NOTES ON RANDOM MATRICES

LEONID PETROV

(notes by Bryce Terwilliger; . . .)

ABSTRACT. These are notes for the MATH 8380 "Random Matrices" course at the University of Virginia in Spring 2016. The notes are constantly updated, and the latest version can be found at the `git` repository `https://github.com/lenis2000/RMT_Spring_2016`

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Lecture #1 on 1/20/2016 ───────────────────────────

1. INTRODUCTION

1.1. Matrices and eigenvalues. The study of random matrices as a field is a patchwork of many fields. The main object we study is a probability distribution on a certain subset of the set of matrices $\mathrm{Mat}(N \times N, \mathbb{R} \text{ or } \mathbb{C})$, thus giving us a random matrix A.

Definition 1.1. An *eigenvalue* λ of the matrix A is a root of the polynomial $f(\lambda) = \det(A - \lambda I)$, where I is the identity matrix (we use this notation throughout the notes). Equivalently, λ is an eigenvalue if A if the matrix $A - \lambda I$ is not invertible. This second way of defining eigenvalues in fact works even when A is not a finite size matrix, but an operator in some infinite-dimensional space.

We will largely be only concerned with real eigenvalues. That is the eigenvalues of a real symmetric matrix over $\mathbb{R}$ or Hermitian over $\mathbb{C}$ that is where $A^* = A$ (here and everywhere below A^* means $\overline{A^T}$, i.e., transposition and complex conjugation).

Remark 1.2. The case when eigenvalues can be complex is also studied in the theory of random matrices, sometimes under the keyword *complex random matrices*. See, for example, [GT10] for a law of large numbers for complex eigenvalues.

Proposition 1.3. *Every eigenvalue of a Hermitian matrix is real.*

Proof. Let A be a Hermitian matrix, so that $A^* = A$. Let λ be an eigenvalue of A. Let v be a non-zero vector in the null space of $A - \lambda I$. Let $a = \overline{v^T} v = |v|^2$, so that a is a positive real number. Let $b = \overline{v^T} A v$. Then $\bar{b} = \overline{b^T} = \overline{\overline{v^T} A v}^T = \overline{v^T} \bar{A}^T v = \overline{v^T} A v = b$, so b is real. Since $b = \lambda a$, λ must be real. $\square$

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Let $\mathcal{H}_N$ be the set of $N \times N$ Hermitian matrices. For each N, let μ_N be a probability measure on $\mathcal{H}_N$ (it can be supported not by the whole $\mathcal{H}_N$, but by a subset of it, too). Then for each matrix $A \in \mathcal{H}_N$ we may order the real eigenvalues $\lambda_1 \geq \cdots \geq \lambda_N$ of A (the collection of eigenvalues is called the *spectrum* of A).

A collection of probability measures μ_N on $\mathcal{H}_N$ for each $N \geq 1$ is said to be a *random matrix ensemble*. For such an ensemble, the eigenvalues $\lambda_1^{(N)} \geq \cdots \geq \lambda_N^{(N)}$ of matrices N form random point configurations on $\mathbb{R}$ with growing numbers of points. Our main goal is to study the asymptotic properties of these collections of points on $\mathbb{R}$, as $N \to \infty$.

1.2. **Why study random matrices?** Let us briefly discuss five possible motivations to study random matrices and asymptotic distributions of random matrix spectra.

1.2.1. Matrices are a natural generalization of real numbers, so studying them would seem natural from a pure probability point of view. However, the development of the theory of Random Matrices was much application driven.

1.2.2. *Hurwitz and theory of invariants.* A. Hurwitz in the 1890s [Hur97] computed the volume of orthogonal and unitary groups of matrices.[1] For example, $U(1)$, the set of unitary 1×1 unitary matrices — the unit circle — has volume 2π. For general N, the volume of $U(N)$ is the normalization constant $Z_N = \int_{U(N)} 1 \cdot d(\text{Haar}_N)$ in probabilistic integrals over the Haar measure on the unitary group,

$$Z_N = 2^{N(N+1)/2} \prod_{k=1}^{N} \frac{\pi^k}{\Gamma(k)} = 2^{N(N+1)/2} \prod_{k=1}^{N} \frac{\pi^k}{(k-1)!}.$$

See [DF15] for a recent survey.

1.2.3. *Statistics.* J. Wishart in 1928 [Wis28] considered random covariance matrices of vector-valued data. For testing the hypothesis of independence of components of the vector, it is natural to study the distribution of the random covariance matrix of the uncorrelated vector (the null-hypothesis distribution). Let us assume that the components of the vector are identically distributed.

This latter matrix ensemble (called the *Wishart ensemble*) can be constructed by taking a rectangular matrix Y with independent (or uncorrelated) identically distributed entries, and taking $A = Y^T Y$. Then A is a square matrix which is said to have the (*real*) *Wishart distribution*.

For the purposes of statistics, the distribution of the Wishart matrix A should be compared with the distribution under the alternate hypothesis that the entries of the vector are correlated. For certain assumed nature of the correlation structure, this leads to considering *spiked random matrices* of the form $A + R$, where A is Wishart and R is a finite-rank perturbation. It turns out that sometimes the presence of a nonzero matrix R may be detected by looking at the spectrum of $A + R$, which again leads to considering spectra of random matrices. One reference (among many others which are not mentioned) relevant for the current research on spiked random matrices is [BBAP05].

1.2.4. *Nuclear physics.* Active development of the theory of random matrices begins in the 1950s when Wigner, Dyson, Mehta, and their collaborators explored nuclear physics applications. In nuclear quantum physics a state of a system is an operator on an L^2 space of functions; its eigenvalues are the energy levels of the system. For large nuclei it is difficult to analyze the operator in L^2 directly, but Wigner postulated that differences in energy levels could be modeled by differences in eigenvalues of certain classes of matrices under appropriate probability measures. That is, the collections $\{\Delta E_i\}$ and $\{\lambda_i - \lambda_{i+1}\}$ should be statistically close. Moreover, the random matrix ensemble should have the same

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[1] The group $O(N)$ of orthogonal $N \times N$ matrices consists of matrices O with real entries, for which $O^T O = O O^T = I$. The group $U(N)$ of unitary $N \times N$ matrices consists of matrices U with complex entries, for which $U U^T = U^T U = I$. Both groups are *compact*, and so possess finite Haar measures, i.e., measures μ which are invariant under left and right shifts on the group.

symmetry as that quantum system. The symmetry classes of random matrices are discussed in detail in a recent survey [Zir10]. Dyson proposed a model of stochastic dynamics of energies (eigenvalues of random matrices). We will study the Dyson's Brownian motion later.

Section 1.1 of the book [Meh04] contains a nice outline of physical applications of random matrices.

1.2.5. *Number theory.* Dyson and Montgomery uncovered number theoretic applications of random matrices in the 1970's [Mon73], with Odlyzko in the 1980's [Odl87] providing powerful numerical simulations.

Consider the Riemann Zeta Function

$$\zeta(s) = \sum_{n=1}^{\infty} \frac{1}{n^s} \qquad \text{for } s \in \mathbb{C} \text{ with the real part of } s > 1$$

Riemann showed that $\zeta(s)$ can be analytically continued to a function on $\mathbb{C}$ with a pole at $s = 1$. The famous Riemann hypothesis is that all the zeroes of the Zeta function with real part greater than 0 lie on the *critical line* $\frac{1}{2} + it$. It turns out that the distribution of the zeroes on the critical line can be linked to the distribution of eigenvalues of random matrices. Consider the zeros $\frac{1}{2} + it_n$ of the zeta function with $t_n \in \mathbb{R}$. Let us define

$$w_n = \frac{t_n}{2\pi} \log\left(\frac{|t_n|}{2\pi}\right),$$

then $\lim_{L\to\infty} \frac{1}{L} \# \{w_n \in [0, L]\} = 1$, i.e., the average density of the w_n's is 1. The theorem/conjecture of Montgomery[2] states that the pair correlations of the zeroes of the zeta function have the form

$$\lim_{L\to\infty} \frac{1}{L} \# \left\{ \begin{array}{c} w_n \in [0, L] \\ \alpha \le w_n - w_m \le \beta \end{array} \right\} \sim \int_{\alpha}^{\beta} \left(\delta(x) + 1 - \frac{\sin^2(\pi x)}{\pi^2 x^2} \right) dx,$$

where $\delta(x)$ is the Dirac delta. Further details on this and other connections between number theory and random matrices can be found in [KS00], [Kea06].

Remark 1.4. There are accounts of Montgomery meeting Dyson at teatime at the IAS; the latter pointed out the connection between Montgomery's formula and the eigenvalue distributions of random matrices. A quick Internet search lead to the following links containing details: `https://www.ias.edu/articles/hugh-montgomery` and `http://empslocal.ex.ac.uk/people/staff/mrwatkin//zeta/dyson.htm`.

1.3. **Course outline.** The course will consist of five main parts, with the last part being optional:

1. Limit shape results for random matrices (such as Wigner's Semicircle Law). Connections to Free Probability.
2. Concrete ensembles of random matrices (GUE, circular, and Beta ensembles). Bulk and edge asymptotics via exact computations. Connection to determinantal point processes.
3. Dyson's Brownian Motion and related stochastic calculus.
4. Universality of random matrix asymptotics.
5. (optional, depending on time available) Discrete analogues of random matrix models: random permutations, random tilings, interacting particle systems.

2. WIGNER'S SEMICIRCLE LAW

After discussing the object and motivations for studying random matrices, let us proceed to the first part of the course — the laws of large numbers for the eigenvalue distributions of random matrices. The first of these laws of large numbers is the *Wigner's Semicircle Law*. It dates back to [Wig55].

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[2]Depending in part on the Riemann hypothesis and in part on how strong is the assumed convergence in the formula below.

⟨er_matrices⟩? 2.1. **Real Wigner matrices.** A particular ensemble of random matrices is the *real Wigner matrices*. Let $A \in \mathrm{Mat}(N \times N, \mathbb{R})$ with $A = (a_{ij})_{i,j=1}^N$ such that $a_{ij} = a_{ji}$. To describe the distribution of the random matrix A we only need to describe the upper triangular portion of A.

⟨real_Wigner⟩? **Definition 2.1.** The law of the real Wigner $N \times N$ matrix is described as follows:
- $\{a_{ij}\}_{i \leq j}$ is an independent collection of random variables
- $\{a_{ii}\}_{i=1}^N$ is iid[3], and $\{a_{ij}\}_{i<j}$ is iid.
- $\mathbb{E}\, a_{ij} = 0$ for all i,j; $\mathbb{E}\, a_{ij}^2 = 2$ for $i = j$; and $\mathbb{E}\, a_{ij}^2 = 1$ for $i \neq j$.
- all moments of a_{ij} are finite.

The last condition greatly simplifies technicalities of the proofs, but most results on real Wigner matrices hold under weaker assumptions.

⟨al_ensemble⟩? 2.2. **Gaussian Orthogonal Ensemble.** A special case of real Wigner matrices is when each a_{ij} is Gaussian. This case is called the *Gaussian Orthogonal Ensemble* (*GOE*).

Lemma 2.2. *The distribution of the GOE is orthogonally invariant, that is, if A has the GOE distribution and $O \in O(N)$ is a fixed orthogonal matrix, then OAO^T has the same probability distribution as A.*

Proof. It is not hard to check that the probability density of A with respect to the Lebesgue measure on $\mathrm{Mat}(N \times N, \mathbb{R})$ (this space is isomorphic to $\mathbb{R}^{N(N+1)/2}$ by considering the upper triangular part) has the form

$$f(A) = c \exp(-\operatorname{tr}(A^2)),$$

where c is a normalization constant.[4] Since the matrix trace is invariant under cyclical permutations,

$$\operatorname{tr}(OA^2O^T) = \operatorname{tr}(A^2O^TO) = \operatorname{tr}(A^2).$$

Thus, $OA^2O^T \overset{\mathcal{D}}{=} A$. $\qquad\square$

We will discuss the GOE (and its close relative GUE, Gaussian Unitary Ensemble) in detail in the course later, but for now we will focus on properties of real Wigner matrices with general entry distribution.

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⟨icircle_law⟩? 2.3. **Formulation of the Wigner Semicircle Law.** For a real Wigner matrix $A_N \in \mathrm{Mat}(N \times N)$ let $\lambda_1^{(N)} \geq \cdots \geq \lambda_N^{(N)}$ be the eigenvalues of A_N. The empirical distribution of the eigenvalues is

$$L_N = \frac{1}{N} \sum_{i=1}^N \delta_{N^{-1/2}\lambda_i^{(N)}}. \tag{2.1}$$

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The semicircle distribution is

$$SC(x) = \frac{1}{2\pi}\sqrt{4 - x^2}, \qquad -2 \leq x \leq 2. \tag{2.2}$$

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⟨micircleLaw⟩? **Theorem 2.3.** *L_N converges weakly in probability to SC.*

This means that for each bounded continuous function on $\mathbb{R}$ ($f \in C_B(\mathbb{R})$) and each $\epsilon > 0$ we have

$$\lim_{N \to \infty} \mathbb{P}\left(\left| \int_{\mathbb{R}} f\, dL_N - \int_{\mathbb{R}} f\, dSC \right| > \epsilon \right) = 0.$$

The words "in probability" mean in the usual case. Where as weakly specifies the metric.

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[3]Independent identically distributed.

[4]Here and below $\operatorname{tr}(A) = a_{11} + a_{22} + \ldots + a_{NN}$ is the trace of a matrix.

To deal with this type of statement it is convenient to define $\langle \mu, f \rangle = \int f \, d\mu = \int_{\mathbb{R}} f(x) \, \mu(dx)$ for a given function f and measure μ. If μ is a random measure (such as L_N since L_N depends on A_N which is random) then $\langle \mu, f \rangle$ is a random element of $\mathbb{R}$ (usually we say random variable). Since SC is not random $\langle SC, f \rangle$ is fixed for a given function f. The Semicircle Law states, for any given $f \in C_B(\mathbb{R})$ the random variable $\langle L_N, f \rangle$ converges in probability to the constant $\langle SC, f \rangle$ which may be written

$$\forall \epsilon > 0, \ \lim_{N \to \infty} \mathbb{P}\left(|\langle L_N, f \rangle - \langle SC, f \rangle| > \epsilon \right) = 0. \tag{2.3}$$

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Remark 2.4. This type of convergence is reminiscent of the weak law of large numbers: for $\{X_i\}_{i=1}^{\infty}$ iid with $\mathbb{E}\,|X_1| < \infty$ the random variables $\frac{1}{N} \sum_{i=1}^{N} X_i$ converge to the constant $\mathbb{E}\,X_1$ in probability as $N \to \infty$.

References

[BBAP05] J. Baik, G. Ben Arous, and S. Péché, *Phase transition of the largest eigenvalue for nonnull complex sample covariance matrices*, Annals of Probability (2005), 1643–1697, arXiv:math/0403022 [math.PR].

[DF15] P. Diaconis and P.J. Forrester, *A. Hurwitz and the origins of random matrix theory in mathematics*, arXiv:1512.09229 [math-ph].

[GT10] F. Götze and A. Tikhomirov, *The circular law for random matrices*, Ann. Probab. **38** (2010), no. 4, 1444–1491, arXiv:0709.3995 [math.PR].

[Hur97] A. Hurwitz, *Über die Erzeugung der Invarianten durch Integration*, Nachr. Ges. Wiss. Göttingen (1897), 71–90.

[Kea06] J. Keating, *Random matrices and number theory*, Applications of random matrices in physics, Springer, 2006, pp. 1–32.

[KS00] J. Keating and N. Snaith, *Random matrix theory and ζ (1/2+ it)*, Communications in Mathematical Physics **214** (2000), no. 1, 57–89.

[Meh04] M.L. Mehta, *Random matrices*, Academic press, 2004.

[Mon73] H. Montgomery, *The pair correlation of zeros of the zeta function*, Proc. Symp. Pure Math, vol. 24, 1973, pp. 181–193.

[Odl87] A. Odlyzko, *On the distribution of spacings between zeros of the zeta function*, Mathematics of Computation **48** (1987), no. 177, 273–308.

[Wig55] E. Wigner, *Characteristic vectors of bordered matrices with infinite dimensions*, Annals of Mathematics (1955), 548–564.

[Wis28] J. Wishart, *The generalised product moment distribution in samples from a normal multivariate population*, Biometrika **20A** (1928), 32–43.

[Zir10] Martin R. Zirnbauer, *Symmetry classes*, arXiv:1001.0722 [math-ph].