

New topic: Schur generating functions.

NYU

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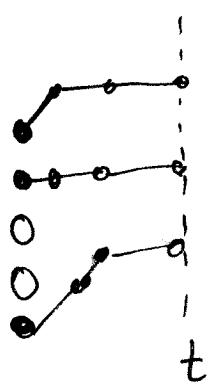
Lecture 3

We still want LLN / CLT for random $\lambda_1 \geq \dots \geq \lambda_N$

Last 2 lectures: distribution is somewhat known and is given by log-gas (discrete).

Now: When no simple formulas for the distribution itself exist, what can we do?

Two examples



Distribution at time t of non-int. r.w. with arbitrary initial condition.

$T_\lambda = \text{irrep of } U(N)$
 $\lambda_1 \geq \dots \geq \lambda_N$ (who knows?
 $U(1)$ at least?)

$$T_\lambda \otimes T_\mu = \bigoplus C_{\lambda\mu}^{\nu} T_\nu$$

Littlewood-Richardson coefficients
— hard combinatorial object

(=? Horn, Kostka-Tao, Klyachko)

Biane: treat as prob. measure!

$$P(\nu) = \frac{C_\nu \cdot \dim T_\nu}{\dim T_\lambda \cdot \dim T_\mu}$$

Analogy in continuum

→ random matrices.

Dyson Brownian Motion with arbitrary initial conditions

= eigenvalues of $\begin{pmatrix} a_1 & 0 & \dots & 0 \\ 0 & a_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & a_N \end{pmatrix} + GUE$?

eigenvalues of $A+B$?
where A, B has independent uniform eigen vectors and fixed eigenvalues $\{a_i\}, \{b_i\}$

RM problems are well-known and solved.
One efficient method \rightarrow moments \oplus

$$C: \text{e.v. } c_1, \dots, c_N$$

$$\mathbb{E} (\text{Tr } C^k)^m = \mathbb{E} \left(\sum (c_i)^k \right)^m$$

↑
compute through
matrix elements

gives LLN/CLT for
polynomial statistics.

Discrete case remained open until recently.
No RM \Rightarrow How to compute moments?

Approach of ~~E.G. Buff~~ [Bufetov - G.]
Alexey?

Schur polynomial (who knows?)

$$S_\lambda(x_1, \dots, x_N) = \frac{\det [x_i^{\lambda_j + N - j}]_{i,j=1}^N}{\prod_{i < j} (x_i - x_j)}$$

Homogeneous Laurent symmetric polynomial of
degree $|\lambda| = \lambda_1 + \dots + \lambda_N$.

Def. Schur generating function of probability
measure $P(\lambda)$ on $\lambda \geq \dots \geq \lambda_N$
is $S_p(x_1, \dots, x_N) = \sum_{\lambda} P(\lambda) \frac{S_\lambda(x_1, \dots, x_N)}{S_\lambda(1, \dots, 1)}$

Always converges on torus $|x_1| = \dots = |x_N| = 1$,
we will assume convergence on $1-\epsilon < |x_i| < 1+\epsilon \rightarrow$
 \rightarrow tail behavior (trivially true in most natural examples)

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Examples:

1) $N=1$

$$\sum P(k) x^k$$

- usual moment
generating function

2) Not int. random walks

$$S_{P_t} = \frac{S_x(x_1, \dots, x_N)}{S_{\lambda^0}(1, \dots, 1)} \prod_{i=1}^N (1-p + p \cdot x_i)^t$$

at time t initial condition

"Proof" $t=0 \rightarrow$ immediate.

$$S_x \cdot \prod_{i=1}^N (1-p + p \cdot x_i) =$$

$$= \sum_{\mu: \mu_i = \lambda_i + \{0/1\}} p^{|\lambda| - |\lambda|} (1-p)^{N - (|\lambda| - |\lambda|)} S_\mu$$

These are independent jumps.

Conjugation by $S_\lambda(1, \dots, 1) \rightarrow$ transitional probabilities for non-intersecting walks.

3) Tensor products

$$S_{P_\lambda} = \frac{S_x(x_1, \dots, x_N) S_\mu(x_1, \dots, x_N)}{S_x(1, \dots, 1) S_\mu(1, \dots, 1)}$$

Schur function = character of $T_\lambda =$
 $= \text{Trace } T_\lambda(U)$

unitary matrix with e.v. = x_1, \dots, x_N .

Character of tensor product = product of characters

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4) See handout?

Lozenge tilings: Section

$$\frac{S_{\lambda}(x_1, \dots, x_n, 1^{N-k})}{S_{\lambda}(1^n)}$$

Domino tilings: Section

$$\frac{S_{\lambda}(x_1, \dots, x_n, 1^{N-k})}{S_{\lambda}(1^n)} \cdot \left(\frac{1+x_i}{2}\right)^k$$

Main Theorem (Bufetov - G.).

Take a sequence of measures P_N on $\lambda \in \mathbb{Z} \geq \lambda_0$
 $N=1, 2, \dots$ The LLN [polynomial linear statistics] $\frac{1}{N} \sum_{i=1}^N \left(\frac{\lambda_i + N-i}{N}\right)^k \rightarrow p(k)$ (Ak)and CLT: $E\left(\sum_{i=1}^N \left[\left(\frac{\lambda_i + N-i}{N}\right)^k - E\left(\frac{\lambda_i + N-i}{N}\right)^k\right]\right)$.covariance $\rightarrow \sum_{i=1}^N \left[\left(\frac{\lambda_i + N-i}{N}\right)^l - E\left(\frac{\lambda_i + N-i}{N}\right)^l\right] \rightarrow \text{cov}(k, l)$ (Ak, l)higher moments $\rightarrow \sum \left(\frac{\lambda_i + N-i}{N}\right)^k - E\left(\frac{\lambda_i + N-i}{N}\right)^k$ asymptotically (jointly) gaussian.

Hold if and only if

L) $\frac{1}{N} \left(\frac{\partial}{\partial x_i}\right)^k \ln S_{P_N} \Big|_{x_1 = \dots = x_n = 1} \rightarrow C_k \quad (k=0?)$

can be any i !

2) $\left(\frac{\partial}{\partial x_i}\right)^k \left(\frac{\partial}{\partial x_j}\right)^l \ln S_{P_N} \Big|_{x_1 = \dots = x_n = 1} \rightarrow d_{k,l}$

 $\overset{k}{\underset{i=1}{\prod}}$ can be i and j

3) $\prod_{a=1}^k \left(\frac{\partial}{\partial x_{ia}}\right) \ln S_{P_N} \Big|_{x_1 = \dots = x_n = 1} \rightarrow 0 \quad \text{when } |\{i_a\}| > 2$

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Where

$$p(k) = [z^{-1}] \frac{1}{(k+1)(z+1)} \left((1+z) \left(\frac{1}{z} + \sum_{a=1}^{\infty} \frac{c_a z^{a-1}}{(a-1)!} \right)^{k+1} \right)$$

$$\text{cov}(k, l) = [z^{-1} w^{-1}] \left((1+z) \left(\frac{1}{z} + \sum_{a=1}^{\infty} \frac{c_a z^{a-1}}{(a-1)!} \right)^k \right) \cdot$$

$$\cdot \left((1+w) \left(\frac{1}{w} + \sum_{a=1}^{\infty} \frac{c_a w^{a-1}}{(a-1)!} \right)^l \right) \cdot \left(\left(\sum_{a=0}^{\infty} \frac{z^a}{w^{2+a}} \right)^2 + \sum_{a,b=1}^{\infty} \frac{d_{a,b}}{(a-1)!(b-1)!} z^{a-1} w^{b-1} \right)$$

$\frac{1}{(z-w)^2}$

Break ???

1-d analogy : ξ_1, ξ_2, \dots Char. functions.

$$K_m(z) = \left(\frac{\partial}{\partial z} \right)^m \ln \mathbb{E} \exp(i z \xi) \Big|_{z=0} \cdot \frac{1}{i^m}$$

[under technical conditions]

$$1) K_1(\xi_n) \xrightarrow{n \rightarrow \infty} c, \quad K_2(\xi_n) \xrightarrow{n \rightarrow \infty} 0 \iff \xi_n \xrightarrow{\sim} C$$

$$2) K_2(\xi_n) \rightarrow 0^2, \quad K_m(\xi_n) \xrightarrow{n \rightarrow \infty} 0, \quad m > 2$$

\uparrow

$$\xi_n - \mathbb{E} \xi_n \xrightarrow{n \rightarrow \infty} N(0, 0^2).$$

Same "ln", same orders of derivatives, same gaussianity
But only 1 variable?

why Schur gfn. functions?

$$\mathbb{E} \frac{s_n(x_1, \dots, x_n)}{s_n(s, \dots, s)}$$

characters of $U(N)$
parameterized by
 $\lambda_1, \dots, \lambda_N$

multiplicative characters
of unit circle are
parameterized by integers.

So we extended harmonic analysis on
unit circle to unitary groups!

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What's coming next.

Today: application of LLN \rightarrow free probability

4th lecture: elements of proof

5th lecture: application of CLT \rightarrow gaussian free field.

We now return to tensor products problem

$$T_x \otimes T_y = \bigoplus C_v T_v \quad \text{discrete version of } A + B = C$$

$$P(j) = \frac{C_v \dim T_v}{\dim T_x \dim T_y} \quad \begin{matrix} N \rightarrow \infty \\ \text{"Free convolution"} \end{matrix}$$

Theorem: (Bercov-Gorin) Assume that $\lambda = \lambda(N)$ is such that

$$\frac{1}{N} \sum_{i=1}^N \delta_{\frac{\lambda_i + N - i}{N}} \rightarrow P \quad \frac{1}{N} \sum_{i=1}^N \delta_{\frac{\mu_i + N - i}{N}} \rightarrow P'$$

$$\text{Then } \frac{1}{N} \sum_{i=1}^N \delta_{\frac{\lambda_i + N - i}{N}} \xrightarrow[\text{random}]{\text{weakly, in prob.}} P \boxtimes P' \quad \begin{matrix} \uparrow \\ \text{deterministic.} \end{matrix}$$

Moreover, set ~~$G_p(z)$~~ $G_p(z) = \int \frac{p(x)}{z-x} dx$

$$R_p^q(z) = (G_p(z))^{(-1)} - \frac{1}{1-e^{-z}} = \text{power series in } z.$$

"Quantized R-transform"

$$\text{Then } R_p^q(z) + R_{p'}^q(z) = R_{p \boxtimes p'}^q(z), \text{ i.e.}$$

this operation on measures is linearized by

$-R^P$ — just as log of Fourier transform
linearizes usual convolution

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Comparison

in RM setting a similar theorem is due to Voiculescu. Then $R^A(z)$ is replaced by $R(z) = \mathcal{S}_1(G_p(z))^{(-1)} - \frac{1}{z}$,

Operation — "free convolution" —

- ~~spectrum~~ of the sum of two free random variables (= spectrum of sum of 2 operators in ∞ dim space).

In our setting $\lambda_i \sim N$ (discrete).

If they grow faster than N , then tensor products degenerate to sums in "semiclassical limit"
(Group $U(N)$) \rightsquigarrow its Lie algebra = skew-sym. complex matrices = Hermitian complex matrices

and one gets $R(z)$ directly (Biane; Collins-Sniady).

Proof of theorem

S.G.F.

$$S_{\delta\lambda} = \frac{S_\lambda(x_1, \dots, x_N)}{S_\lambda(1^N)}$$

$$S_{\delta\mu} = \frac{S_\mu(x_1, \dots, x_N)}{S_\mu(1^N)}$$

$$S_\nu = \frac{S_\lambda(x_1, \dots, x_N) S_\mu(x_1, \dots, x_N)}{S_\lambda(1^N) S_\mu(1^N)}$$

So the logarithms are added.

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λ, μ satisfy LLN + CLT with 0 covariance.

\Rightarrow conditions of theorem hold, i.e.

$\ln S_{\delta_1}, \ln S_{\delta_m}$ satisfy 1), 2) 3) \Rightarrow so is $S_v \Rightarrow$
 \Rightarrow LLN + CLT for S_v holds.

Linearization: By definition, c_n in 1) are added, i.e.

$$\frac{\partial}{\partial x} \lim_{N \rightarrow \infty} \frac{1}{N} \ln(S(x+1, 1^{N-1})) = \sum_{a=1}^{\infty} \frac{c_a x^{a-1}}{(a-1)!} \text{ linearizes.}$$

It remains to use $p(k) \leftrightarrow c_a$ relation
and simplify the result.

(version of Lagrange inversion).

Conclusion: You do not really need
to know anything about Schur functions
to use our theorem!