlet density, but we plug in  $w = \varphi$ , and also multiply by the Jacobian. This completes the proof.  $\square$ 

Corollary 1.3 (Joint density of the corners). The eigenvalues  $\lambda^{(k)}_j$ ,  $1 \leq j \leq k \leq n$ , of a random matrix from  $Orbit(\lambda)$  form an interlacing array, with the joint density

$$\propto \prod_{k=1}^{n} \prod_{1 \leq i < j \leq k} \left( \lambda_{j}^{(k)} - \lambda_{i}^{(k)} \right)^{2-\beta} \prod_{a=1}^{k+1} \prod_{b=1}^{k} \left| \lambda_{a}^{(k+1)} - \lambda_{b}^{(k)} \right|^{\beta/2-1}.$$

For  $\beta = 2$ , all factors disappear, and we get the uniform distribution on the interlacing array. This is the *uniform Gibbs property* which is important for other models, including discrete ensembles.

### 2 Loop equations

Let us write down the *loop equations* for the passage from the eigenvalues  $\lambda$  to the eigenvalues  $\mu$ . These loop equations are due to [GH24] by a limit from a discrete system (related to Jack symmetric polynomials). Note that despite the name, these are not **equations**, but rather a statement that some expectations are holomorphic. We stick to the random matrix setting, and present a formulation and a proof given by [Gor25].

#### 2.1 Formulation

**Theorem 2.1.** We fix n = 1, 2, ... and n + 1 real numbers  $\lambda_1 \ge ... \ge \lambda_{n+1}$ . For  $\beta > 0$ , consider n + 1 i.i.d.  $\chi^2_{\beta}$  random variables  $\xi_i$  and set

$$w_i = \frac{\xi_i}{\sum_{j=1}^{n+1} \xi_j}, \qquad 1 \le i \le n+1.$$

We define n random points  $\{\mu_1, \ldots, \mu_n\}$  as n solutions to the equation

$$\sum_{i=1}^{n+1} \frac{w_i}{z - \lambda_i} = 0. {(2.1)}$$

Take any polynomial W(z) and consider the complex function:

$$f_W(z) = \mathbb{E}\left[\prod_{j=1}^n \exp(W(\mu_j)) \frac{\prod_{i=1}^{n+1} (z - \lambda_i)}{\prod_{j=1}^n (z - \mu_j)} \left(W'(z) + \sum_{i=1}^{n+1} \frac{\beta/2 - 1}{z - \lambda_i} + \sum_{j=1}^n \frac{1}{z - \mu_j}\right)\right].$$
(2.2)

Then  $f_W(z)$  is an entire function of z, in the following sense:

- For  $z \in \mathbb{C} \setminus [\lambda_{n+1}, \lambda_1]$ , the expectation in (2.2) defines a holomorphic function of z.
- This function has an analytic continuation to  $\mathbb{C}$ , which has no singularities.

**Remark 2.2.** Note that for z in  $[\lambda_{n+1}, \lambda_1]$ , the integral determining (2.2) might be divergent, and, therefore, analytic continuation is the proper way to define  $f_W(z)$ ,  $z \in [\lambda_{n+1}, \lambda_1]$ .

Corollary 2.3. We have

$$f_0(z) = \frac{(n+1)\beta}{2} - 1.$$

Here  $f_0$  means  $f_W$  with  $W \equiv 0$ .

*Proof.* This is obtained by sending  $z \to \infty$  in (2.2).

### **2.2** Proof of Theorem **2.1** for $\beta > 2$

Theorem 2.1 remains valid for  $\beta > 0$ , but we only prove it for  $\beta > 2$  here. We also assume that  $\lambda_1 > \ldots > \lambda_n$ .

We begin by observing that for  $z \in \mathbb{C} \setminus [\lambda_{n+1}, \lambda_1]$ , the expectation in (2.2) is well-defined and holomorphic in z. This follows since for such z, the denominators  $z - \lambda_i$  and  $z - \mu_j$  are bounded away from zero with probability 1. The key challenge is to show that  $f_W(z)$  can be analytically continued to an entire function. Potential singularities of  $f_W(z)$  are inside the intervals  $(\lambda_{i+1}, \lambda_1)$ . We will show that these singularities do not actually occur.

Consider a specific interval  $(\lambda_2, \lambda_1)$ . We need to show that  $f_W(z)$  has no singularities in this interval. From Theorem 1.2, the probability distribution of  $\mu = (\mu_1, \dots, \mu_n)$  has density proportional to:

$$\prod_{i < j} (\mu_i - \mu_j) \prod_{i=1}^n \prod_{j=1}^{n+1} |\mu_i - \lambda_j|^{\beta/2 - 1}.$$

Let us analyze the function in (2.2). For  $z \in (\lambda_2, \lambda_1)$ , we need to demonstrate that the expectation

$$\mathbb{E}\left[\prod_{j=1}^{n} \exp(W(\mu_j)) \frac{\prod_{i=1}^{n+1} (z - \lambda_i)}{\prod_{j=1}^{n} (z - \mu_j)} \left(W'(z) + \sum_{i=1}^{n+1} \frac{\beta/2 - 1}{z - \lambda_i} + \sum_{j=1}^{n} \frac{1}{z - \mu_j}\right)\right]$$

is holomorphic. We need to show that the integral

$$\int_{\mu_i \in [\lambda_{i+1}, \lambda_i]} \prod_{i < j} (\mu_i - \mu_j) \prod \prod (\mu_j - \lambda_i)^{\beta/2 - 1} \prod e^{W(\mu_j)} \frac{\prod (z - \lambda_i)}{\prod (z - \mu_j)}$$

$$\times \left(W'(z) + \sum \frac{\beta/2 - 1}{z - \lambda_i} + \sum \frac{1}{z - \mu_i}\right) d\mu_1 \dots d\mu_n$$

is holomorphic for  $z \in (\lambda_2, \lambda_1)$ . Note that (here we are using the fact that  $\beta > 2$ )

$$0 = \int_{\mu_{i} \in [\lambda_{i+1}, \lambda_{i}]} \frac{\partial}{\partial \mu_{1}} \left( \underbrace{\prod_{i < j} (\mu_{i} - \mu_{j}) \prod \prod (\mu_{j} - \lambda_{i})^{\beta/2 - 1} \prod e^{W(\mu_{j})} \frac{\prod (z - \lambda_{i})}{\prod (z - \mu_{j})}}_{(*)} \right) d\mu_{1} \dots d\mu_{n}$$

$$= \int_{\mu_{i} \in [\lambda_{i+1}, \lambda_{i}]} (*) \cdot \left[ \sum_{j=2}^{n} \frac{1}{\mu_{1} - \mu_{j}} + \sum_{i=1}^{n+1} \frac{\beta/2 - 1}{\mu_{1} - \lambda_{i}} + W'(\mu_{1}) + \frac{1}{z - \mu_{1}} \right] d\mu_{1} \dots d\mu_{n}$$

Subtracting this expression from our original integral and noting that

$$\left(W'(z) + \sum \frac{\beta/2 - 1}{z - \lambda_i} + \sum \frac{1}{z - \mu_j}\right) - \left(\sum_{j=2}^n \frac{1}{\mu_1 - \mu_j} + \sum_{i=1}^{n+1} \frac{\beta/2 - 1}{\mu_1 - \lambda_i} + W'(\mu_1) + \frac{1}{z - \mu_1}\right)$$

has zero at  $z = \mu_1$ , we conclude that our integral has no singularity at  $\mu_1$ , and therefore no singularities in the  $[\lambda_2, \lambda_1]$  interval. This completes the proof of Theorem 2.1 for  $\beta > 2$ .

### 3 Applications of loop equations

The loop equations provide a powerful tool for analyzing the spectral properties of random matrices through their eigenvalue distributions. Let us derive an equation for the Stieltjes transform of the empirical measures.

#### 3.1 Stieltjes transform equations

Starting from Theorem 2.1 with W = 0, we have:

$$\mathbb{E}\left[\frac{\prod_{i=1}^{n+1}(z-\lambda_i)}{\prod_{j=1}^{n}(z-\mu_j)}\left(\sum_{i=1}^{n+1}\frac{\beta/2-1}{z-\lambda_i}+\sum_{j=1}^{n}\frac{1}{z-\mu_j}\right)\right] = \frac{(n+1)\beta}{2}-1.$$
(3.1)

Let us introduce the empirical Stieltjes transforms:

$$G_{\lambda}(z) = \frac{1}{n} \sum_{i=1}^{n+1} \frac{1}{z - \lambda_i},$$

$$G_{\mu}(z) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{z - \mu_{i}}.$$

We also define the logarithmic potentials (indefinite integrals of the Stieltjes transforms):

$$\int G_{\lambda}(z)dz = \frac{1}{n} \sum_{i=1}^{n+1} \ln(z - \lambda_i),$$
$$\int G_{\mu}(z)dz = \frac{1}{n} \sum_{i=1}^{n} \ln(z - \mu_i).$$

Noting that

$$\frac{\prod_{i=1}^{n+1}(z-\lambda_i)}{\prod_{i=1}^{n}(z-\mu_i)} = \exp\left(n\left(\int G_{\lambda}(z) - \int G_{\mu}(z)\right)\right),\,$$

we can rewrite equation (3.1) as:

$$\mathbb{E}\left[\exp\left(n\left(\int G_{\lambda}(z)\,dz - \int G_{\mu}(z)\,dz\right)\right)\left(\left(\frac{\beta}{2} - 1\right)G_{\lambda}(z) + G_{\mu}(z)\right)\right] = \frac{\beta}{2} + \frac{1}{n}\left(\frac{\beta}{2} - 1\right). \tag{3.2}$$

### 3.2 Asymptotic behavior

Equation (3.2) can be reinterpreted in terms of a time evolution of eigenvalue distributions. This perspective offers significant insights into the asymptotic behavior of the corners process.

If we think of  $\lambda$  as configuration at time t=1 and  $\mu$  as configuration at time  $t=1-\frac{1}{n}$ , then denoting the general time parameter as t and setting  $G_{\lambda}=G_1$ ,  $G_{\mu}=G_{1-\frac{1}{n}}$ , we obtain a continuous time evolution of Stieltjes transforms. (And similarly for all t, of course.)

As  $n \to \infty$ , equation (3.2) transforms into:

$$\frac{\beta}{2} \exp\left(\frac{\partial}{\partial t} \int G_t(z) dz\right) \cdot G_t(z) = \frac{\beta}{2}.$$

This implies

$$\frac{\partial}{\partial t} \int G_t(z) dz + \ln G_t(z) = 0.$$

Taking the derivative with respect to z, we get:

$$\frac{\partial}{\partial t}G_t(z) + \frac{1}{G_t(z)}\frac{\partial}{\partial z}G_t(z) = 0. \tag{3.3}$$

This is precisely the inviscid Burgers equation, a fundamental nonlinear PDE in fluid dynamics. The appearance of this equation indicates that the eigenvalue distributions evolve according to a hydrodynamic flow as we move through the corners of the random matrix from full size down to zero.

**Remark 3.1.** We see that the Burgers equation (3.3) does not depend on  $\beta$ , which is expected. Indeed, for example,  $G\beta E$  eigenvalues have the same Wigner semicircle law as  $\beta = 2$ , up to an overall rescaling.

### 3.3 Example with semicircle law

The Stieltjes transform of the semicircular law is given by:

$$G(z) = \int_{-2}^{2} \frac{1}{z - x} \frac{\sqrt{4 - x^2}}{2\pi} dx = \frac{1}{2} \left( z - \sqrt{z^2 - 4} \right).$$

Let us define

$$G^{(c)}(z) \coloneqq \frac{z - \sqrt{z^2 - 4c^2}}{2c^2},$$

this is the Stieltjes transform of the semicircular law on [-2c, 2c].

### H Problems (due 2025-03-25)

### H.1 Cauchy determinant

Prove the Cauchy determinant formula:

$$\det\left(\frac{1}{x_i - y_j}\right)_{1 \le i, j \le n} = \frac{\prod_{i < j} (x_i - x_j)(y_i - y_j)}{\prod_{i, j} (x_i - y_j)}.$$

### H.2 Jacobian from n-1 to n dependent variables

Explain how the factor  $\prod_{i=1}^{n-1} \prod_{j=1}^{n} |\mu_i - \lambda_j|$  appears from the Jacobian of the transformation from  $\varphi$  to  $\mu$  (1.2), even though  $\partial \varphi_a/\partial \mu_b$  is defined for  $a=1,\ldots,n,\ b=1,\ldots,n-1$ , but the  $\varphi_i$ 's are not independent.

#### H.3 Dirichlet density

Find in the literature or prove on your own the first statement in the proof of Theorem 1.2 about the symmetric Dirichlet density arising from normalizing the  $\xi_i$ 's to  $\varphi_i$ 's.

#### H.4 General $\beta$ Corners Process Simulation

This problem explores computational aspects of the general  $\beta$  corners process.

- (a) Write code for generating a sample from the distribution of  $\mu = (\mu_1, \dots, \mu_{n-1})$  given  $\lambda = (\lambda_1, \dots, \lambda_n)$  for arbitrary  $\beta > 0$ , using the polynomial equation characterization.
- (b) Let  $\lambda = (n, n-1, \dots, 2, 1)$ . For n = 7, compute (numerically) the expected values  $\mathbb{E}[\mu_i]$  for each i, when  $\beta = 1, 2, 4$ , and 10. Describe the behavior as  $\beta$  increases.

### References

[GH24] V. Gorin and J. Huang, Dynamical loop equation, Ann. Probab. **52** (2024), no. 5, 1758–1863. arXiv:2205.15785 [math.PR].  $\uparrow 3$ 

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