



# Free Probability & The Free Central Limit Theorem

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- **Free probability** is the study of non-commutative random variables
- Combines probability, random matrices, operator algebras, functional and complex analysis, and more
- Idea first came about when Voiculescu [10] equated free independence to freeness of subgroups  $(G_i)_{i \in \mathcal{I}}$  of a group algebra  $\mathbb{C}G$ .
- Extends classical results in probability theory to this new setting: a **free law of large numbers**, **free central limit theorem**, etc.

# Free Probability Background

To understand free probability, we first consider Kolmogorov's classical foundations:

1. We select a **sample space**  $\Omega$ , with **states**  $\omega \in \Omega$ .
  2. We then construct a  $\sigma$ -algebra  $\mathcal{B} \subseteq 2^\Omega$  of **events**, such that  $P(\Omega) = 1$ .
  3. We build a commutative algebra of random variables  $X : \Omega \rightarrow \mathbb{C}$ , with an expectation function  $\mathbb{E}(X)$ .
- $(\Omega, \mathcal{B}, P)$  is our **probability space**. We “abstract away” both (1) and (2), to help us both compute limits and work with more general, non-commutative objects.

# Free Probability Background

## Definition

A (non-commutative)  $C^*$ -probability space  $(\mathcal{A}, \varphi)$  consists of a unital  $C^*$ -algebra  $\mathcal{A}$  over  $\mathbb{C}$ , and a unital, positive linear functional  $\varphi : \mathcal{A} \rightarrow \mathbb{C}$ .

- Recall that a  $C^*$ -algebra is a vector space over  $\mathbb{C}$  equipped with a bi-linear product, and has a norm under which it is complete.

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- Recall that a  $C^*$ -algebra is a vector space over  $\mathbb{C}$  equipped with a bi-linear product, and has a norm under which it is complete.
- We often also assume that  $\varphi(ab) = \varphi(ba)$  (**tracial**) and  $\varphi(a^*a) = 0 \implies a = 0$  (**faithful**).
- A good working example to keep in mind is  $\mathcal{A} = M_d(L^{\infty-}(\Omega, P))$ , the space of  $d \times d$  random matrices, and the linear functional

$$\varphi(a) = \frac{1}{d} \mathbb{E}[\text{tr}(a)].$$

- We now wish to understand the distribution of an arbitrary  $a \in \mathcal{A}$ .
- Let  $\mathbb{C}\langle X, X^* \rangle$  be the unital algebra freely generated by non-commuting  $X, X^*$ .

## \*-Distributions

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### Definition

The **\*-distribution** of  $a \in \mathcal{A}$  is the linear functional  $\mu : \mathbb{C}\langle X, X^* \rangle \rightarrow \mathbb{C}$  such that

$$\mu(X^{\varepsilon_1} \cdots X^{\varepsilon_k}) = \varphi(a^{\varepsilon_1} \cdots a^{\varepsilon_k}),$$

where each  $\varepsilon_i \in \{1, *\}$ .

- Having a \*-distribution makes computing moments such as  $\varphi(a^k) = \int t^k d\mu(t)$  much easier.

## Definition

The **spectrum** of  $a \in \mathcal{A}$  is given by

$$\text{spec}(a) := \{z \in \mathbb{C} : z1_{\mathcal{A}} - a \text{ is not invertible}\}.$$

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## Proposition

Let  $a \in \mathcal{A}$  be normal. Then  $a$  has a  $*$ -distribution  $\mu$  whose support is contained in  $\text{spec}(a)$ . If  $\varphi$  is faithful, then the support is exactly  $\text{spec}(a)$ .

# Free Independence

Recall that in classical independence,  $X \perp\!\!\!\perp Y$  if

$$\mathbb{E}[f(X)] = \mathbb{E}[g(Y)] = 0 \implies \mathbb{E}[f(X)g(Y)] = 0.$$

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## Definition

Let  $(A, \varphi)$  be a  $C^*$ -probability space. Then  $(A_i)_{i \in \mathcal{I}}$  are **freely independent (free)** if

$$\varphi(a_1 \cdots a_k) = 0$$

whenever  $a_j \in \mathcal{A}_{i_j}$  with  $\varphi(a_j) = 0$  for all  $1 \leq j \leq k$ , and no neighboring indices are from the same subalgebra:  $i_1 \neq i_2, i_2 \neq i_3, \dots, i_{k-1} \neq i_k$ .

- Random variables  $(a_i)_{i \in \mathcal{I}}$  are free ( $*$ -free) when their generated subalgebras  $\sigma(1, a_i)$  ( $\sigma(1, a_i, a_i^*)$ ) are free.

# Connection to Freeness

- Recall that in group theory, if  $G$  be a group, then subgroups  $(G_i)_{i \in \mathcal{I}}$  are **free** if for every  $k \geq 1$  and  $i_1, \dots, i_k \in \mathcal{I}$  all distinct, we have

$$g_1 \in G_{i_1} \setminus \{e\}, \dots, g_k \in G_{i_k} \setminus \{e\} \implies g_1 \cdots g_k \neq e.$$

## Proposition

Let  $G$  be a group. Then the subgroups  $(G_i)_{i \in \mathcal{I}}$  are free in  $G$  if and only if the subalgebras  $(\mathbb{C}G_i)_{i \in \mathcal{I}}$  are freely independent in  $(\mathbb{C}G, \tau_G)$ .

- The group algebra  $\mathbb{C}G$  consists of all finite linear combinations of the form  $\sum_{g \in G} \alpha_g g$  with coefficients in  $\mathbb{C}$ , and  $\tau_G$  maps such a linear combination to its identity coefficient  $\alpha_e$ 
  - This is a proper non-commutative probability space!

# Free Central Limit Theorem

- In the non-commutative case, we say that  $a_N$  converges in distribution to  $a$  if every moment converges:  $\varphi(a_N^n) \rightarrow \varphi(a^n)$ .

## Theorem (Free CLT)

Let  $(\mathcal{A}, \varphi)$  be a  $C^*$ -probability space and  $a_1, a_2, \dots \in \mathcal{A}$  be free, identically distributed, and self-adjoint with common mean  $\varphi(a_i) = 0$  and variance  $\varphi(a_i^2) = \sigma^2$ . Then

$$\frac{a_1 + \dots + a_N}{\sqrt{N}} \xrightarrow{d} \mu_S,$$

where  $\mu_S$  is the distribution of a semi-circular element of radius  $2\sigma$ .

- In the lecture notes, we are given a proof using R-transforms. I will provide a short combinatorial proof on the board!

# Free Probability for Concentration Inequalities

- Free probability can be applied toward concentration inequalities in random matrix theory.

## Theorem (Non-commutative Khintchine Inequality)

Let  $X = \sum_{i=1}^n g_i A_i$  for  $g_i \sim \mathcal{N}(0, 1)$  independent and  $A_i$  fixed coefficient matrices. Then

$$\sigma(X) \lesssim \mathbb{E}\|X\| \lesssim \sigma(X) \sqrt{\log(d)},$$

where  $\sigma(X)^2 = \|E(X^2)\| = \|A_1^2 + \dots + A_n^2\|$ .

- Bounds expected spectral norm up to  $\log(d)^{1/2}$  factor
- Can be sub-optimal in high dimensions ( $d \gg n$ )

# Free Probability for Concentration Inequalities

- Let our original and “free” models be defined as

$$X := A_0 + \sum_{i=1}^n g_i A_i, \quad X_{\text{free}} := A_0 \otimes 1 + \sum_{i=1}^n A_i \otimes S_i.$$

## Theorem 2.1 of [2]

For the above model with  $A_0, \dots, A_n$  all self-adjoint, we have that for every  $t \geq 0$ ,

$$P(\text{spec}(X) \subseteq \text{spec}(X_{\text{free}}) \pm c_t) \geq 1 - e^{-t^2},$$

where  $c_t := C\tilde{v}(X) \log(d)^{3/4} + C\sigma_*(X)t$  quantifies the non-commutativity of the matrices  $A_i$  (for some universal  $C > 0$ ).

- They also provide bounds of the form

$$P(\|X\| > \|X_{\text{free}}\| + c_t) \leq e^{-t^2}, \quad \mathbb{E}\|X\| \leq \|X_{\text{free}}\| + C\tilde{v}(X) \log(d)^{3/4}.$$

# Free Probability for Concentration Inequalities

- In order for these bounds to be useful,  $\|X_{\text{free}}\|$  must be readily computable in practice, in which case the following lemma can help us:

## Lemma

When the  $A_i$  are self-adjoint, we have

$$\|X_{\text{free}}\| = \max_{\varepsilon=\pm 1} \inf_{Z>0} \lambda_{\max} \left( Z^{-1} + \varepsilon A_0 + \sum_{i=1}^n A_i Z A_i \right),$$

where this infimum is over all positive-definite, self-adjoint  $Z \in M_d(\mathbb{C})$ , and  $\lambda_{\max}(\cdot)$  is the largest eigenvalue.

- In the proof, authors show that even though the moments of the matrix  $X$  might depend on all pairings, the crossing pairings still come close to vanishing in many cases via the non-commutativity of the  $A_i$ .
  - Similar to how only non-crossing pairings survive in free CLT



# Extensions of Free CLT

- Of course, the Free CLT relies on the crucial assumption of free independence, and only works for empirical averages
- Not very desirable for real-world applications as independence is often violated, such as the case of a single random matrix of growing dimension
- Many popular statistics, such as  $U$ -statistics  $\frac{1}{n^2} \sum_{i,j=1}^n f(a_i, a_j)$  do not fit this form
- Not a problem for the classical CLT, in which independence, taking empirical averages, and even identical distribution assumptions can be relaxed to varying degrees of generality.

# Extensions of Free CLT

- In [1], they study under what conditions a free CLT can be extended to both empirical averages and  $U$ -statistics of dynamical systems
  - stationary or quantum exchangeable sequences

## Definition

For a sequence of classical random variables, the **strong-mixing coefficients** are defined as

$$\alpha_j := \sup_{\substack{A \in \sigma(X_{-\infty:0}) \\ B \in \sigma(X_j:\infty)}} |P(A \cap B) - P(A)P(B)|.$$

Can do a similar method to define “free mixing” coefficients in the non-commutative case (but is much more elaborate), and these coefficients provide a bound on the normed difference between such a dynamical system and semi-circular elements.

# Conclusion

- Many results in the non-commutative case mirror those in the classical setting, but with subtle changes
  - Partitions  $\rightarrow$  non-crossing partitions
  - Normal distribution  $\rightarrow$  semi-circular distribution
- Free probability has recently found applications in several fields, and is an active area of research (dependent free CLT, high-dimensional free CLT, etc.)
  - Another main goal is to construct new invariants of von Neumann algebras via free probability.

**Thanks for a great course!!!**

# References

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