

Spectral Statistics of Random Matrices

A Thesis
Presented to
The Division of Mathematics and Natural Sciences
Reed College

In Partial Fulfillment
of the Requirements for the Degree
Bachelor of Arts

Ali Taqi

May 2021

Approved for the Division
(Mathematics)

Jonathan M. Wells

Table of Contents

Introduction	1
Chapter 1: Random Matrices	3
1.1 Introduction	3
1.2 The Crew: Ensembles	5
1.3 Special Ensembles	5
1.3.1 Hermite β -Ensembles	5
1.3.2 Erdos-Renyi p -Ensembles	6
1.4 Analytical Results	6
Chapter 2: Spectra	7
2.1 Introduction	7
2.1.1 The Quintessential Spectral Statistic: the Eigenvalue	7
2.1.2 Interlude: Ensembles	8
2.2 Ordered Spectra	8
2.2.1 Eigenvalue Ordering	8
2.2.2 Singular Values	9
2.2.3 Order Statistics	9
2.2.4 Case Study: Tracy-Widom Distribution	9
2.3 Symmetric and Hermitian Matrices	10
2.3.1 Introduction	10
2.3.2 Case Study: Wigner's Semicircle Distribution	10
2.4 Findings	10
Chapter 3: Dispersions	11
3.1 Introduction	11
3.1.1 Dispersion Metrics	11
3.1.2 Pairing Schema	12
3.1.3 Dispersions!	13
3.2 Order Statistics	13
3.2.1 Introduction	13
3.2.2 Conditional Statistics	14
3.3 Analytical Results	14
3.3.1 Case Study: Wigner's Surmise	14
3.4 Findings	14

Chapter 4: β-Ensembles	15
4.1 Introduction	15
4.1.1 Hermite β -Ensembles	15
4.1.2 Dimitriu's Matrix Model	16
4.2 Spectra	17
4.3 Dispersions	18
Appendix A: Math Review	19
A.1 Linear Algebra	19
A.1.1 Introduction	19
A.1.2 Proof: Real Symmetric Matrices have Real Eigenvectors	20
A.2 Probability Theory	22
A.2.1 Introduction	22
A.3 Markov Chains	23
A.3.1 Classification of states	24
Appendix B: Algorithm Appendix	25
B.1 Matrix Simulation	25
B.1.1 Stochastic Matrices	25
B.1.2 Normal Matrices	25
Appendix C: Code Appendix	27
Appendix D: Mixing Time Simulations	29
D.1 Introduction	29
D.2 Mixing Time Simulations	29
D.3 Erdos-Renyi Ensemble Simulations	30
D.4 Questions	31
D.4.1 Cauchy Distributed Ratios	31
References	33

Abstract

On their own, random variables exude deterministic properties regarding their uncertainty. The same generalization can be made for random matrices, which are matrices whose entries are random variables. One particular statistic worth investigating is the distribution of a matrix ensemble's eigenvalues, or its spectrum. In this thesis, there will be an exploration of various classes of random matrices and relevant spectral statistics like their spectra and mixing times.

Dedication

For my mother.

Introduction

So, what are *spectral statistics*? Do they have to do with rainbows? Sceptres? No, they don't, but they're almost as colorful and regal. The word spectral is borrowed from the spectral-like patterns observed in statistical physics - whether it may be atomic spectra or other quantum mechanical phenomena. The borrowing is loose and not literal, but still somewhat well founded.

The field of Random Matrix Theory was extensively developed in the 1930s by the nuclear physicist Eugene Wigner. He found connections between the deterministic properties of atomic nuclei and their random and stochastic behaviors. The link? Random matrices.

So in the context of this thesis, *Spectral statistics* will be an umbrella term for random matrix statistics that somehow involve that matrix's eigenvalues and eigenvectors.

To explore these spectral statistics, this thesis will use the **RMAT** package. This package was developed alongside this thesis in order to facilitate the simulation of these random matrices and spectral statistics. As such, there is a large simulation component to this thesis. To showcase the methodology of the simulations, code snippets will be sprinkled about the thesis. It will use code derived from the package RMAT which can be found on GitHub; minimal source code will also be available in the appendix, as well as pre-simulated data available on the Reed database.

Chapter 1

Random Matrices

As discussed in the introduction, this thesis will be an exploration of spectral statistics of random matrices. This means that we must first be able to understand what random matrices are. At a fundamental level, random matrices are simply matrices whose entries are randomly distributed in accordance to some distribution or method. To formalize all these notions, we will define what random matrices are and what it means for them to be \mathcal{D} -distributed.

1.1 Introduction

When it comes to random simulation, there must always be a rule to which our randomness must conform, regardless of complexity. For example, sampling a vector from a distribution is a rudimentary example of this. For random matrices, there will be a few methods of generating their entries that are not just sampling from theoretical distributions. As such, we motivate the \mathcal{D} -distribution.

Definition 1.1.1 (\mathcal{D} -distribution). *When we define a random matrix that is \mathcal{D} -distributed, we say that $P \sim \mathcal{D}$. In the simplest of terms, \mathcal{D} is essentially the algorithm that generates the random matrix P . There are two primary types of algorithms that will be covered: explicit distribution and implicit distribution. If \mathcal{D} is an explicit distribution, then we simply sample every entry of P to be from that distribution. Otherwise, if it is implicit, we utilize an algorithm that enforces an implicit distribution of the entries.*

Explicit Distributions

The simplest case is explicitly distributed random matrices. If \mathcal{D} is an explicit distribution, then we overload the notation \mathcal{D} to mean a probability distribution in the classical sense (see Appendix A.1). So, if \mathcal{D} is a probability distribution, the matrix $P \sim \mathcal{D}$ when $p_{ij} \sim \mathcal{D}$. In other words, we simply perform entry-wise sampling from that distribution.

1. If $\mathcal{D} = \mathcal{N}(0, 1)$, then $p_{ij} \sim \mathcal{N}(0, 1)$.
2. If $\mathcal{D} = \text{Unif}(0, 1)$, then $p_{ij} \sim \text{Unif}(0, 1)$.

Implicit Distributions

In the latter case, we are concerned less about the distribution of the matrix entries and moreso about its holistic properties.

1. If \mathcal{D} = Stochastic, then the matrix is a row of random stochastic rows. (See Algorithm B.1.)
2. If \mathcal{D} is any distribution (implicit or explicit), then \mathcal{D}^\dagger is the Symmetric/Hermitian version of \mathcal{D} . (See Algorithm B.2.)

Definition 1.1.2 (Random Matrix). *Assuming \mathcal{D} is an explicit distribution, a random matrix is any matrix over the field \mathbb{F} is a matrix $M \in \mathbb{F}^{N \times N}$ is a matrix whose entries are i.i.d random variables. So, if a random matrix $M = (m_{ij})$ is \mathcal{D} -distributed, then we say $m_{ij} \sim \mathcal{D}$. In the scope of this thesis, assume every random matrix to be homogenously distributed. Otherwise, if \mathcal{D} is an implicit distribution, then P is a matrix whose entries are determined by the algorithm imposed by \mathcal{D} .*

Code Example 1.1.1 (Standard Normal Matrix). *Let $\mathcal{D} = \mathcal{N}(0, 1)$. We can generate $P \sim \mathcal{D}$, a 4×4 standard normal matrix, as such:*

```
# Using the RMAAT package
library(RMAT)
P <- RM_norm(N = 4, mean = 0, sd = 1)

# Outputs the following
P
```

	[,1]	[,2]	[,3]	[,4]
[1,]	0.1058257	-1.0835598	-0.7031727	1.01608625
[2,]	-0.2170453	1.8206070	-0.4539230	0.06828296
[3,]	1.3002145	0.1254992	-0.5214005	-0.61516174
[4,]	-1.0398587	0.1975445	-0.8511950	0.86366082

1.2 The Crew: Ensembles

With a random matrix well defined, we may now motivate one of the most important ideas - the random matrix ensemble. One common theme in this thesis will be that random matrices on their own provide little information. When we consider them at the ensemble level, we start to obtain more fruitful results. Without further ado, we motivate the random matrix ensemble.

Definition 1.2.1 (Random Matrix Ensemble). *A \mathcal{D} -distributed random matrix ensemble \mathcal{E} over $\mathbb{F}^{N \times N}$ of size K is defined as a set of \mathcal{D} -distributed random matrices $\mathcal{E} = \{P_i \sim \mathcal{D} \mid P_i \in \mathbb{F}^{N \times N}\}_{i=1}^K$. In simple words, it is simply a collection of K iterations of a specified class of random matrix.*

So, for example, we could compute a simple ensemble of matrices as follows.

Code Example 1.2.1 (Standard Normal Hermitian Ensemble). *Let $\mathcal{D} = \mathcal{N}(0, 1)^\dagger$. We can generate $\mathcal{E} \sim \mathcal{D}$ over \mathbb{C} , an ensemble of 4×4 complex Hermitian standard normal matrices of size 10 as such:*

```
# Using the RMAT package
library(RMAT)
# Note that RM_norm takes mean = 0 and sd = 1 as default values.
ensemble <- RME_norm(N = 4, cplx = TRUE, herm = TRUE, size = 10)

# Outputs the following
ensemble

...
[[10]]
      [,1]      [,2]      [,3]      [,4]
[1,] 0.1058257 -1.0835598 -0.7031727  1.01608625
[2,] -0.2170453  1.8206070 -0.4539230  0.06828296
[3,]  1.3002145  0.1254992 -0.5214005 -0.61516174
[4,] -1.0398587  0.1975445 -0.8511950  0.86366082
```

1.3 Special Ensembles

With this in mind, we will gloss over, characterize, and briefly discuss a few special recurring ensembles in this thesis.

1.3.1 Hermite β -Ensembles

The Hermite β -Ensembles will be one of the primary ensembles discussed in this thesis. This ensemble will be characterized, motivated, and defined more thoroughly in **Chapter 4**. However, we will give a brief introduction to the ensemble.

At a practical level, all one would need to know is that the matrices are generated in accordance to an algorithm found in the appendix (B.1.4) and in Chapter 4.

1.3.2 Erdos-Renyi p -Ensembles

The Hermite β -ensembles are a normal-like class of random matrices. Now, we will veer away from the normal distribution as a whole and switch to a different class of matrices: stochastic matrices. Stochastic matrices, in short, are matrices that represent Markov Chains (see A.3.1). We can also think of them as the matrix representation of a specific setup of a walk on a random graph.

A particular class of random graphs that we will consider are the Erdos-Renyi random graphs. Essentially, these are graphs whose vertices are connected with a uniform probability p . We can interpret this as saying an Erdos-Renyi graph is a simple random walk on a graph with parameterized sparsity (given by p). Without further ado, we motivate the Erdos-Renyi graph:

Definition 1.3.1 (Erdos-Renyi Graph). *An Erdos-Renyi graph is a graph $G = (V, E)$ with a set of vertices $V = \{1, \dots, N\}$ and edges $E = \mathbb{1}_{i,j \in V} \sim \text{Bern}(p_{ij})$. It is homogenous if $p_{ij} = p$ is fixed for all i, j .*

Essentially, an Erdos-Renyi graph is a graph whose 'connectedness' is parameterized by a probability p (assuming it's homogenous, which this document will unless otherwise noted). As $p \rightarrow 0$, we say that graph becomes more sparse; analogously, as $p \rightarrow 1$ the graph becomes more connected.

Recall from probability theory that a sum of i.i.d Bernoulli random variables is a Binomial variable. As such, we may alternatively say that the degree of each vertex v is distributed as $\deg(v) \sim \text{Bin}(N, p)$ where N is the number of vertices. This makes simulating the graphs much easier.

Code Example 1.3.1 (Erdos-Renyi $p = 0.5$ Ensemble). *Let $\mathcal{D} = \text{Erdos}(p = 0.5)$. We can generate $\mathcal{E} \sim \mathcal{D}$, an ensemble of 4×4 Erdos-Renyi matrices ($p = 0.5$) of size 10 as such:*

```
# Using the RMat package
library(RMat)
ensemble <- RME_erdos(N = 4, p = 0.5, size = 10)

# Outputs the following
ensemble

...
[[10]]
      [,1]      [,2]      [,3]      [,4]
[1,] 0.0000000 0.37154735 0.6284527 0.0000000
[2,] 0.0000000 0.08954572 0.3362090 0.5742453
[3,] 0.6058502 0.00000000 0.3941498 0.0000000
[4,] 0.0000000 0.64146116 0.0000000 0.3585388
```

1.4 Analytical Results

Chapter 2

Spectra

2.1 Introduction

So, what are *spectral statistics*? Do they have to do with rainbows? Sceptres? No, they don't, but they're almost as colorful and regal. The word spectral is borrowed from the spectral-like patterns observed in statistical physics - whether it may be atomic spectra or other quantum mechanical phenomena. The borrowing is loose and not literal, but still somewhat well founded. In fact, the field of Random Matrix Theory was extensively developed in the 1930s by the nuclear physicist Eugene Wigner. He found connections between the deterministic properties of atomic nuclei and their random and stochastic behaviors. The link? Random matrices.

So in the context of this thesis, *spectral statistics* will be an umbrella term for random matrix statistics that somehow involve that matrix's eigenvalues and eigenvectors. That being said, if we fix a *random matrix*, we can study its features by studying its eigenvalues - fundamental numbers that tell us a lot about the matrix. They are quite important for many reasons. For instance in statistical physics, many processes are represented by operators or matrices, and as such, their behaviours could be partially determined by the eigenvalues of their corresponding matrices. The study of eigenvalues and eigenvectors primarily falls in the scope of Linear Algebra, but their utility is far-reaching. So, what exactly are *eigenvalues* exactly?

2.1.1 The Quintessential Spectral Statistic: the Eigenvalue

Given any standard square matrix $P \in \mathbb{F}^{N \times N}$, its *eigenvalues* are simply the roots of the characteristic polynomial $\text{char}_P(\lambda) = \det(P - \lambda I)$. By the Fundamental Theorem of Algebra, we know that there is always have as many complex eigenvalues $\lambda \in \mathbb{C}$ as the dimension of the matrix.

That being said, when our random matrix has a specified distribution (say, standard normal), we can see patterns in the eigenvalue distributions. So, an eigenvalue is a **spectral statistic** of a random matrix! To talk about a matrix's eigenvalues in a more formal and concise manner, we motivate what is the eigenvalue spectrum.

Definition 2.1.1 (Spectrum). Suppose $P \in \mathbb{F}^{N \times N}$ is a square matrix of size N over \mathbb{F} . Then, the (eigenvalue) spectrum of P is defined as the multiset of its eigenvalues and it is denoted $\sigma(P) = \{\lambda_i \in \mathbb{C}\}_{i=1}^N$. Note that it is important to specify that a spectrum is a multiset and not just a set; eigenvalues could be repeated due to algebraic multiplicity and we opt to always have N eigenvalues.

2.1.2 Interlude: Ensembles

While the spectrum of a matrix provides a good summary of the matrix, a matrix is only considered a single point/observation in random matrix theory. Additionally, simulating large matrices and computing their eigenvalues becomes harder and more computationally expensive as $N \rightarrow \infty$. As such, to obtain more eigenvalue statistics efficiently, another dimension is introduced by motivating the *random matrix ensemble*.

[Definition was here]

Now that matrix ensembles are well defined, we can motivate a core object of our study - the spectrum of a random matrix ensemble. From its name, it is indeed what one might expect it to be.

Definition 2.1.2 (Ensemble Spectrum). If we have an ensemble \mathcal{E} , then we can naturally extend the definition of $\sigma(\mathcal{E})$. To take the spectrum of an ensemble, simply take the union of the spectra of each of its matrices. In other words, if $\mathcal{E} = \{P_i \sim \mathcal{D} \mid P_i \in \mathbb{F}^{N \times N}\}_{i=1}^K$, then $\sigma(\mathcal{E}) = \bigcup_{i=1}^K \sigma(P_i)$.

A common theme in this thesis will be that singleton matrices do not provide insightful information on their own. Rather, it is the collective behavior of a \mathcal{D} -distributed ensemble that tells us about how \mathcal{D} impacts our spectral statistics. So in a way, ensemble statistics are the engine of this research.

2.2 Ordered Spectra

2.2.1 Eigenvalue Ordering

When we motivate the idea of matrix dispersion in the next section, we will consider order statistics of that matrix's eigenvalues in tandem with its dispersion. However, to do so presupposes that we have a sense of what *ordered* eigenvalues means. Take a matrix P and its *unordered* spectrum $\sigma(P) = \{\lambda_j\}$. It is paramount to know what ordering scheme $\sigma(P)$ is using, because otherwise, the eigenvalue indices are meaningless! So, to eliminate confusion, we add an index to σ that indicates how the spectrum is ordered. Often, the ordering context will be clear and the indexing will be omitted. Consider the two following *ordering schema*:

Standard definitions of an ordered spectrum follows the standard ordering in the reals; denote this as the ordering by the **sign scheme**. Note that because total-ordering is only well-defined on the reals, we can only use this scheme when on a spectrum with real entries. So, we write the *sign-ordered spectrum* as follows:

$$\sigma_S(P) = \{\lambda_j : \lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_N\}_{j=1}^N$$

Alternatively, we can motivate a different scheme that properly handles complex eigenvalues. We could sort the spectrum by the norm of its entries; denote this as ordering using the *norm scheme*. This way, all the eigenvalues are mapped to a real value, in which we could use the sign-scheme of ordering. Without further ado, we write the *norm-ordered spectrum* as follows:

$$\sigma_N(P) = \{\lambda_j : |\lambda_1| \geq |\lambda_2| \geq \dots \geq |\lambda_N|\}_{j=1}^N$$

Note that when we take the norms of the eigenvalues, we essentially ignore "rotational" features of the eigenvalues. Signs of eigenvalues indicate reflection or rotation, so when we take the norm, we essentially become more concerned with scaling.

2.2.2 Singular Values

An alternative to using the norm ordering scheme is using the singular values of the matrix. If a matrix is symmetric, the singular values are simply the norm of the eigenvalues. We ignore rotational features and focus solely on scale when we do so.

2.2.3 Order Statistics

With eigenvalue ordering unambiguous and well-defined, we may proceed to start talking about their order statistics. In short, given a random sample of fixed size, order statistics are random variables defined as the value of an element conditioning on its rank within the sample. (See A.2.2)

In general, order statistics are quite useful and tell us a lot about how the eigenvalues distribute given a distribution. They tell us how the eigenvalues space themselves and give us useful upper and lower bounds.

For example, the maximum of a sample is an order statistic concerned with the highest ranked element. In our case, this could correspond to the largest eigenvalue of a spectrum. After all, a spectrum is a random sample of fixed size, so this statistic is well-defined.

Example 2.2.1 (The Largest Eigenvalue). *Suppose we have seek the largest eigenvalue distribution for a ensemble distribution \mathcal{D} , we would simulate an ensemble \mathcal{E} and observe λ_1 for each of its matrices. Then, we can set the distribution of the largest eigenvalue for \mathcal{D} by observing the distribution of λ_1 .*

So, we will consider the conditional order statistics $\mathbb{E}(\lambda_i | i)$ and $\text{Var}(\lambda_i | i)$.

2.2.4 Case Study: Tracy-Widom Distribution

Distribution of the normalized largest eigenvalue. Let λ_1 denote the largest eigenvalue. Then, let $\langle \lambda_j - \lambda_i \rangle$ be the mean eigenvalue spacing (of consecutive eigenvalues).

The Tracy-Widom distribution is the distribution of $\frac{(\lambda_1 - 2\sqrt{N})n^{1/6}}{\langle \lambda_j - \lambda_i \rangle}$.

[Plot]

2.3 Symmetric and Hermitian Matrices

2.3.1 Introduction

A very important class of matrices in Linear Algebra is that of Symmetric or Hermitian matrices (See A.1.2). Simply put, those are matrices which are equal to their conjugate transpose.

Note: Since real numbers are their own conjugate transpose, every Symmetric matrix is Hermitian. However, we will still delineate the two terms to avoid confusion.

In any case, one critical result in Linear Algebra that will be extensively wielded in this thesis is the fact that a matrix is Symmetric or Hermitian if and only if it has real eigenvalues. In other words:

$$P = \overline{P^T} \iff \sigma(P) = \{\lambda_i \mid \lambda_i \in \mathbb{R}\}$$

Having a complete set of real eigenvalues yields many great properties. For instance, if all eigenvalues are real, we have the option of observing either the sign-ordered spectrum or the norm-ordered spectrum. This way, we can preserve negative signs and we would not lose the rotational aspect of the eigenvalue when we study its statistics. That is just one reason out of many more why having real eigenvalues is quite nice.

2.3.2 Case Study: Wigner's Semicircle Distribution

2.4 Findings

Chapter 3

Dispersions

3.1 Introduction

In this section, we define the final spectral statistic studied in this chapter: eigenvalue dispersions. As the name suggests, these statistics are concerned with the distribution of the spacings between the eigenvalues.

Oddly enough, this is almost as literal as it gets when we use the word "spectral". In physics and chemistry, atomic spectra are essentially differences between energy levels or quanta, so the translation is close.

In any case, we motivate a few definitions and formalisms in this section, then motivate the definition of a matrix's eigenvalue dispersion. To start off, we define an object useful for pairing our eigenvalues together, the pairing scheme.

3.1.1 Dispersion Metrics

Before we may even start to consider studying dispersions of eigenvalues, we must first formalize and make clear what version of spacing we are using. To do so, we motivate the dispersion metric.

Definition 3.1.1 (Dispersion Metric). *A dispersion metric $\delta : \mathbb{C} \times \mathbb{C} \rightarrow \mathbb{R}^+$ is defined as a function from the space of pairs of complex numbers to the positive reals. In simple terms, it is a way of measuring "space" between two complex numbers - our eigenvalues.*

Note, there is one special case where the domain of δ is not \mathbb{R}^+ , that is when we are taking the simple difference of two complex numbers. In this case, the range of δ is also \mathbb{C} . We will denote this as the "identity difference" metric and call it δ_{id} .

Consider the following dispersion metrics below. Out of those 4 dispersion metrics, only the first one has a range of \mathbb{C} . The rest have a range of \mathbb{R}^+ . Additionally, the second and third metrics are *symmetric* operations while the rest are not. The β -norm is only a symmetric operation when β is even.

1. The identity difference: $d_{id}(z, z') = z' - z$

2. The standard norm: $d_n(z, z') = |z' - z|$
3. The β -norm: $d_\beta(z, z') = |z' - z|^\beta$
4. The difference of absolutes: $d_{ad}(z, z') = |z'| - |z|$

3.1.2 Pairing Schema

You are a studious student, earnest to learn about eigenvalue spacings, for some reason. So you begin, and the first question pops into your head.

Student: For which eigenvalue pairs will we observe their dispersion?

Wigner's Ghost: The ones specified by the pairing scheme.

Unphased by the fact you are meeting a ghost from the 1990s - a wild spirit you are - you find it a good idea to interrogate the ghost physicist.

The student, irritated about having to learn yet another snippet of loaded notation complains and asks:

Student: Aha! Why don't we just look at all the eigenvalue pairs? Isn't more information always better?

Wigner's Ghost: Actually, no. We will later find out a few reason taking all pairs isn't best. For instance, some spacings are linear combination of others. Or if we have a dispersion metric that is symmetric, half of the information is going to be repeated!

1. The unique pair combinations are two related pair schema. By specifying $i > j$ or $i < j$, we are able to obtain all unique pairs of unique indices. The reason we call them upper and lower pair combinations is in reference to the indices of the upper and lower triangular matrices.

- (a) Let $\Pi_{>}$ be the set of unique (lower-pair) combinations of ordered eigenvalues. This will be the standard ordered pair scheme used in lieu of our dispersion metric argument orders (more later). In this pairing scheme, the eigenvalue with the lower rank is always listed first, and the higher rank second.

$$\Pi_{>} = \{\pi_{ij} = (\lambda_i, \lambda_j) \mid i > j\}_{i=1}^{N-1}$$

- (b) For completeness, we will also define $\Pi_{<}$. This is the set of (upper-pair) unique combinations of ordered eigenvalues. Wont be used because we want bigger - smaller to make positive definite.

$$\Pi_{<} = \{\pi_{ij} = (\lambda_i, \lambda_j) \mid i < j\}_{i=1}^{N-1}$$

Benefits: Solves the issue of repeated pairs for symmetric metrics.

2. Let Π_C be the consecutive pairs of eigenvalues in a spectrum. This pairing scheme gives us the minimal information needed to express important bounds and spacings in terms of its elements.

$$\Pi_C = \{\pi_j = (\lambda_{j+1}, \lambda_j)\}_{j=1}^{N-1}$$

Special pairs:

1. Let Π_1 be the largest pair of eigenvalues of a spectrum. Nice and simple.

$$\Pi_1 = \{(\lambda_2, \lambda_1)\}$$

[Plot showing difference when using different graphs]

3.1.3 Dispersions!

Finally, we are able to motivate the definition of a matrix dispersion! Suppose we have a \mathcal{D} -distributed random matrix $P \in \mathbb{F}^{N \times N}$ or a random matrix ensemble $\mathcal{E} = \{P_i \sim \mathcal{D} \mid P_i \in \mathbb{F}^{N \times N}\}$. Then we define their dispersion as follows.

Definition 3.1.2 (Dispersion). *The dispersion of a matrix $P \in \mathbb{F}^{N \times N}$ with respect to a dispersion metric $d : \mathbb{C} \times \mathbb{C} \rightarrow \mathbb{F}$ and pairing scheme Π , call it $\Delta_d(P, \Pi)$, is defined as follows. Suppose $\sigma(P) := \mathbb{S}$ is the ordered spectrum of P where $\sigma(P) = \{\lambda_1, \dots, \lambda_N\}$. Then, let $\Pi = \{\pi_{ij} = (\lambda_i, \lambda_j)\} \subseteq \mathbb{S}^2$ be a subset of eigenvalue ordered pairs. Then, the dispersion of P with respect to d is simply the set $\Delta_d(P, \Pi) = \{\delta_{ij} = d(\pi_{ij}) \mid \pi_{ij} = (\lambda_i, \lambda_j) \in \Pi\}$.*

As we usually do, we define the dispersion of an ensemble in a similar fashion.

Definition 3.1.3 (Ensemble Dispersion). *If we have an ensemble \mathcal{E} , then we can naturally extend the definition of $\Delta_d(\mathcal{E}, \Pi)$. To take the dispersion of an ensemble, simply take the union of the dispersions of each of its matrices. In other words, if $\mathcal{E} = \{P_i \sim \mathcal{D} \mid P_i \in \mathbb{F}^{N \times N}\}_{i=1}^K$, then $\Delta_d(\mathcal{E}, \Pi) = \bigcup_{i=1}^K \Delta_d(P_i, \Pi)$.*

With our spectral statistics defined, we are prepared to discuss prominent results in Random Matrix Theory alongside our new findings from the simulations.

3.2 Order Statistics**3.2.1 Introduction**

With eigenvalue dispersions and eigenvalue orderings well-defined, we may proceed to start talking about their order statistics.

In addition to these simple order statistics, we introduce a new variant statistic called the **ranking difference class**. Instead of observing a single eigenvalue at a given rank, we will now observe a pair of eigenvalues at a time. To standardize the process, we introduce a new equivalence class called the *ranking difference*. As suggested, it is precisely the integer difference of the eigenvalue ranks.

Definition 3.2.1 (Ranking Difference). *The ranking difference is a function $\delta : \mathbb{N} \times \mathbb{N} \rightarrow \mathbb{N}$ which takes the index of two eigenvalues (from an ordered spectrum) and returns their difference. In other words, $\delta : (\lambda_i, \lambda_j) \mapsto (i - j)$.*

With the function δ , we may take the set of unique eigenvalue pairs $(i > j)$ and partition it into equivalence classes. To do so, we define the equivalence relation \sim_δ which says $(\lambda_a, \lambda_b) \sim_\delta (\lambda_c, \lambda_d) \iff (a - b) = (c - d)$. These equivalence classes then naturally correspond to pairs a set distance $\rho = i - j$ apart. So, for an $N \times N$ matrix, δ assumes a range $\rho \in \{1, \dots, N - 1\}$.

In summary, \sim_δ takes the set $\{(\lambda_i, \lambda_j) \mid \lambda_i, \lambda_j \in \sigma(P) \text{ and } i > j\}$ and surjectively partitions it onto the equivalence classes $[(\lambda_i, \lambda_j)]_\rho$ for $\rho \in \{1, \dots, N - 1\}$. For example, if we consider $\rho = 1$, then we are considering all pairs of eigenvalue neighbors.

Note that the sizes of each equivalence class are **never equal**. With this partition in mind, we can consider various statistics conditioning on the value of ρ . Conditioning on ρ will be especially useful in the cases where we are considering matrices like the Hermite- β matrices; the eigenvalues of those matrices tend to *repel*, so to speak, and we can observe these patterns using ρ .

3.2.2 Conditional Statistics

We will considering the conditional statistics $\mathbb{E}(\delta_{ij} \mid \rho)$ and $\text{Var}(\delta_{ij} \mid \rho)$.

3.3 Analytical Results

3.3.1 Case Study: Wigner's Surmise

Limiting distribution of the eigenvalue spacings of symmetric matrices.

[Plot]

3.4 Findings

Chapter 4

β -Ensembles

4.1 Introduction

In this chapter, we will talk about the Hermite β -ensembles more in depth. The beta ensembles have wide applications in statistical physics, engineering, and many other places. They are defined by the joint density of their eigenvalues, and have a special characterization discussed in the next subsection.

4.1.1 Hermite β -Ensembles

The Hermite β -ensembles, also called the Gaussian ensembles, are an important class of random matrix ensembles studied in engineering, statistical physics, and probability theory. Parameterized by $\beta \in \mathbb{N}$ through the Dyson index, this ensemble is characterized by a few things.

- The Dyson index β corresponds to the number of real number of components the subject matrices have.
- The subject matrices are classically defined for $\beta = 1, 2, 4$ and they correspond to matrices with real, complex, and quaternionic entries. The corresponding fields are \mathbb{R} , \mathbb{C} , and \mathbb{H} .
- The matrices in this ensemble, most importantly, have a feature called conjugation invariance. With respect to the conjugation by the respective group of matrices.
- Most importantly, the eigenvalues are determined by the joint probability density function given below.

Definition 4.1.1 (Hermite β -ensembles). *The Hermite β -ensembles, commonly known as the Gaussian ensembles, are an ensemble of random matrices parameterized by β , and their eigenvalues have the joint probability density function:*

$$f_{\beta}(\Lambda) = c_H^{\beta} \prod_{i < j} |\lambda_i - \lambda_j|^{\beta} e^{-1/2 \sum_i \lambda_i^2}$$

where the normalization constant c_H^β is given by:

$$c_H^\beta = (2\pi)^{-n/2} \prod_{j=1}^n \frac{\Gamma(1 + \beta/2)}{\Gamma(1 + \beta j/2)}$$

To simulate matrices from the β -ensemble, we will be using a recent result published in “Matrix Models for Beta Ensembles” Dumitriu (2018). This makes the β -ensemble a canonical example of an implicitly distributed matrix; we do not care about the actual distribution of the entries, but rather the effect they have on the eigenvalues (trace) of the matrices. The algorithm used is directly cited from the results of Dumitriu’s paper, and can be found in Algorithms B.1.3.

Code Example 4.1.1 (Hermite Beta = 2 Ensemble). *Let $\mathcal{D} = \mathcal{H}(\beta = 2)$. We can generate $\mathcal{E} \sim \mathcal{D}$, an ensemble of 4×4 Hermite matrices ($\beta = 2$) of size 10 as such:*

```
# Using the RMAT package
library(RMAT)
ensemble <- RME_beta(N = 4, beta = 2, size = 10)

# Outputs the following
ensemble

...
[[10]]
      [,1]      [,2]      [,3]      [,4]
[1,] 0.3812855 2.592124 0.0000000 0.0000000
[2,] 2.5921244 1.362211 1.4197438 0.0000000
[3,] 0.0000000 1.419744 0.8220259 0.3917667
[4,] 0.0000000 0.000000 0.3917667 -0.9740052
```

4.1.2 Dimitriu’s Matrix Model

To generate Hermite β matrices, we consider the result of Dimitriu’s paper. We obtain the following algorithm.

Algorithm 4.1.1 (Dimitriu’s Beta Matrix).

1. Fix $N \in \mathbb{N}$.
2. Start by taking a diagonal of $\mathcal{N}(0, 2)$ variables.
3. Set both of the nearest off-diagonals to the row that samples from a $\chi(df_i = df_i)$ where $df_i = \beta * i$ for columns going from $i = 1$ to $i = n - 1$.

4.2 Spectra

We know that β -matrices must be symmetric. So, their eigenvalues must be real. Any imaginary component we observe is simply computational error, and we may safely ignore it. It is good to see that the error is uniform and small.

4.3 Dispersions

Consider the following plot of the sign-sorted eigenvalue dispersions below.

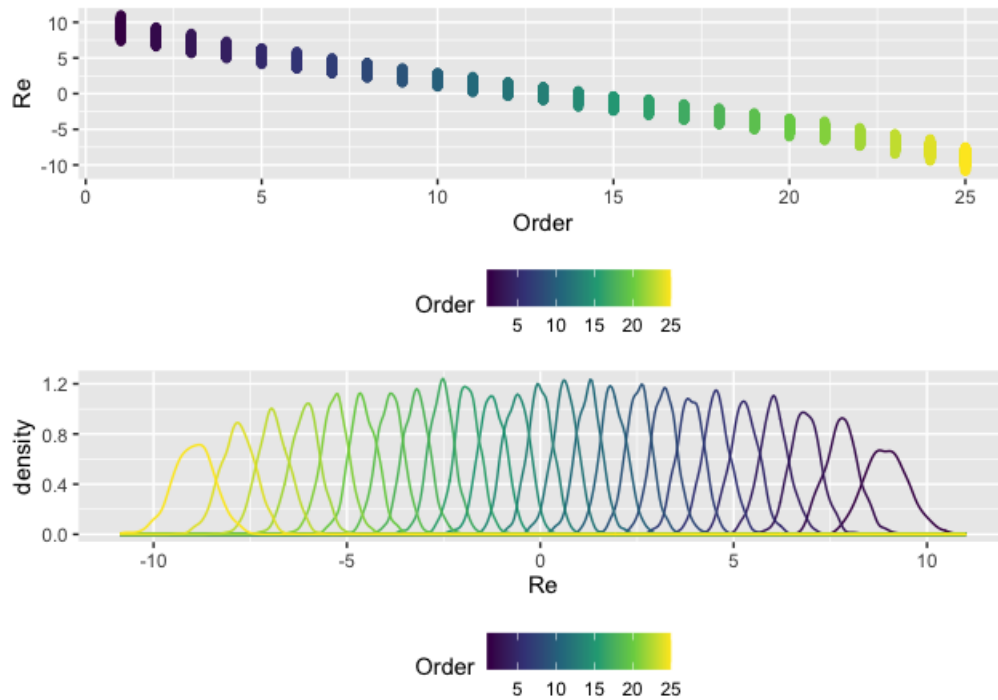


Figure 4.1: Dispersions of a $\beta = 4$ matrix with respect to ranking difference

Appendix A

Math Review

A.1 Linear Algebra

A.1.1 Introduction

Definition A.1.1 (Eigenvalue).

Definition A.1.2 (Eigenvector).

Definition A.1.3 (Transpose Matrix).

Definition A.1.4 (Symmetric Matrix).

Definition A.1.5 (Hermitian Matrix).

A.1.2 Proof: Real Symmetric Matrices have Real Eigenvectors

Notation. For notational convenience, for any $N \in \mathbb{N}$, let $\widetilde{N} = \{1, \dots, N\}$.

In this document, we prove that for any $M \times M$ real symmetric matrix, S_M , there exists for some eigenvalue λ , a corresponding ****real**** eigenvector $\vec{v} \in \mathbb{R}^M$. Prior to starting the main proof, we begin with a lemma.

Lemma. Suppose we have a $M \times M$ real symmetric matrix with a some eigenvalue λ . If there we have a corresponding eigenvector $v \in \mathbb{C}^M$, then every entry of v , say v_i is equal to a ****real**** linear combination of the other entries $v_j \mid j \neq i$.

So, we will show that:

$$\forall i \in \widetilde{M} : v_i = \sum_{j \neq i} c_j v_j \quad (c_j \in \mathbb{R})$$

Proof of Lemma. Begin by taking a real symmetric matrix S_M for some $M \in \mathbb{N}$. Suppose we have an eigenvalue λ . Then, if we have some eigenvector v , we know that:

$$(1) : \forall i \in \widetilde{M} : a_1 v_1 + \dots + d_i v_i + \dots + a_{m-1} v_m = \lambda v_i \quad (a_j \in \mathbb{R})$$

We obtain (1) by expanding the equality $Av = \lambda v$ and noticing that every row of Av is expressible as the sum of the non-diagonal entries multiplied by $v_j \mid j \neq i$ plus $d_i v_i$. Note that since our matrix is symmetric, for some rows, some of the constants a_j are not distinct but this should not raise any issues. Next, we collect the terms:

$$\forall i \in \widetilde{M} : a_1 v_1 + \dots + a_{m-1} v_m = v_i(\lambda - d_i)$$

Since S_M is a real symmetric matrix, the a_j terms are real so we can say:

$$\forall i \in \widetilde{M} : v_i(\lambda - d_i) = \sum_{j \neq i} a_j v_j \quad (a_j \in \mathbb{R})$$

Finally, divide both sides by $(\lambda - d_i)$. Since S_M is a real symmetric matrix, we know $\lambda \in \mathbb{R}$ then also $(\lambda - d_i) \in \mathbb{R}$. On the right hand side, the coefficients of the v_j become $\frac{a_j}{(\lambda - d_i)}$. Since $a_j \in \mathbb{R}$, then also $\frac{a_j}{(\lambda - d_i)} \in \mathbb{R}$. Letting $c_j = \frac{a_j}{(\lambda - d_i)}$, we obtain:

$$\forall i \in \widetilde{M} : v_i = \sum_{j \neq i} c_j v_j \quad (\forall j : c_j \in \mathbb{R})$$

Thus, for any $M \in \mathbb{N}$, a real symmetric matrix with eigenvalue λ must have a corresponding eigenvector v such that each of its entries is expressible as a real linear combination of the other entries. \square

Now, we will prove the main theorem.

Theorem (Taqi). Suppose we have a $M \times M$ real symmetric matrix, S_M . Then, we will show that there exists for some eigenvalue λ , a corresponding ****real**** eigenvector $\vec{v} \in \mathbb{R}^M$.

Proof. For this proof we will induct on the dimension of the matrix, M . So let the inductive statement be

$$f(M) : S_M \text{ has a real eigenvector } v \text{ corresponding to an eigenvalue } \lambda$$

Base Case. Take the base case $M = 2$. Then by **Zoom Meeting 11.12**, we know $f(2)$ is true.

Inductive Step. For our inductive step, we need to show that $f(M) \Rightarrow f(M+1)$. So, let us assume $f(M)$. This means that we can assume any real symmetric matrix S_M has a real eigenvector $v \in \mathbb{R}^M$ corresponding to λ .

Next, we will write S_{M+1} as the matrix S_M augmented by some $u \in \mathbb{R}^M$ as follows:

$$S_{M+1} = \left[\begin{array}{c|c} S_M & u \\ \hline u^T & d_{M+1} \end{array} \right]$$

From our lemma, we use the fact that S_{M+1} is symmetric and our assumption of $f(M)$ to obtain:

$$(1) : \forall i \in \{1, \dots, m+1\} : v_i = \sum_{j \neq i} c_j v_j \quad (c_j \in \mathbb{R})$$

$$(2) : \forall i \in \tilde{M} : v_i \in \mathbb{R}$$

In particular for (2), we know that $v_i = \left(\sum_{j \neq i} \frac{a_j}{d_i - \lambda} v_j \right)$.

From (1), we know that for row $i = m+1$: $v_{m+1} = \sum_{j \neq m+1} c_j v_j$ ($c_j \in \mathbb{R}$) By (2), this is a linear combination of real entries v_i . Since $v_{m+1} \in \mathbb{R}$, it follows that:

$$\forall i \in \{1, \dots, m+1\} : v_i \in \mathbb{R}$$

So, we have established that $f(m) \Rightarrow f(M+1)$.

By the induction, the theorem is proved. \square .

A.2 Probability Theory

A.2.1 Introduction

Definition A.2.1 (Random Variable). *A random variable $X : \Omega \rightarrow \mathbb{R}$ is a function from some sample space $\Omega = \{s_i\}_{i=1}^n$ to the real numbers \mathbb{R} . The sample space is taken to be any set of events such that the probability function corresponding to the random variable, p_X exhausts over all the events in Ω . In other words, we expect $\int_{\Omega} p_X(s) = 1$.*

Definition A.2.2 (Order Statistic). *The i th order statistic*

A.3 Markov Chains

Definition A.3.1 (Markov Chain). *Say a set of random variables X_i each take a value in a set, called the state space, $S_M = \{1, 2, \dots, M\}$. Then, a sequence of such random variables X_0, X_1, \dots, X_n is called a Markov Chain if the following conditions are satisfied:*

- $\forall X_i : X_i$ has support and range $S_M = \{1, 2, \dots, M\}$.
- (Markov Property) The transition probability from state $i \rightarrow j$, $P(X_{n+1} = j \mid X_n = i)$ is conditionally independent from all past events in the sequence $X_{n-1} = i', X_{n-2} = i'', \dots, X_0 = i^{(n-1)}$, excluding the present/last event in the sequence. In other words, given the present, the past and the future are conditionally independent.

$$\forall i, j \in S_M : P(X_{n+1} = j \mid X_n = i) = P(X_{n+1} = j \mid X_n = i, X_{n-1} = i', \dots, X_0 = i^{(n-1)})$$

Definition A.3.2 (Transition Matrix). *Let X_0, X_1, \dots, X_M be a Markov Chain with state space S_M . Letting $q_{ij} = P(X_{n+1} = j \mid X_n = i)$ be the transition probability from $i \rightarrow j$, then the matrix $Q \in \mathcal{M}_{\mathbb{R}^+}[M \times M] : Q = (q_{ij})$ is the transition matrix of the chain. Q must satisfy the following conditions to be a valid transition matrix:*

Definition A.3.3 (Transition Matrix). *Take a Markov Chain with states $1, \dots, M$. Letting $q_{ij} = P(X_{n+1} = j \mid X_n = i)$ be the transition probability from $i \rightarrow j$, then the matrix $Q = (q_{ij})$ is the transition matrix of the chain. For this transition matrix to be valid, its rows have to be stochastic, meaning their entries sum to 1; $\forall i \in 1, \dots, M : \sum_{j \in 1, \dots, M} q_{ij} = 1$.*

- Q is a non-negative matrix. That is, note that $Q \in \mathcal{M}_{\mathbb{R}^+}[M \times M]$ so every $q_{ij} \in \mathbb{R}^+$. This follows because probabilities are necessarily non-negative values.
- The entries of every row i of Q must sum up to 1. This may be understood as applying the law of total probability to the event of transitioning from any given state $\forall i \in S_M$. In other words, the chain has to go somewhere with probability 1.

$$\forall i \in S_M : \sum_{j \in S_M} q_{ij} = 1$$

- Note, it is NOT necessary that the converse holds. The columns of our transition matrix need not sum to 1 for it to be a valid transition matrix.

Definition A.3.4 (n-Step Transition Probability). *The n -step transition probability of $i \rightarrow j$ is the probability of being at j exactly n steps after being at i . We denote this value $q_{ij}^{(n)}$:*

$$q_{ij}^{(n)} : P(X_n = j \mid X_0 = i)$$

Realize:

$$q_{ij}^{(2)} = \sum_{k \in S_M} q_{ik} \cdot q_{kj}$$

Because by definition, a Markov Chain is closed under a support/range of S_M so the event $i \rightarrow j$ may have taken any intermediate step $k \in S_M$. Realize by notational equivalence, $Q^2 = (q_{ij}^{(2)})$. Inducting over n , we then obtain that:

$$q_{ij}^{(n)} \text{ is the } (i, j) \text{ entry of } Q^n$$

Definition A.3.5 (Marginal Distribution of X_n). *Let $\mathbf{t} = (t_1, t_2, \dots, t_M)$ such that $\forall i \in S_M : t_i = P(X_0 = i)$ So, $\mathbf{t} \in \mathcal{M}_{\mathbb{R}}[1, M]$. Then, the marginal distribution of X_n is given by the product of the vector $\mathbf{t}Q^n \in \mathcal{M}_{\mathbb{R}}[1, M]$. That is, the j^{th} component of that vector is $P(X_n = j)$ for any $j \in S_M$. We may call \mathbf{t} an initial state distribution.*

A.3.1 Classification of states

- A state $i \in S_M$ is said to be **recurrent** if starting from i , the probability is 1 that the chain will *eventually* return to i . If the chain is not recurrent, it is **transient**, meaning that if it starts at i , there is a non-zero probability that it never returns to i .
- Caveat: As we let $n \rightarrow \infty$, our Markov chain will guarantee that all transient states will be left forever, no matter how small the probability is. This can be proven by letting the probability be some ε , then realizing that by the support of $\text{Geom}(\varepsilon)$ is always some finite value, then the equivalence between the Markov property and independent Geometric trials guarantees the existence of some finite value such that there is a success of never returning to i .

Definition A.3.6 (Reducibility). *A Markov chain is said to be **irreducible** if for any $i, j \in S_M$, it is possible to go from $i \rightarrow j$ in a finite number of steps with positive probability. In other words:*

$$\forall i, j \in S_M : \exists n \in \mathbb{N} : q_{ij}^{(n)} > 0$$

- From our quantifier formulation of irreducible Markov chains, note that we can equivalently say that a chain is irreducible if there is integer $n \in \mathbb{N}$ such that the (i, j) entry of Q^n is positive for any i, j .
- A Markov chain is **reducible** if it is not **irreducible**. Using our quantifier formulation, it means that it suffices to find transient states so that:

$$\exists i, j \in S_M : \nexists n \in \mathbb{N} : q_{ij}^{(n)} > 0$$

Appendix B

Algorithm Appendix

B.1 Matrix Simulation

B.1.1 Stochastic Matrices

Algorithm B.1.1 (Stochastic Matrix).

1. Fix $N \in \mathbb{N}$.

Algorithm B.1.2 (Symmetric Stochastic Matrix).

1. Fix $N \in \mathbb{N}$.

Algorithm B.1.3 (Transition Matrix of an Erdos-Renyi Graph).

1. Fix $N \in \mathbb{N}$ and $p \in [0, 1]$.
2. Generate a matrix Q such that every entry $i, j \in 1, \dots, N$ is $x_{ij} \sim \text{Unif}(0, 1)$.
3. For each v_i in $\{1, \dots, N\}$, generate $\deg(v_i) \sim \text{Bin}(N, p)$.
4. Randomly chose $(1 - \deg(v_i))$ vertices, set the entries x_{ij} in the j columns to 0.
5. Renormalize the matrix by dividing each row by its sum; let $(x_i) \leftarrow (x_i) / \sum_j (x_i)$.

B.1.2 Normal Matrices

Algorithm B.1.4 (Hermite β -Matrix).

1. Fix $N \in \mathbb{N}$. Use L 's result.

Algorithm B.1.5 (Matrix).

1. Fix $N \in \mathbb{N}$.

Algorithm B.1.6 (Matrix).

1. Fix $N \in \mathbb{N}$.

Algorithm B.1.7 (Matrix).

1. Fix $N \in \mathbb{N}$.

Appendix C

Code Appendix

Appendix D

Mixing Time Simulations

D.1 Introduction

In this chapter, we'll talk about ratio-mixing time simulations. Essentially, these simulations are a method of approximating the distribution of a random transition matrix's mixing time. There will be a fun exploration of the Erdos-Renyi matrix ensembles and we will computationally show that the parameterized ensemble has a mixing time inversely proportional to graph sparsity.

D.2 Mixing Time Simulations

With the Erdos-Renyi graph defined, we may now motivate the simulation of random walks on them. First, however, we need to generate their corresponding transition matrices. An algorithm for this is outlined below.

Suppose we have simulated a transition matrix for an Erdos-Renyi graph called Q . Now, fixing some initial probability distribution $\vec{x} \in \mathbb{R}^M$, we may consider the evolution sequence of a random walk on this Erdos-Renyi graph by taking its evolution sequence $\mathcal{S}(Q, x)$.

Definition D.2.1 (Random Batches). *Let \mathbb{F} be a field, and fix some $M \in \mathbb{N}$. Let $\mathcal{B}_\lambda \subset \mathbb{F}^M$ be a uniformly random batch of points in the M -hypercube of length λ . That is,*

$$\mathcal{B}_\lambda = \{\vec{x} \mid x_i \sim \text{Unif}(-\lambda, \lambda) \text{ for } i = 1, \dots, M\}$$

Note: If $\mathbb{F} = \mathbb{C}$, then take $\vec{x} \in \mathcal{B}_\lambda$ to mean $\vec{x} = a + bi$ where $a, b \sim \text{Unif}(-\lambda, \lambda)$.

Definition D.2.2 (Evolution Sequence). *An evolution sequence of a vector $\vec{\pi}$ and a transition matrix Q is defined as the sequence $\mathcal{S}(Q, \pi) = (\pi'_n)_{n=1}^N$ where $\pi'_n = \pi Q^n$*

Definition D.2.3 (Finite Evolution Sequences). *Suppose we sample a random point from \mathcal{B}_λ , emulating a random point $\vec{v} \in \mathbb{F}^M$. Additionally, let $Q \in \mathbb{F}^{M \times M}$ be a transition matrix over \mathbb{F} . Fixing a maximum power ('time') $T \in \mathbb{N}$, define the evolution sequence of \vec{v} as follows:*

$$\mathcal{S}(v, Q, T) = (\alpha_n)_{n=1}^T \text{ where } \alpha_k = vQ^k$$

If we do not impose a finiteness constraint on the sequence, we consider powers for $n \in \mathbb{N}$ or $t = \infty$

Definition D.2.4 (Consecutive Ratio Sequences). *Accordingly, define the consecutive ratio sequence (CST) of \vec{v} as follows:*

$$\mathcal{R}(v, Q, T) = (r_n)_{n=2}^T \text{ where } (r_n)_j = \frac{(\alpha_n)_j}{(\alpha_{n-1})_j} \text{ for } j = 1, \dots, M$$

In other words, the consecutive ratio sequence of v can be obtained by performing **component-wise division** on consecutive elements of the evolution sequence of v .

Definition D.2.5 (Near Convergence). *Because these sequences may never truly converge to eigenvectors of the matrix, we formalize a notion of "near convergence". As a preliminary, we first define ε -equivalence. Let \mathbb{F} be a field, and fix $\varepsilon \in \mathbb{R}^+$. Suppose we have vectors $v, v' \in \mathbb{F}^M$. Then, $v \sim_\varepsilon v'$ if $\|v - v'\| < \varepsilon$ where $\|\cdot\|$ is the norm on \mathbb{F} .*

Let $\varepsilon \in \mathbb{R}^+$, and suppose we have an evolution sequence $(a[\vec{v}])_n$. Then, a_n ε -converges at $N \in \mathbb{N}$ if:

$$\forall n \geq N \mid a_n \sim_\varepsilon a_N$$

D.3 Erdos-Renyi Ensemble Simulations

Definition D.3.1 (Erdos-Renyi Graph). *An Erdos-Renyi graph is a graph $G = (V, E)$ with a set of vertices $V = 1, \dots, M$ and edges $E = \mathbb{1}_{i,j \in V} \sim \text{Bern}(p_{ij})$. It is homogenous if $p_{ij} = p$ is fixed for all i, j .*

Essentially, an Erdos-Renyi graph is a graph whose 'connectedness' is parameterized by a probability p (assuming it's homogenous, which this document will unless otherwise noted). As $p \rightarrow 0$, we say that graph becomes more sparse; analogously, as $p \rightarrow 1$ the graph becomes more connected.

Recall from probability theory that a sum of i.i.d Bernoulli random variables is a Binomial variable. As such, we may alternatively say that the degree of each vertex v is distributed as $\deg(v) \sim \text{Bin}(M, p)$. This is helpful to know because the process of simulating graphs becomes much simpler.

D.4 Questions

1. How are the entries of the CRS distributed? Are they normal, and if so, what is its mean?
2. Are the entries of the CRS i.i.d as $t \rightarrow \infty$?
3. For an Erdos-Renyi matrix, is the mixing time t dependent on the parameter p ?
4. What impact does the running time parameter T have on σ (the variance of the distribution of the CRS entries)?

D.4.1 Cauchy Distributed Ratios

It seems to be the case that the **log-transformed** entries of the CRS are Cauchy distributed about $\log \lambda_1$ where $\lambda_1 = \max(\sigma(Q))$, the largest eigenvalue of Q . That is,

$$r_i \sim \text{Cauchy}(\ln \lambda_1) \text{ for } i = 1, \dots, M$$

References

Dumitriu, I. (2018). Matrix models of beta ensembles. *Journal of Mathematical Physics* 43, 5830, (pp. 1–5).