Lectures on Random Matrices (Spring 2025) Lecture 14: Matching Random Matrices to Random Growth II

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Wednesday, April 16, 2025*

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1 Recap

1.1 Main goal

In the previous Lecture 13, we began establishing a remarkable correspondence between two a priori different objects:

- The spiked Wishart ensemble: an $n \times n$ Hermitian random-matrix process $\{M(t)\}_{t\geq 0}$ whose entries come from columns of independent Gaussian random vectors of suitably chosen covariance.
- An inhomogeneous last-passage percolation (LPP) model: an array $\{W_{i,j}\}$ of exponential random weights on a portion of the two-dimensional lattice, whose last-passage times L(t,n) match the largest eigenvalues of M(t), jointly for all $t \in \mathbb{Z}_{>0}$.

This equivalence, originally due to [DW08] (following [Def10], [FR06]; see also [Bar01], [Joh00] for earlier results of this kind), can be fully understood by passing to a *discrete* version of LPP with geometric site-weights and then applying the *Robinson–Schensted–Knuth* (RSK) correspondence.

^{*}Course webpage • Live simulations • TeX Source • Updated at 11:12, Tuesday 15th April, 2025

1.2 Spiked Wishart ensembles and the largest eigenvalue process

We defined the generalized (or spiked) Wishart matrix M(t) of size $n \times n$ by setting

$$M(t) = \sum_{m=1}^{t} A^{(m)} (A^{(m)})^*$$

where $\{A^{(m)}\}_{m=1}^{\infty}$ are i.i.d. complex Gaussian column vectors of length n, with

$$\operatorname{Var}(A_i^{(m)}) = \frac{1}{\pi_i + \hat{\pi}_m}.$$

Here, $\pi = (\pi_1, \dots, \pi_n)$ and $\hat{\pi} = (\hat{\pi}_1, \hat{\pi}_2, \dots)$ are positive and nonnegative parameters, respectively. Writing $\lambda_1(t) \geq \dots \geq \lambda_n(t) \geq 0$ for the eigenvalues of M(t), we then saw:

- 1. The vectors $\lambda(t) = (\lambda_1(t), \dots, \lambda_n(t))$ form a Markov chain in the Weyl chamber $\mathbb{W}^n = \{x_1 \geq \dots \geq x_n \geq 0\}$.
- 2. There is an *interlacing* property: each update $M(t-1) \mapsto M(t)$ via the rank-one matrix $A^{(t)}(A^{(t)})^*$ forces $\lambda(t)$ to interlace with $\lambda(t-1)$:

$$\lambda_1(t) \geq \lambda_1(t-1) \geq \lambda_2(t) \geq \cdots \geq \lambda_n(t-1) \geq \lambda_n(t).$$

In Lecture 13, we wrote down the transition kernel from $\lambda(t-1)$ to $\lambda(t)$:

Theorem 1.1 ([DW08]). Fix an integer $n \geq 1$. Let $\pi = (\pi_1, \ldots, \pi_n)$ be a strictly positive n-vector, and let $\widehat{\pi} = (\widehat{\pi}_1, \widehat{\pi}_2, \ldots)$ be any sequence of nonnegative real parameters. Under the probability measure $P^{\pi,\widehat{\pi}}$, the eigenvalues of the $n \times n$ generalized Wishart matrices $\{M(t)\}_{t\geq 0}$ form a time-inhomogeneous Markov chain $\{\operatorname{sp}(M(t))\}_{t\geq 0}$ in the Weyl chamber

$$\mathbb{W}^n = \{ x = (x_1, \dots, x_n) \in \mathbb{R}^n_{\geq 0} : x_1 \geq x_2 \geq \dots \geq x_n \}.$$

More precisely, writing $x = \operatorname{sp}(M(t-1))$ and $y = \operatorname{sp}(M(t))$, the one-step transition law from time (t-1) to t is absolutely continuous on the interior of \mathbb{W}^n and can be factored as

$$Q_{t-1,t}^{\pi,\widehat{\pi}}(x, dy) = \left[\prod_{i=1}^{n} (\pi_i + \widehat{\pi}_t) \right] \cdot \frac{h_{\pi}(y)}{h_{\pi}(x)} \exp\left(-(\widehat{\pi}_t - 1) \sum_{i=1}^{n} (y_i - x_i) \right) \times Q^{(0)}(x, dy), \quad (1.1)$$

where

• $Q^{(0)}(x, dy)$ is the standard (null-spike) Wishart transition kernel, given explicitly by

$$Q^{(0)}(x, dy) = \frac{\Delta(y)}{\Delta(x)} \exp\left(-\sum_{i=1}^{n} (y_i - x_i)\right) \mathbf{1}_{\{x \prec y\}} dy, \tag{1.2}$$

with $\Delta(z) = \prod_{1 \leq i < j \leq n} (z_i - z_j)$ the Vandermonde determinant.

• The function h_{π} is the (continuous) Harish-Chandra orbit integral factor

$$h_{\pi}(z) = \frac{(-1)^{\binom{n}{2}}}{0!1!\cdots(n-1)!} \frac{\det(e^{-\pi_i z_j})_{i,j=1}^n}{\Delta(\pi)\Delta(z)}.$$

Note that $h_{\pi}(0) = 1$.

In particular, the chain starts from sp(M(0)) = 0 (the zero matrix).

1.3 Inhomogeneous last-passage percolation

On the random growth side, we considered an array of site-weights $\{W_{i,j}\}_{i,j\geq 1}$ such that each $W_{i,j}$ is exponentially distributed with rate $\pi_i + \hat{\pi}_j$. For every integer $t \geq 1$, we define L(t,n) to be the maximum total weight of all up-right paths from (1,1) to (t,n):

$$L(t,n) = \max_{\Gamma: (1,1) \to (t,n)} \sum_{(i,j) \in \Gamma} W_{i,j}.$$

One checks that $L(\cdot, n)$ satisfies a simple additive recursion:

$$L(i,j) = W_{i,j} + \max\{L(i-1,j), L(i,j-1)\},\$$

The main claim which we show in today's lecture is the equality in distribution:

$$(L(1,n), L(2,n), \dots, L(t,n)) \stackrel{d}{=} (\lambda_1(1), \lambda_1(2), \dots, \lambda_1(t)).$$
 (1.3)

1.4 RSK via toggles: definitions and weight preservation

The Robinson-Schensted-Knuth correspondence (RSK) was the main new mechanism in Lecture 13. In our setup, we adopt a toggle-based viewpoint: we encode arrays by diagonals and successively toggle the diagonals to achieve a fully ordered array R. The key to how RSK links LPP and random matrices is its weight preservation property.

We work with arrays $W = \{W_{ij}\}_{1 \leq i \leq ,\ 1 \leq j \leq n}$ and $R = \{R_{ij}\}_{1 \leq i \leq ,\ 1 \leq j \leq n}$, where W is a non-negative integer array and R is an ordered array, that is, $R_{i,j} \leq \overline{R}_{i,j+1}$ and $R_{i,j} \leq R_{i+1,j}$ for all i,j. Using RSK, we showed in Lecture 13 that there is a bijection which maps W to R.

We also started to prove the following result, which we now complete:

Theorem 1.2 (Weight preservation). Let $W = \{W_{i,j}\}$ be a nonnegative integer array, and R = RSK(W). Denote

$$row_i = \sum_{j=1}^{n} W_{i,j}, \quad col_j = \sum_{i=1}^{t} W_{i,j}$$

(which are essentially the cdf's of the array W), and for R define the diagonal sums starting at each (i, j) and going diagonally down and to the right:

$$\operatorname{diag}_{i,j} = \sum_{k=0}^{\min(i,j)-1} R_{i-k,j-k}.$$

Then for each $1 \le j \le n$ and $1 \le i \le t$, we have

$$\operatorname{diag}_{t,j} = \sum_{m=1}^{j} \operatorname{col}_{m}, \quad \operatorname{diag}_{i,n} = \sum_{m=1}^{i} \operatorname{row}_{m}.$$
 (1.4)

In particular, the total sum of W over all cells equals the total sum of R over all cells.

Proof (sketch). One inductively builds R by adding the sites (i, j) one at a time. Each toggle modifies exactly one diagonal. After adding a box (i, j), the diagonal-sum identity

$$\mathrm{diag}_{i,j} \ = \ \mathrm{diag}_{i-1,j} + \mathrm{diag}_{i,j-1} \ - \ \mathrm{diag}_{i-1,j-1} \ + \ W_{i,j}$$

holds, expressing that W captures the discrete "mixed second differences" of the diagonal sums in R. Thus, the cdf's of W must coincide with the diagonal sums of R, as desired.

2 Distributions of last-passage times in geometric LPP

2.1

N Problems (due 2025-04-29)

N.1 Non-Markovianity

Show that the sequence of random variables defined in the exponential LPP model,

$$L(1, n), L(2, n), \dots, L(t, n),$$

is **not** a Markov chain. By virtue of the equivalence with the spiked Wishart ensemble (1.3), you may alternatively show that the sequence of maximal eigenvalues

$$\lambda_1(1), \lambda_1(2), \ldots, \lambda_1(t)$$

of successive Wishart matrices $M(1), M(2), \ldots, M(t)$ is **not** a Markov chain either.

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