NOTES ON RANDOM MATRICES

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(notes by Stephen Hardy; 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`

(before TEXing, please familiarize yourself with style suggestions at https://github.com/lenis2000/RMT_Spring_2016/blob/master/TeXing.md)

Contents

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 $N \to \infty$.

m_matrices_⟩? 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 $Z_N = \int_{U(N)} 1 \cdot d(\mathrm{Haar}_N)$ 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

[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 $\lim\limits_{L\to\infty} \frac{1}{L} \# \{w_n \in [0, L]\} = 1$, 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

$$\lim_{L\to\infty} \frac{1}{L} \# \left\{ \begin{array}{c} w_n \in [0, L] \\ \alpha \le w_n - w_m \le \beta \end{array} \right\} \sim \int_{\alpha}^{\beta} \left(\delta(x) + 1 - \frac{\sin^2(\pi x)}{\pi^2 x^2} \right) dx, \tag{1.1}$$ Montgomery_z

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`.

_the_course⟩? 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 and its combinatorial proof

icircle_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].

[2]Depending in part on the Riemann hypothesis and in part on how strong is the assumed convergence in (1.1).

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:

- $\{a_{ij}\}_{i \le j}$ 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.

Example 2.2. A large class of Wigner random matrices (which helps justify why in A the variances on the diagonal must be twice the off-diagonal variances) can be constructed as follows. Suppose the collection of random variables x_{ij} for $1 \le i, j \le N$ is iid with $\mathbb{E}\, x_{ij} = 0$ and $\mathbb{E}\, x_{ij}^2 = 1$. Let $X = (x_{ij})$ be an $N \times N$ matrix. Define

$$A := \frac{X + X^T}{\sqrt{2}}.$$

One readily sees that A is real Wigner. Namely, for example, $a_{11} = \frac{x_{11}+x_{11}}{\sqrt{2}} = \sqrt{2}x_{11}$, so $\mathbb{E}\, a_{11} = 0$ and $\mathbb{E}\, a_{11}^2 = 2\,\mathbb{E}\, x_{11}^2 = 2$. If $N \ge 2$ then $a_{12} = a_{21}$ with $a_{12} = \frac{x_{12}+x_{21}}{\sqrt{2}}$, and we have $\mathbb{E}\, a_{12} = 0$ and $\mathrm{Var}\, a_{12} = \frac{1}{2}\mathrm{Var}(x_{12} + x_{21}) = 1$ because x_{12} and x_{21} are independent.

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 2.3. *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, $OA^2O^T \stackrel{\mathcal{D}}{=} A$. ☐

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.

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

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

[3]Independent identically distributed.

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

That is, we put delta masses of size $1/N$ into the N positions of rescaled eigenvalues $\lambda_i^{(N)}/\sqrt{N}$. This rescaling will turn out to be appropriate for the law of large numbers. Note that L_N is a probability measure on $\mathbb{R}$.

Remark 2.4. For the purposes of asymptotic statements, we will always assume that the off-diagonal entries of real Wigner matrices $A = A_N$ have the same fixed distribution independent of N, and similarly the diagonal entries have the same fixed (but different) distribution.

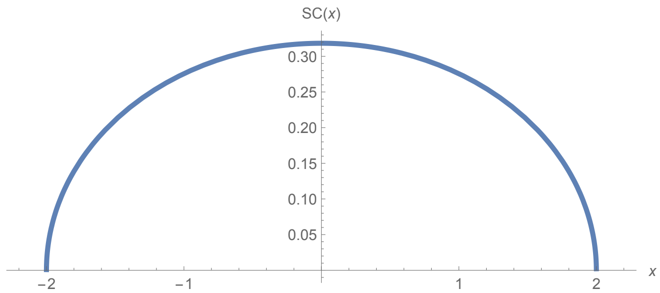

FIGURE 1. Semicircle density $\mathsf{SC}(x)$.

g:semicircle⟩

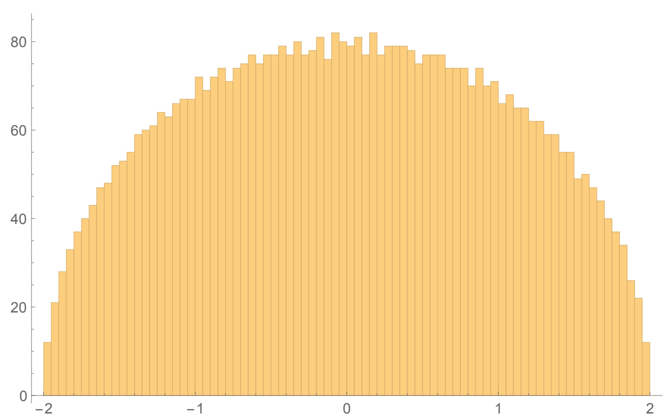

FIGURE 2. Histogram of the empirical distribution L_N for $N = 5000$.

⟨fig:Wigner⟩?

Definition 2.5. The semicircle distribution SC is a fixed probability distribution on $\mathbb{R}$ supported on $[-2, 2]$ which is absolutely continuous with respect to the Lebesgue measure and has the density

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

See Fig. 1.

Note that slightly abusing the notation, by SC we will denote both the semicircle distribution and its probability density (2.2).

micircleLaw⟩? **Theorem 2.6** (Wigner's Semicircle Law)**.** *As $N \to \infty$, the empirical distributions L_N converge weakly, in probability to the semicircle distribution* SC.

Let us explain what we mean by convergence "weakly in probability". Formally this means that for any bounded continuous function f on $\mathbb{R}$ ($f \in C_B(\mathbb{R})$) and each $\epsilon > 0$ we have

$$\lim_{N\to\infty} \mathbb{P}\left(\left| \int_{\mathbb{R}} f \, dL_N - \int_{\mathbb{R}} f \, d\mathsf{SC} \right| > \epsilon \right) = 0. \tag{2.3}$$ WignerSemici

That is, "in probability" means the usual convergence in probability of random elements L_N to a (non-random) element SC. On the other hand, "weakly" specifies the metric on the space of probability measures on $\mathbb{R}$ (to which all L_N and SC belong). Convergence of probability measures in this metric simply means weak convergence of probability measures on $\mathbb{R}$.

In other words, let us use a convenient notation for the pairing $\langle f,\mu\rangle = \int_{\mathbb{R}} f\,d\mu = \int_{\mathbb{R}} f(x)\,\mu(dx)$ 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 $\langle f,\mu\rangle$ is a random element of $\mathbb{R}$ (usually we say random variable). Since SC is not random, the pairing $\langle f,\mathsf{SC}\rangle$ is a fixed number for a given function f. The Semicircle Law thus states that for any given $f \in C_B(\mathbb{R})$ the random variable $\langle f, L_N\rangle$ converges in probability to the constant $\langle f,\mathsf{SC}\rangle$ which may be written as

$$\forall \epsilon > 0, \qquad \lim_{N\to\infty} \mathbb{P}\left(|\langle f, L_N\rangle - \langle f,\mathsf{SC}\rangle| > \epsilon\right) = 0, \tag{2.4}$$ WignerSemici

which is the same as (2.3).

Remark 2.7. This type of convergence is reminiscent of the classical weak law of large numbers: for $\{X_i\}_{i=1}^{\infty}$ iid random variables with $\mathbb{E}\,|X_1| < \infty$, the random variables $\dfrac{1}{N}\sum_{i=1}^{N} X_i$ converge to the constant $\mathbb{E}\,X_1$ in probability as $N \to \infty$.

Lecture #2 on 1/25/2016

f_the_proof⟩? 2.4. **Strategy of the proof.** We will employ the following strategy in our proof of the Wigner's semicircle law. This is only the first of the proofs we will consider, and it is based on the computation of moments and on the related combinatorics. Recall that for a probability measure μ the quantities $\langle x^k,\mu\rangle$, $k = 0,1,2,\ldots$, are called the *moments* of μ.

First, in §2.5 we will compute the moments $m_k := \langle x^k,\mathsf{SC}\rangle$ of the limiting semicircle distribution, and identify the answer in terms of the Catalan numbers. Our second step in the proof is to show the convergence $\lim_{N\to\infty}\mathbb{E}\langle x^k, L_N\rangle = m_k$ for each k. We do this in §2.7 below. The third step (in §2.8) is to show that the variance of $\langle x^k, L_N\rangle$ goes to zero as $N\to\infty$ for each k. Finally, to complete the proof we will need to justify that the convergence (2.4) for any function $f(x)$ follows from the case of $f(x) = x^k$, $k = 0,1,2,\ldots$. This is done in §2.9.

distribution⟩ 2.5. **Moments of the semicircle distribution.** Here we will compute the moments of the semicircle distribution:

$$m_k = \langle x^k,\mathsf{SC}\rangle = \int_{-2}^{2} x^k\,\mathsf{SC}(x)\,dx = \int_{-2}^{2} x^k \left(\frac{\sqrt{4-x^2}}{2\pi}\right)dx.$$

Clearly, by symmetry we have $m_k = 0$ for k odd. If k is even, let us perform a trigonometric substitution $x = 2\sin\theta$, $-\frac{\pi}{2} \le \theta \le \frac{\pi}{2}$, in the above integral:

$$m_{2k} = \frac{2^{2k+1}}{\pi}\int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \sin^{2k}\theta\cos^2\theta\,d\theta. \tag{2.5}$$ SC_moments_m

Lemma 2.8. *We have*

$$\frac{1}{\pi}\int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \sin^{2k}\theta\,d\theta = \frac{(2k-1)!!}{2^k k!},$$

where recall that $(2k-1)!! = 1\cdot 3\cdot 5\cdots(2k-3)(2k-1)$.

Proof. Denote the integral in the right-hand side by α_k. Observe that $\alpha_0 = 1$. Integrating by parts for $k \ge 1$, we have

$$\alpha_k = -\frac{1}{\pi}\int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \sin^{2k-1}\theta\,d(\cos\theta) = \frac{1}{\pi}\int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} (2k-1)\sin^{2k-2}\theta\cos^2\theta\,d\theta = (2k-1)\alpha_{k-1} - (2k-1)\alpha_k.$$

Therefore, the quantities α_k satisfy

$$\frac{\alpha_k}{\alpha_{k-1}} = \frac{2k-1}{2k},$$

which is the same relation as for the quantities $\frac{(2k-1)!!}{2^k k!}$. This completes the proof. $\square$

By relating m_{2k} (2.5) and α_k in the above lemma, we see that the even moments of the semicircle distribution are given by

$$m_{2k} = \frac{1}{k+1}\binom{2k}{k}, \qquad k = 0, 1, 2, \ldots. \tag{2.6}$$?m_2k_Catalan

These quantities are called the *Catalan numbers.*

lan_numbers⟩? 2.6. **Catalan numbers.** The Catalan numbers C_k are defined as

$$C_k := \frac{1}{k+1}\binom{2k}{k}, \qquad k = 0, 1, 2, \ldots. \tag{2.7}$$ Catalan_def

The first twenty one of them are

$$1, 1, 2, 5, 14, 42, 132, 429, 1430, 4862, 16796, 58786, 208012, 742900, 2674440,$$
$$9694845, 35357670, 129644790, 477638700, 1767263190, 6564120420.$$

They are ubiquitous in combinatorics: for example, there are more than 200 families of objects enumerated by the Catalan numbers [Sta15]. A list of references and properties of Catalan numbers may be found at [Cat].

Here we will list a number of properties of the Catalan numbers which will be important for our proof of the semicircle law.

:dyck_paths⟩? 2.6.1. *Dyck paths.*

Definition 2.9. A *Dyck path* of length $2n$ is a sequence $d_0, d_1, \ldots, d_{2n}$ such that $d_0 = d_{2n} = 0$, $d_{i+1} - d_i = \pm 1$ for all i, and that $d_i \geq 0$ for all i. Graphically Dyck paths can be represented as on Fig. 3.

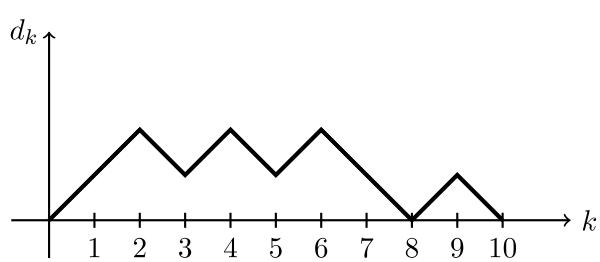

FIGURE 3. A Dyck path of length $2n = 10$.

⟨fig:Dyck⟩

yck_Catalan⟩? **Exercise 2.10.** The number of Dyck paths of length $2n$ is equal to the Catalan number C_n.

Idea. Use the *reflection principle* — a tool used in the study of random walks and Brownian motion. See `https://en.wikipedia.org/wiki/Catalan_number#Second_proof` for details.

Another way to count the Dyck paths is to first establish the recurrence (2.8), and then use generating functions to solve the recurrence (see Remark 2.12 below). $\square$

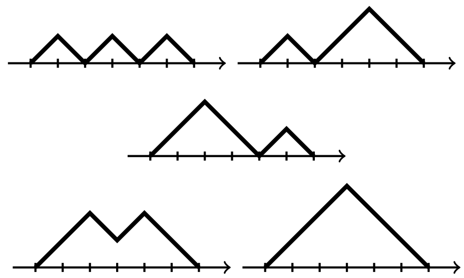

FIGURE 4. All five Dyck paths of length $2n = 6$. The first two paths first return to zero at time $2j = 2$, the third path first returns to zero at time $2j = 4$, and the last two paths first return to zero at time $2j = 6$.

⟨fig:Dyck3⟩

:recurrence⟩? 2.6.2. *Recurrence.*

d_recurrence⟩ **Lemma 2.11.** *The Catalan numbers satisfy the recurrence relation*

$$C_0 = 1, \qquad C_n = \sum_{j=0}^{n} C_{j-1} C_{n-j}. \tag{2.8}$$ Catalan_recu

Proof. The easiest way to see this is by counting the Dyck paths: let the first time a Dyck path reaches 0 be $2j$, then j can be any number from 1 to n (see Fig. 4). The part of the Dyck path after time $2j$ is independent from the part before $2j$. The number of paths from $2j$ to $2n$ is exactly C_{n-j}. The number of paths from 0 to $2j$ (with the condition that they do not get to 0 in the meantime) can be seen to be C_{j-1} by cutting out the first up and the last down steps. This implies the recurrence. □

icit_formula⟩ **Remark 2.12.** The recurrence (2.8) provides a way to get the explicit formula (2.7). Namely, considering the generating function $G(z) = \sum_{n=0}^{\infty} C_n z^n$, we see that (2.8) implies

$$G(z) = zG(z)^2 + 1.$$

This equation on $G(z)$ has two solutions $\frac{1 \pm \sqrt{1-4z}}{2z}$, of which we should pick $\frac{1-\sqrt{1-4z}}{2z}$ because the other solution diverges as $z \to 0$. The Taylor expansion of this function is

$$\frac{1-\sqrt{1-4z}}{2z} = \sum_{n=0}^{\infty} \frac{1}{n+1} \binom{2n}{n} z^n = 1 + z + 2z^2 + 5z^3 + 14z^4 + 42z^5 + 132z^6 + \dots,$$

which converges for $|z| < \frac{1}{4}$. This shows that the Dyck paths are enumerated by the Catalan numbers.

beled_trees⟩? 2.6.3. *Trees.* As was mentioned before, the Catalan numbers enumerate numerous families of combinatorial objects. We will need one more family of such objects — *rooted ordered trees.* An ordered tree is a rooted tree (i.e., a tree with a distinguished vertex R called the *root*) in which children of every vertex are linearly ordered. On pictures this ordering will be represented from left to right (see Fig. 5).

_are_Catalan⟩ **Lemma 2.13.** *The number of rooted ordered trees with $n+1$ vertices (including the root) is equal to the Catalan number C_n.*

Proof. Assume that the leftmost subtree contains j vertices (without the root), then the rest of the tree including the root contains $n-j+1$ vertices. This readily implies the recurrence (2.8), which establishes the claim. □

_are_Catalan⟩ **Exercise 2.14.** By comparing the proof of Lemma 2.11 and Lemma 2.13, come up with a bijection between Dyck paths and ordered rooted trees.

Idea. Consider the walk around the tree (such that the tree is always to the left of the walker), which starts to the left of the root. Let d_k be the distance of the walker from the root. The Dyck paths corresponding to trees on Fig. 5 are given on Fig. 6. □

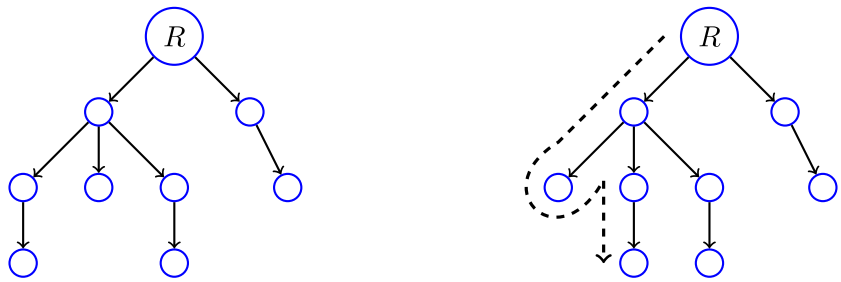

FIGURE 5. These trees are isomorphic as rooted trees, but are different as rooted ordered trees. A beginning of the walk of Exercise 2.14 is displayed for the second tree.

ordered_tree⟩

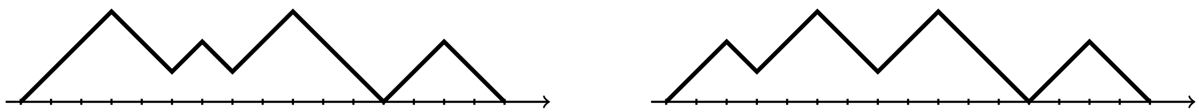

FIGURE 6. Dyck paths corresponding to the rooted ordered trees on Fig. 5 (see Exercise 2.14).

ed_tree_Dyck⟩

xpectations_⟩ 2.7. **Convergence of expectations $\mathbb{E}\langle x^k, L_N\rangle \to m_k$.**

nrangleto0⟩ 2.8. **Variances $\langle x^k, L_N\rangle \to 0$.**

e_proof_WSCL⟩ 2.9. **Completing the proof.**

Lecture #3 on 1/26/2016

Lecture #4 on 2/1/2016

Lecture #5 on 2/3/2016

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