

On general criteria for when the spectrum of a combination of random matrices depends only on the spectra of the components

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Main question

Given \mathbf{A} , \mathbf{B} two $n \times n$ independent square Hermitian (or symmetric) random matrices

1. What can we say about the eigenvalue distribution of \mathbf{A} , once we know those of $\mathbf{A} + \mathbf{B}$ and \mathbf{B} ?
2. What can we say about the eigenvalue distribution of \mathbf{A} , once we know those of \mathbf{AB} and \mathbf{B} ?

Such questions can also be asked starting with any functional of \mathbf{A} and \mathbf{B} . When we can infer on the mentioned eigenvalue distributions, the corresponding operation is called *deconvolution*.

Two main techniques used in the literature:

- ▶ The Stieltjes transform method,
- ▶ The method of moments.

We will focus on the latter.

Moments and mixed moments

Many probability distributions are uniquely determined by their moments $\int t^n d\mu(t)$ (Carlemans theorem), and can thus be used to characterize the spectrum of a random matrix.

- ▶ Let tr be the normalized trace, and $\mathbb{E}[\cdot]$ the expectation.
- ▶ The quantities $A_k = \mathbb{E}[\text{tr}(\mathbf{A}^k)]$ are the moments (or individual moments) of \mathbf{A} .
- ▶ More generally, if \mathbf{A}_i are random matrices,

$$\mathbb{E}[\text{tr}(\mathbf{A}_{i_1} \mathbf{A}_{i_2} \cdots \mathbf{A}_{i_k})]$$

is called a mixed moment in the \mathbf{A}_i , when $i_1 \neq i_2, i_2 \neq i_3, \dots$

- ▶ More generally, we can define a mixed moment in terms of algebras: if \mathcal{A}_i are algebras, $\mathbf{A}_i \in \mathcal{A}_{k_i}$ with $k_i \neq k_{i+1}$ for all i .

Freeness: a computational rule for mixed moments

Definition

A family of unital $*$ -subalgebras $\{A_i\}_{i \in I}$ is called a free family if

$$\left\{ \begin{array}{l} a_j \in A_{i_j} \\ i_1 \neq i_2, i_2 \neq i_3, \dots, i_{n-1} \neq i_n \\ \phi(a_1) = \phi(a_2) = \dots = \phi(a_n) = 0 \end{array} \right\} \Rightarrow \phi(a_1 \cdots a_n) = 0. \quad (1)$$

- ▶ Defined at the algebraic level. Can be thought of as “spectral separation”.
- ▶ A concrete rule for computing mixed moments in terms of individual moments ($\mathbb{E}[\text{tr}(\cdot)]$ replaced with general ϕ).
- ▶ Defining σ as the partition where $k \sim l$ if and only if $i_k = i_l$, the same formula for the mixed moment applies for any $a_1 \cdots a_n$ giving rise to σ . Is in this way a particularly nice type of spectral separation.

Instead of free algebras, assume that we have subalgebras A_i of random matrices, where any random matrix from one algebra is independent from those in the other algebras.

- ▶ For which collection of algebras do mixed moments

$$\mathbb{E}[\text{tr}(\mathbf{A}_{i_1} \mathbf{A}_{i_2} \cdots \mathbf{A}_{i_k})], \quad (2)$$

depend only on individual moments? In other words: when do we have spectral separation?

- ▶ The question is often more easily answered in the large n -limit:

$$\lim_{n \rightarrow \infty} \mathbb{E}[\text{tr}(\mathbf{A}_{i_1}^{(n)} \mathbf{A}_{i_2}^{(n)} \cdots \mathbf{A}_{i_k}^{(n)})],$$

where we now assume that we have ensembles of random matrices, their dimensions growing so that $\lim_{N \rightarrow \infty} \frac{N}{L} = c$.

- ▶ In the large n -limit, the problem is coupled with finding what modes of convergence apply. Almost sure convergence?
- ▶ When is the computational rule for computing (2) the same for any choice of matrices from the algebras, as for freeness?

If positive answers: good starting point for deconvolution.

Gaussian matrices

- ▶ If the \mathbf{A}_i are Gaussian matrices, there exist results in the finite regime [1], on computational rules for mixed moments of Gaussian matrices and matrices independent from them.
- ▶ combinations of Gaussian matrices converge almost surely.
- ▶ Asymptotically free, so same convenient computational rule in the limit as for freeness.
- ▶ No need to expect that the same computational rule applies in the finite regime!

Vandermonde matrices

An $N \times L$ Vandermonde matrix with entries on the unit circle [2] is on the form

$$\mathbf{V} = \frac{1}{\sqrt{N}} \begin{pmatrix} 1 & \dots & 1 \\ e^{-j\omega_1} & \dots & e^{-j\omega_L} \\ \vdots & \ddots & \vdots \\ e^{-j(N-1)\omega_1} & \dots & e^{-j(N-1)\omega_L} \end{pmatrix} \quad (3)$$

$\omega_1, \dots, \omega_L$, also called phases, are assumed i.i.d., taking values in $[0, 2\pi)$. N and L go to infinity at the same rate, $c = \lim_{N \rightarrow \infty} \frac{L}{N}$ (the aspect ratio).

Algebraic result for Vandermonde matrices [3]

Theorem

Let $\{\mathbf{V}_i\}_{i \in I}, \{\mathbf{V}_j\}_{j \in J}$ be independent Vandermonde matrices, with arbitrary phase distributions $\{\omega_i\}_{i \in I}$ and $\{\omega_j\}_{j \in J}$, respectively, with continuous density.

- ▶ Let \mathcal{A}_I be the algebra generated by $\{(\mathbf{V}_{i_1})^H \mathbf{V}_{i_2}\}_{i_1, i_2 \in I}$.
- ▶ Let \mathcal{A}_J be the algebra generated by $\{(\mathbf{V}_{j_1})^H \mathbf{V}_{j_2}\}_{j_1, j_2 \in J}$.

We have that any mixed moment

$$\lim_{N \rightarrow \infty} \mathbb{E} [\text{tr}(a_{i_1} a_{j_1} a_{i_2} a_{j_2} \cdots a_{i_n} a_{j_n})] \text{ with } a_{i_k} \in \mathcal{A}_I, a_{j_k} \in \mathcal{A}_J, \quad (4)$$

depends only on individual moments of the form

$$\begin{aligned} & \lim_{N \rightarrow \infty} \mathbb{E} [\text{tr}(a)] \text{ with } a \in \mathcal{A}_I, \\ & \lim_{N \rightarrow \infty} \mathbb{E} [\text{tr}(a)] \text{ with } a \in \mathcal{A}_J. \end{aligned} \quad (5)$$

Sketch of proof

We need to compute

$$\lim_{N \rightarrow \infty} \mathbb{E} \left[\text{tr} \left(\mathbf{V}_{k_1}^H \mathbf{V}_{k_2} \cdots \mathbf{V}_{k_{2n-1}}^H \mathbf{V}_{k_{2n}} \right) \right].$$

- ▶ Define $\sigma \in \mathcal{P}(2n)$ defined by $r \sim_{\sigma} s$ if and only if $\omega_{k_r} = \omega_{k_s}$,
- ▶ let σ_j be the block of σ where $\omega_{k_i} = \omega_j$ for $i \in \sigma_j$.
- ▶ For $\pi \in \mathcal{P}(n)$, define $\rho(\pi) \in \mathcal{P}(2n)$ as the partition in $\mathcal{P}(2n)$ generated by the relations:

$$k \sim_{\rho(\pi)} l \text{ if } \begin{cases} \lfloor k/2 \rfloor + 1 \sim_{\pi} \lfloor l/2 \rfloor + 1 \text{ and} \\ k \sim_{\sigma_1} l \end{cases}$$

where σ_1 defined by $r \sim_{\sigma_1} s$ if and only if $\mathbf{V}_{k_r} = \mathbf{V}_{k_s}$.

- ▶ $\mathcal{B}(n) \subset \mathcal{P}(n)$ be defined as in [3],
- ▶ write $\rho(\pi) \vee [0, 1]_n = \{\rho_1, \dots, \rho_{r(\pi)}\}$, with each $\rho_i \geq [0, 1]_{\|\rho_i\|/2}$ ($r(\pi)$ the number of blocks). Can be written so in a unique way.

By carefully collecting terms we obtain in the limit

$$\sum_{\pi \in \mathcal{B}(n)} K_{\rho, u}(2\pi)^{|\rho|-1} \prod_{i=1}^{r(\pi)} \int \prod_j \rho_{\omega_j}(x)^{|\rho_i \cap \sigma_j|} dx, \quad (6)$$

- ▶ Here ρ_{ω} is the density of the phase distribution ω .
- ▶ The $K_{\rho, u}$ are called *Vandermonde mixed moment expansion coefficients*
- ▶ When each $\mathbf{V}_{k_{2j-1}}^H \mathbf{V}_{k_{2j}}$ is in either \mathcal{A}_I or \mathcal{A}_J , in each integral $\int \prod_j \rho_{\omega_j}(x)^{|\rho_i \cap \sigma_j|} dx$, all ω_j are either contained in $\{\omega_i\}_{i \in I}$, or in $\{\omega_j\}_{j \in J}$,
- ▶ Each such integral can be written in terms of moments from either \mathcal{A}_I or \mathcal{A}_J , showing that we have spectral separation.

Due to (6), the moments of Vandermonde matrices are in the large n -limit essentially determined from

$$I_{k,\omega} = (2\pi)^{k-1} \int_0^{2\pi} p_\omega(x)^k dx. \quad (7)$$

- ▶ Reduces the dimensionality of the problem.
- ▶ In the finite regime, the moments are probably not uniquely determined from such simple quantities.

Vandermonde mixed moment expansion coefficients

- ▶ Write $\rho(\pi) = \{W_1, \dots, W_{|\rho(\pi)|}\}$,
- ▶ write $W_j = W_j \cup W_j^H$, with W_j the even elements of W_j (the \mathbf{V} -terms), W_j^H the odd elements of W_j (the \mathbf{V}^H -terms).
- ▶ Form the $|\rho(\pi)|$ equations

$$\sum_{k \in W_r^H} x_{(k+1)/2+1} = \sum_{k \in W_r} x_{k/2+1} \quad (8)$$

in n variables x_1, \dots, x_n .

- ▶ $K_{\rho,u}$ is the volume of the solution set to (8), when all x_i are constrained to $[0, 1]$.
- ▶ $K_{\rho,u}$ can be found with Fourier-Motzkin elimination, and always computes to a rational number in $[0, 1]$.
- ▶ Matrices such as Hankel and Toeplitz matrices also have asymptotic eigenvalue distributions which can be determined from such quantities.

Generalized Vandermonde matrices

Similar result exists

$$\mathbf{V} = \frac{1}{\sqrt{N}} \begin{pmatrix} e^{-j \lfloor Nf(0) \rfloor \omega_1} & \dots & e^{-j \lfloor Nf(0) \rfloor \omega_L} \\ e^{-j \lfloor Nf(\frac{1}{N}) \rfloor \omega_1} & \dots & e^{-j \lfloor Nf(\frac{1}{N}) \rfloor \omega_L} \\ \vdots & \ddots & \vdots \\ e^{-j \lfloor Nf(\frac{N-1}{N}) \rfloor \omega_1} & \dots & e^{-j \lfloor Nf(\frac{N-1}{N}) \rfloor \omega_L} \end{pmatrix}, \quad (9)$$

where f is called the *power distribution* (a function from $[0, 1)$ to $[0, 1)$). Theorem 2 will hold for such matrices also, as long as

- ▶ The power distribution is “sufficiently uniform”,
- ▶ all $\{\mathbf{V}_i\}_{i \in I}$ have the same power distribution,
- ▶ all $\{\mathbf{V}_j\}_{j \in J}$ have the same power distribution.

Note that the power distribution governing each algebra may be different!

Related matrices: Euclidean matrices [4]

- ▶ Entry (k, l) has the form $\frac{1}{n}F(\omega_k - \omega_l)$, where $\omega_1, \dots, \omega_n$ are i.i.d. with uniform distribution.
- ▶ A generalized Vandermonde matrix where the power distribution is a sum of Dirac measures corresponds to a Euclidean matrix.
- ▶ Empirical eigenvalue distribution converges to a counting measure with an accumulation point at 0, expressible in terms of the Fourier transform of F [4].
- ▶ Unknown whether we have spectral separation in the same nice way as for Vandermonde matrices, although an Euclidean matrix corresponds to a generalized Vandermonde matrix (the problem is that the power distribution is not uniform enough!).

Permutational invariance

Definition

\mathbf{A} is called permutationally invariant if the distribution of \mathbf{A} is the same as that of $P\mathbf{A}P^{-1}$ for any permutation matrix P .

Assume that \mathbf{D}_i are diagonal matrices, and consider

$$\text{tr}(\mathbf{D}_1\mathbf{A}_1 \cdots \mathbf{D}_n\mathbf{A}_n). \quad (10)$$

- ▶ If \mathbf{A}_i are permutationally invariant, the moments of the \mathbf{D}_i -matrices can be factored out in (10). Used for Vandermonde matrices. Permutational invariance thus ensures spectral separation partially.
- ▶ Permutational invariance also ensures that (10) can be split into a sum, the sum indexed over $\mathcal{P}(n)$.
- ▶ Spectral separation in \mathbf{A}_i depends on the joint distribution of the entries of the \mathbf{A}_i , which perhaps only in the limit factors into nice expressions, some which may involve only moments.

Random Matrix Library [5]






1. Implementation with support for many types of matrices: Vandermonde matrices, Gaussian matrices, Toeplitz matrices, Hankel matrices e.t.c.
2. Can generate symbolic formulas for several convolution operations,
3. Can compute the convolution with a given set of moments numerically, as would be needed in real-time applications.
4. Can perform deconvolution, where this is possible, to infer on the parameters in an underlying model.

Further work

- ▶ Find as general criteria as possible for when spectral separation is possible.
- ▶ Support for more matrices in the Random Matrix Library [5]
- ▶ Optimization of the methods in the Random Matrix Library.

- ▶ This talk is available at
<http://folk.uio.no/oyvindry/talks.shtml>
- ▶ My publications are listed at
<http://folk.uio.no/oyvindry/publications.shtml>

THANK YOU!

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