

# FREE PROBABILITY AND RANDOM MATRICES

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Mathematical Methods of Modern statistics

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## A simple example: random vectors in large dimensions

$v_1, \dots, v_k \in \mathbf{R}^N$ .

$a_i = \|v_i\|^2$  fixed.

$v_1/\|v_1\|, \dots, v_k/\|v_k\| \in \mathbf{R}^N$  chosen independently uniformly on the sphere

As  $N \rightarrow \infty$ , with high probability  $v_i$  become orthogonal: for every  $\epsilon > 0$ ,

$$P(|\langle v_i, v_j \rangle - a_i \delta_{ij}| > \epsilon) \xrightarrow{N \rightarrow \infty} 0$$

We will obtain analogous results for matrices

The geometry of matrices is more complex than that of vectors so the description will use more information

We will use the theory of *free probability*

Example:

$\Pi_1$  and  $\Pi_2$  two  $N \times N$  matrices

= orthogonal projections on subspaces of dimensions  $N/2$ .

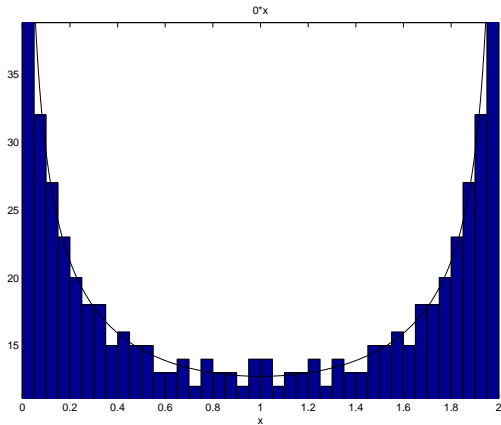
We chose the two subspaces independently and uniformly

$$\Pi_i = U_i \begin{pmatrix} I_{N/2} & 0 \\ 0 & 0 \end{pmatrix} U_i^*$$

$U_i$  = independent unitary matrices chosen with the Haar measure on  $U(N)$ .

One computes the spectrum of  $\Pi_1 + \Pi_2$ .

# Histogram of the spectrum of $\Pi_1 + \Pi_2$ ( $N = 800$ )



$$y = \frac{1}{\pi \sqrt{x(2-x)}}$$

# BASIC INVARIANT THEORY FOR MATRICES

Two complex self-adjoint  $N \times N$  matrices  $L$  and  $M$  have the same spectrum if and only if there exists a unitary  $U$  such that

$$L = U M U^*$$

Moreover  $L$  and  $M$  have the same spectrum if and only if for all  $r \geq 0$

$$\frac{1}{N} \text{Tr}(L^r) = \frac{1}{N} \text{Tr}(M^r)$$

i.e. the matrices have the same moments

In the sequel I will use

$$tr = \frac{1}{N} \text{Tr}$$

Let  $M_1, \dots, M_n$  be  $N \times N$  self-adjoint matrices.

**Theorem** (Procesi, 1978)

The "non-commutative joint moments"

$$\operatorname{tr}(M_{i_1} \dots M_{i_r}), \quad r \geq 1, \quad i_1, \dots, i_r \in \{1, \dots, n\}$$

form a complete set of invariants of the matrices up to conjugation.

This means that

$$\operatorname{tr}(L_{i_1} \dots L_{i_r}) = \operatorname{tr}(M_{i_1} \dots M_{i_r}) \quad \text{for all } r, i_1, \dots, i_r$$

if and only if there exists a unitary matrix  $U$  such that

$$L_i = UM_iU^* \quad \text{for all } i$$

**$U$  does not depend on  $i$ !**

Let  $X_i = U_i D_i U_i^{-1}$

$D_i$  = diagonal matrices

$U_i$  = independent unitary random matrices taken with Haar measure.

The spectra of the  $X_i$  are fixed, their eigenvectors are chosen at random.

**Theorem** (Voiculescu, 1990)

As  $N \rightarrow \infty$  the mixed moments

$$\text{tr}(X_{i_1} \dots X_{i_k})$$

are given by explicit polynomials in the  $\text{tr}(D_i^k) = \text{tr}(X_i^k)$  (with high probability and with a small error)



Exemples:

$$\operatorname{tr}(X_1 X_2) \sim \operatorname{tr}(X_1) \operatorname{tr}(X_2)$$

$$\operatorname{tr}(X_1^k X_2^l) \sim \operatorname{tr}(X_1^k) \operatorname{tr}(X_2^l)$$

$$\operatorname{tr}(X_1 X_2 X_1 X_2) \sim \operatorname{tr}(X_1^2) \operatorname{tr}(X_2^2) + \operatorname{tr}(X_1)^2 \operatorname{tr}(X_2^2) - \operatorname{tr}(X_1)^2 \operatorname{tr}(X_2)^2$$

Here  $\sim$  means that the difference is small with high probability.

## Corollary

If we know the spectra of  $X_1, \dots, X_n$  we can compute, with a good approximation the spectrum of any polynomial in the  $X_j$ .

Example:

$$\operatorname{tr}((X_1 + X_2)^n) = \sum_{i_1 \dots i_n} \operatorname{tr}(X_{i_1} \dots X_{i_n})$$

can be computed in terms of the numbers

$$\operatorname{tr}(X_1^k), \operatorname{tr}(X_2^k), \quad k = 1, 2, \dots$$

The explicit computation of these polynomials can be done using the theory of free *random variables*, *free cumulants*, *noncrossing partitions*

This is a sophisticated algebraic and combinatorial theory

Cf Nica, Alexandru; Speicher, Roland

Lectures on the combinatorics of free probability.

London Mathematical Society Lecture Note Series, 335.

Cambridge University Press, Cambridge, 2006.

## Example: the free convolution.

Suppose you know

$$\operatorname{tr}(L^n), \operatorname{tr}(M^n), n = 0, 1, 2, \dots$$

how do you compute  $\operatorname{tr}((L + M)^n)$ ?

The answer is given by *free cumulants*.

Introduce the generating functions of the moments of a matrix  $X$

$$G_X(z) = \text{tr}((z - X)^{-1}) = \frac{1}{z} + \sum_{n=1}^{\infty} z^{-n-1} \text{tr}(X^n)$$

then

$$K_X(G_X(z)) = G_X(K_X(z)) = z; \quad K_X(z) = \frac{1}{z} + \sum_{n=1}^{\infty} R_n(X) z^{n-1}$$

the  $R_n(X)$  are the **free cumulants** of  $X$ .

Free cumulants and moments determine each other by a triangular polynomial system:

$$m_1 = R_1$$

$$m_2 = R_2 + R_1^2$$

$$m_3 = R_3 + 3R_1R_2 + R_1^3$$

etc.

## Free cumulants and random matrices

Recall the model of random matrices

$$L = UDU^* \quad M = VEV^*$$

$D, E$  diagonal with given spectrum;  
 $U, V$  independent Haar unitaries.

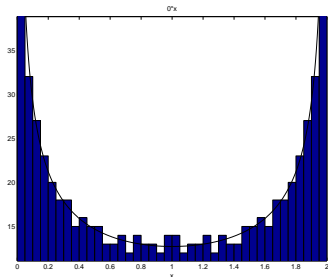
for  $N$  large one has

$$R_n(L + M) \sim R_n(L) + R_n(M)$$

Random matrix model: compute the spectrum of  $\Pi_1 + \Pi_2$  where  $\Pi_1, \Pi_2 =$  orthogonal projections on random subspaces of dimensions  $N/2$ .

The free cumulants computation gives the moments of an arcsine distribution:

$$\frac{dx}{\pi\sqrt{x(2-x)}} \quad \text{arcsine distribution}$$





## Free convolution

$\mu$  probability measure

$$G_\mu(z) = \int \frac{1}{z-x} d\mu(x) = \frac{1}{z} + \sum_{n=1}^{\infty} \frac{1}{z^{-n-1}} \int x^n d\mu(x)$$

then

$$K_\mu(G_\mu(z)) = G_\mu(K_\mu(z)) = z; \quad K_\mu(z) = \frac{1}{z} + \sum_{n=1}^{\infty} R_n(\mu) z^{n-1}$$

the  $R_n(\mu)$  are the **free cumulants** of  $\mu$ .

The free convolution of  $\mu$  and  $\nu$  is given by:

$$R_n(\mu \boxplus \nu) = R_n(\mu) + R_n(\nu)$$

This is the free version of convolution of measures

## Free central limit theorem

$X_1, \dots, X_n$  f.i.d

$$\tau(X_i) = 0 \quad \tau(X_i^2) = \sigma^2$$

**Theorem** (Voiculescu, 1983)

$$\frac{X_1 + \dots + X_n}{\sqrt{n}} \xrightarrow[n \rightarrow \infty]{\text{(in law)}} \frac{1}{\pi\sigma} \sqrt{4\sigma^2 - x^2} dx \quad x \in [-2\sigma, 2\sigma]$$

Semi-circle law with variance  $\sigma^2$

$$w_{\sigma^2}(dx) = \frac{1}{2\pi\sigma^2} \sqrt{4\sigma^2 - x^2} dx; \quad x \in [-2\sigma, 2\sigma]$$

characterized by:

$$K_{w_{\sigma^2}}(z) = \frac{1}{z} + z\sigma^2$$

# Remark

$$w_s \boxplus w_t = w_{s+t}$$

The semi-circle law is freely infinitely divisible

One can characterize freely infinitely divisible distributions, stable distributions, free Poisson distributions, etc.