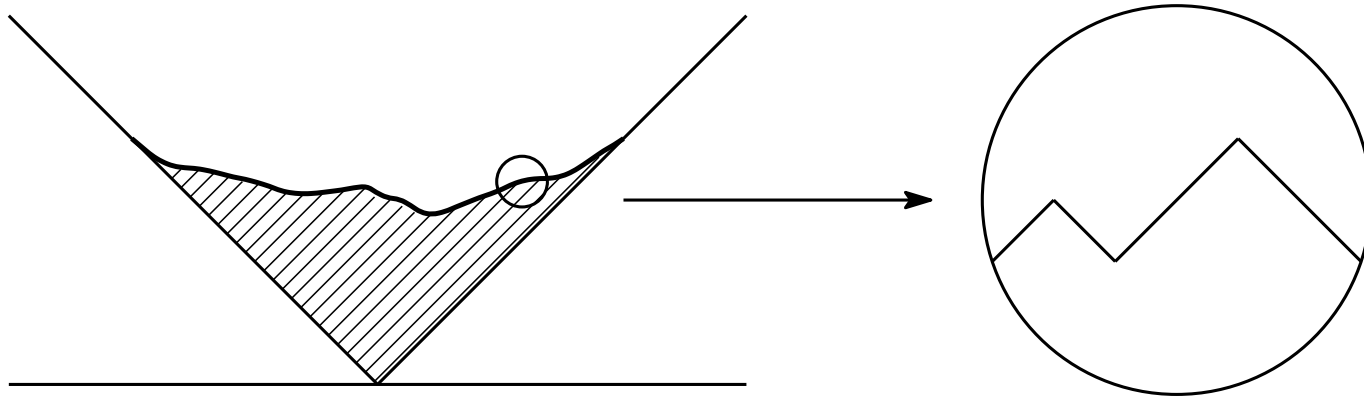


# On Evolution of Macroscopic Profiles (and their Global Fluctuations) for Growing Random Young Diagrams

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## §1 Introduction

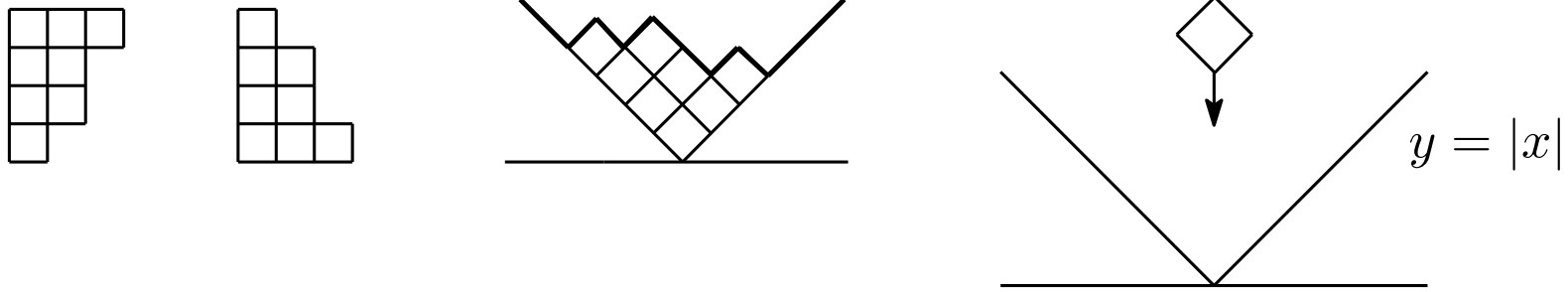


fig. 1 Young diagram  $(3 \geq 2 \geq 2 \geq 1) = (1^1 2^2 3^1)$  and its profile

$\mathbb{Y}_n$  : the set of Young diagrams of  $n$  boxes

$$|\mathbb{Y}_n| = \frac{e^{\pi\sqrt{2n/3}}}{4\sqrt{3n}} \left(1 + O\left(\frac{1}{\sqrt{n}}\right)\right)$$

Young diagram  $\lambda$  is characterized by its profile  $y = \lambda(x)$

## Scheme of the problem

For continuous time Markov chain  $(X_s^{(n)})_{s \geq 0}$  on  $\mathbb{Y}_n$ ,

limiting behavior as  $n \rightarrow \infty$  and  $s \rightarrow \infty$  under scaling in space vs time

– macroscopic profile :  $1/\sqrt{n}$  both horizontally and vertically

$$\lambda \in \mathbb{Y}_n \quad \longrightarrow \quad \lambda^{\sqrt{n}}(x) = \frac{1}{\sqrt{n}} \lambda(\sqrt{n}x), \quad \lambda^{\sqrt{n}} \in \mathbb{D}$$

– macroscopic time :  $t = s/n$  (diffusive scale)

Letting  $n \rightarrow \infty$ , as an effect of LLN(= law of large numbers), the distribution of  $X_{tn}^{(n)}$  concentrates at a point  $\omega_t$ , depending on  $t$ .

$\omega_t$  : macroscopic profile at macroscopic time  $t$

Describe evolution of  $\omega_t$  along  $t$  !

## §2 Markov chain

- transition probability  $p(x, y)$  ( $x, y \in S$ ) :  $p(x, y) \geq 0$ ,  $\sum_{y \in S} p(x, y) = 1$
- initial distribution  $\nu(x) \geq 0$ ,  $\sum_{x \in S} \nu(x) = 1$

Then,  $\exists (X_n)_{n=0,1,2,\dots}$  where  $X_n : \Omega \longrightarrow S$

$$\mathbb{P}(X_{n+1} = y \mid X_n = x) = p(x, y), \quad \mathbb{P}(X_0 = x) = \nu(x)$$

(temporally homogeneous Markov chain on  $S$ )

$P = (p(x, y))_{x, y \in S}$  : transition matrix,  $\nu = (\nu(x))_{x \in S}$  : initial row vector

$$p_n(x, y) = \mathbb{P}(X_n = y \mid X_0 = x) = (P^n)_{x, y}, \quad \mathbb{P}(X_n = x) = (\nu P^n)_x$$

**Continuous time** Markov chain  $(X_{N_s})_{s \geq 0}$  where

$(N_s)_{s \geq 0}$ : Poisson process on  $\{0, 1, \dots\}$ ,  $N_0 = 0$  a.s., independent of  $(X_n)$

$$\tilde{\mathbb{P}}(X_{N_s} = x) = (\nu e^{s(P-I)})_x, \quad x \in S$$

### §3 Plancherel growth process

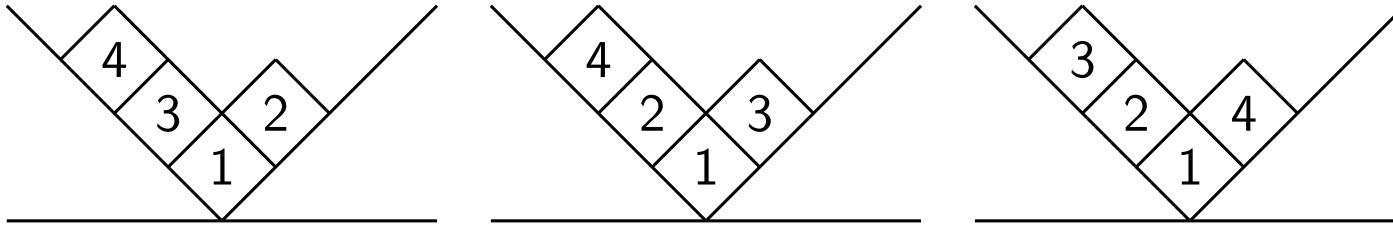


fig. 2 standard tableaux for  $(2 \geq 1 \geq 1) = (1^2 2^1) \in \mathbb{Y}_4$

To Young diagram  $\lambda$ , dimension of  $\lambda$  is assigned:

$$\begin{aligned} \dim \lambda &= \text{number of standard tableaux for } \lambda \\ &= \text{number of paths from } \emptyset \text{ to } \lambda \text{ on the Young graph} \end{aligned}$$

Ex.  $\dim(1^2 2^1) = 3$

Young graph vertices:  $\mathbb{Y} = \bigsqcup_{n=0}^{\infty} \mathbb{Y}_n, \quad \mathbb{Y}_0 = \{\emptyset\}$

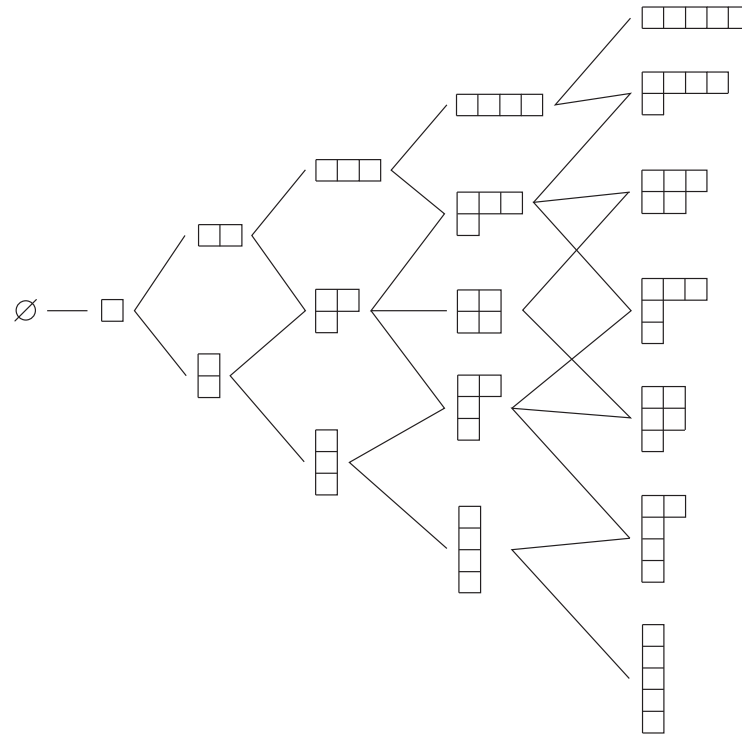


fig. 3 Young graph: dimension in 5th strara — 1, 4, 5, 6, 5, 4, 1 :  
 $1^2 + 4^2 + 5^2 + 6^2 + 5^2 + 4^2 + 1^2 = 5!$

Plancherel growth process is Markov chain  $(Z_n)$  on Young diagrams s.t.

$$\begin{aligned} \nu &= \delta_{\emptyset} \\ p(\lambda, \mu) &= p^\uparrow(\lambda, \mu) : \text{proportional to } \dim \mu \\ &= \frac{\dim \mu}{(|\lambda| + 1) \dim \lambda}, \quad \lambda, \mu \in \mathbb{Y}, \quad \lambda \nearrow \mu \end{aligned}$$

Then, the distribution after  $n$  step is

$$p_n(\emptyset, \lambda) = \mathbb{P}(Z_n = \lambda) = \frac{(\dim \lambda)^2}{n!} = \mathbb{M}_{\text{Pl}}^{(n)}(\lambda)$$

called **Plancherel measure** on  $\mathbb{Y}_n$  ( $\leftarrow$  Fourier transform on  $\mathfrak{S}_n$ )

- rectangular diagram

$\mathbb{D}_0 = \{ \lambda : \mathbb{R} \rightarrow \mathbb{R} \mid \text{continuous, piecewise linear,}$

$$\lambda'(x) = \pm 1, \quad \lambda(x) = |x| \quad (|x| \text{ large enough}) \}$$

- continuous diagram

$$\mathbb{D} = \{ \omega : \mathbb{R} \rightarrow \mathbb{R} \mid |\omega(x) - \omega(y)| \leq |x - y|, \omega(x) = |x| \text{ (} |x| \text{ large enough)} \}$$

$$\lambda^{\sqrt{n}} \in \mathbb{D}_0 \subset \mathbb{D} \quad (\text{recall } \lambda^{\sqrt{n}}(x) = \frac{1}{\sqrt{n}} \lambda(\sqrt{nx}))$$

$$\Omega(x) = \begin{cases} \frac{2}{\pi} \left( x \arcsin \frac{x}{2} + \sqrt{4 - x^2} \right), & |x| \leq 2 \\ |x|, & |x| > 2 \end{cases} \quad \text{limit shape}$$

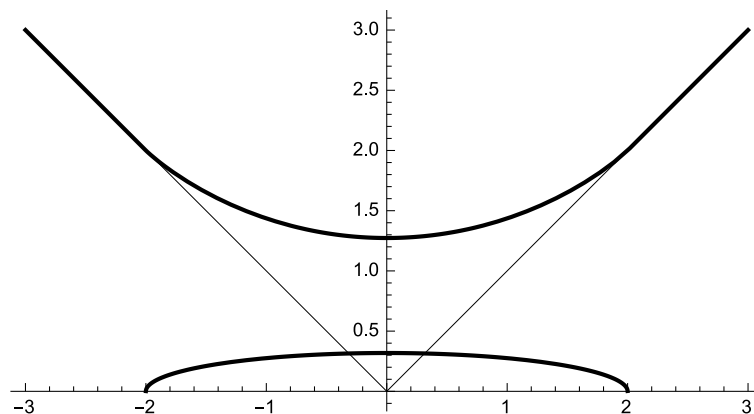


fig. 4 limit shape  $\Omega$  and its transition measure



The following LLN holds (static scaling limit for the Plancherel measure)

Vershik – Kerov (1977), Logan – Shepp (1977)

$$\mathbb{M}_{\text{Pl}}^{(n)} \left( \left\{ \lambda \in \mathbb{Y}_n \mid \sup_{x \in \mathbb{R}} |\lambda^{\sqrt{n}}(x) - \Omega(x)| \geq \epsilon \right\} \right) = \mathbb{P}(\|Z_n^{\sqrt{n}} - \Omega\|_{\text{sup}} \geq \epsilon)$$

$$\xrightarrow[n \rightarrow \infty]{} 0 \quad (\forall \epsilon > 0)$$

Namely, distribution of  $Z_n^{\sqrt{n}}$  converges to  $\delta_\Omega$  as  $n \rightarrow \infty$ . ■

Continuous time Plancherel growth process  $\tilde{Z}_s = Z_{N_s}$

with initial distribution  $\delta_\emptyset$ , transition matrix  $e^{s(P-I)}$

$$\tilde{\mathbb{P}}(\tilde{Z}_s = \lambda) = \sum_{n=0}^{\infty} \frac{e^{-s} s^n}{n!} \mathbb{M}_{\text{Pl}}^{(n)}(\lambda), \quad \lambda \in \mathbb{Y}$$

(Poissonization of the Plancherel measures)

## Dynamical scaling limit

$s$ : microscopic time,  $t$ : macroscopic time  $s = tn$

Then  $\tilde{Z}_{tn}^{\sqrt{n}} \xrightarrow[n \rightarrow \infty]{} ?$

$$\begin{aligned} \tilde{\mathbb{P}}(\|\tilde{Z}_{tn}^{\sqrt{n}} - \Omega_t\|_{\text{sup}} \geq \epsilon) &= \tilde{\mathbb{P}}^{\tilde{Z}_{tn}}(\|\lambda^{\sqrt{n}} - \Omega_t\|_{\text{sup}} \geq \epsilon) \\ &= \sum_{k=0}^{\infty} \frac{e^{-tn} (tn)^k}{k!} \mathbb{M}_{\text{Pl}}^{(k)}(\|\lambda^{\sqrt{n}} - \Omega_t\|_{\text{sup}} \geq \epsilon) \end{aligned}$$

The above Poisson distribution has mean  $tn$  and standard deviation  $\sqrt{tn}$

Under  $\mathbb{M}_{\text{Pl}}^{(\lfloor tn \rfloor)}$ ,  $\lambda^{\sqrt{tn}} \rightarrow \Omega \iff \lambda^{\sqrt{n}} \rightarrow \Omega_t$  where

$$\Omega_t(x) = \begin{cases} \frac{2}{\pi} \left( x \arcsin \frac{x}{2\sqrt{t}} + \sqrt{4t - x^2} \right), & |x| \leq 2\sqrt{t} \\ |x|, & |x| > 2\sqrt{t} \end{cases}$$

**Proposition**  $\tilde{Z}_{tn}^{\sqrt{n}} \xrightarrow[n \rightarrow \infty]{} \Omega_t$  in probability ■

( $\Omega_t$  is “similar” to  $\Omega_1 = \Omega$  (static limit), so this is not very remarkable as a dynamic model.)

## §4 Restriction-induction chain

restriction  $\leftrightarrow$  removing 1 box, induction  $\leftrightarrow$  adding 1 box

$p^\uparrow(\lambda, \mu)$  as before

$$p^\downarrow(\lambda, \mu) \quad (\text{proportional to } \dim \mu) = \begin{cases} \frac{\dim \mu}{\dim \lambda}, & \mu \nearrow \lambda \\ 0, & \text{otherwise} \end{cases}$$

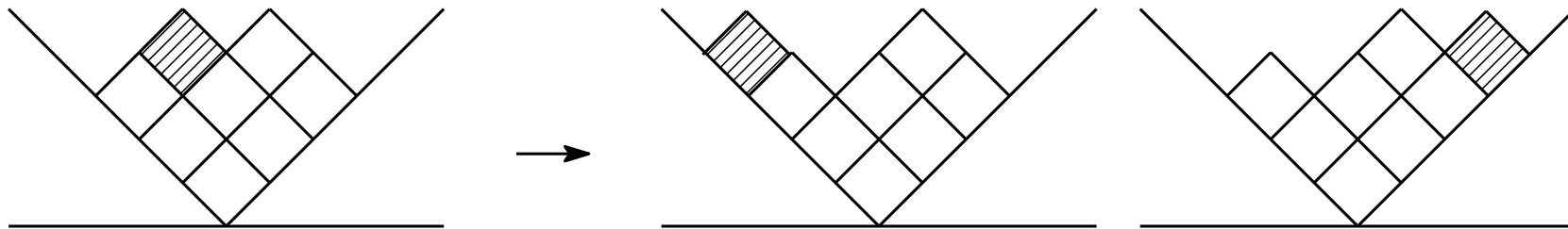


fig. 5 Res-Ind chain: transition from  $\lambda = (3, 3, 2)$

**Res-Ind chain**  $(X_m^{(n)})_{m=0,1,2,\dots}$  on  $\mathbb{Y}_n$  has transition matrix

$$P^{(n)} = P^\downarrow P^\uparrow = (p^{(n)}(\lambda, \mu))_{\lambda, \mu \in \mathbb{Y}_n}$$

$$p^{(n)}(\lambda, \mu) = \sum_{\nu \in \mathbb{Y}_{n-1}: \nu \nearrow \lambda, \nu \nearrow \mu} p^\downarrow(\lambda, \nu) p^\uparrow(\nu, \mu), \quad \lambda, \mu \in \mathbb{Y}_n$$

**Lemma** Res-Ind chain is symmetric w.r.t. the Plancherel measure:

$$\mathbb{M}_{\text{Pl}}^{(n)}(\lambda) p^{(n)}(\lambda, \mu) = \mathbb{M}_{\text{Pl}}^{(n)}(\mu) p^{(n)}(\mu, \lambda), \quad \lambda, \mu \in \mathbb{Y}_n,$$

hence the Plancherel measure is invariant distribution for Res-Ind chain ■

**Continuous time Res-Ind chain**  $\tilde{X}_s^{(n)} = X_{N_s}^{(n)}$  on  $\mathbb{Y}_n$  with

transition matrix  $e^{s(P^{(n)} - I)}$ ,

initial distribution  $\mathbb{M}_0^{(n)}$  (see Remark),

invariant distribution  $\mathbb{M}_{\text{Pl}}^{(n)}$

**Remark** For a sequence of probability spaces  $(\mathbb{Y}_n, \mathbb{M}^{(n)})$ , we know some sufficient condition for LLN

$$\mathbb{M}^{(n)} \left( \left\{ \lambda \in \mathbb{Y}_n \mid \|\lambda^{\sqrt{n}} - \psi\|_{\text{sup}} \geq \epsilon \right\} \right) \xrightarrow[n \rightarrow \infty]{} 0 \quad (\forall \epsilon > 0)$$

to hold with some continuous diagram  $\psi \in \mathbb{D}$ , which we call a **concentration property** at  $\psi$  (a certain approximate factorization property).

Ex. Plancherel measures  $(\mathbb{Y}_n, \mathbb{M}_{\text{Pl}}^{(n)})$  satisfy this concentration property.

## Dynamic scaling limit

$s$ : microscopic time,  $t$ : macroscopic time  $s = tn$

Then  $\tilde{X}_{tn}^{(n)} \xrightarrow[n \rightarrow \infty]{} ?$  (macroscopic profile depending on  $t$ )

Let  $\mathbb{M}_t^{(n)} = \tilde{\mathbb{P}}^{\tilde{X}_{tn}^{(n)}}$  : distribution of  $\tilde{X}_{tn}^{(n)}$  on  $\mathbb{Y}_n$

**Theorem** The concentration property is propagated as time goes by, i.e. if initial distributions  $\mathbb{M}_0^{(n)}$  satisfy the concentration property at  $\omega_0 \in \mathbb{D}$ , then for  $\forall t > 0$   $\mathbb{M}_t^{(n)}$  also satisfy the concentration property, hence there exists  $\omega_t \in \mathbb{D}$  s.t. LLN

$$\mathbb{M}_t^{(n)} \left( \left\{ \lambda \in \mathbb{Y}_n \mid \|\lambda^{\sqrt{n}} - \omega_t\|_{\text{sup}} \geq \epsilon \right\} \right) \xrightarrow[n \rightarrow \infty]{} 0 \quad (\forall \epsilon > 0)$$

holds. ■

- $\omega_0$  can be taken arbitrarily in  $\mathbb{D}$
  - $\omega_t$  converges to  $\Omega$  (limit shape) in  $\mathbb{D}$  as  $t \rightarrow \infty$
  - The area is kept invariant:  $\int_{\mathbb{R}} (\omega_t(x) - |x|) dx = 2$  for  $\forall t$
  - $\omega_t$  is described precisely by using **free probability**
- (see the following sections)

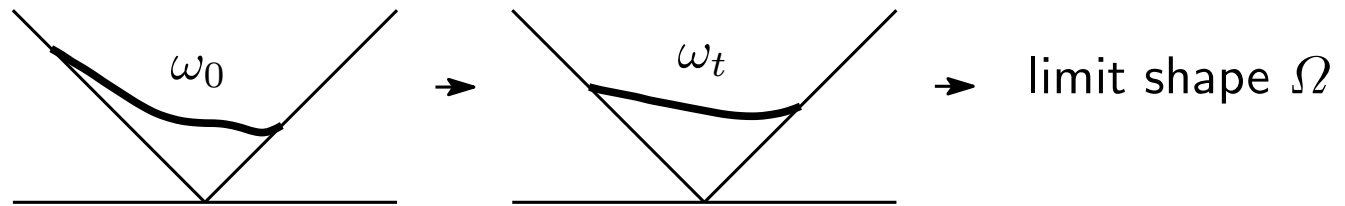
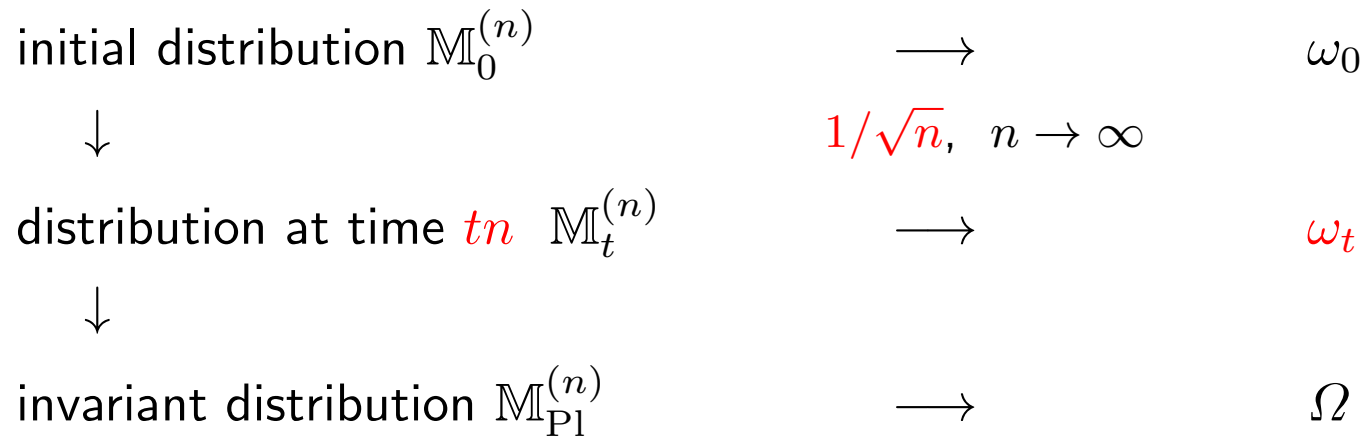


fig. 6 evolution of macroscopic profile

## §5 Technical digressions — Markov transform and free probability

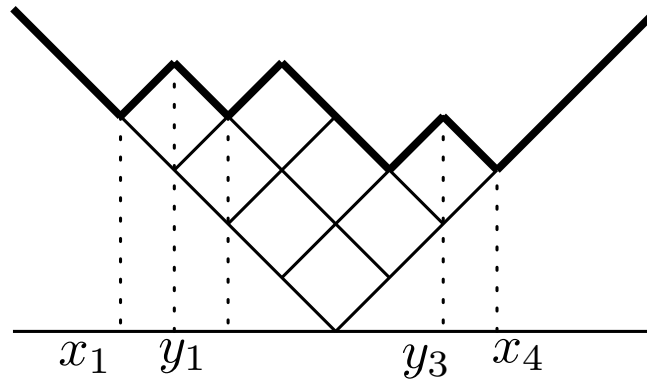


fig. 7 peak-valley coordinates of a Young diagram

peak-valley coordinates of  $\lambda \in \mathbb{D}_0$  :  $(x_1 < y_1 < x_2 < \cdots < y_{r-1} < x_r)$

$$G_\lambda(z) = \frac{(z - y_1) \cdots (z - y_{r-1})}{(z - x_1) \cdots (z - x_r)} = \frac{\mu_1}{z - x_1} + \cdots + \frac{\mu_r}{z - x_r}$$



Then,  $\mu_i > 0$  and  $\sum_{i=1}^r \mu_i = 1$ , so  $\mathfrak{m}_\lambda = \sum_{i=1}^r \mu_i \delta_{x_i} \in \mathcal{P}(\mathbb{R})$

**Lemma**  $\mathbb{D}_0 \cong \{\mu \in \mathcal{P}(\mathbb{R}) \mid \text{mean } 0, \text{supp}\mu \text{ is a finite set}\}$  by  $\lambda \leftrightarrow \mathfrak{m}_\lambda$

**Lemma** Extended to embedding  $\mathbb{D} \longrightarrow \mathcal{P}(\mathbb{R})$  : **Markov(-Krein) transform**

$\omega \mapsto \mathfrak{m}_\omega$  : **transition measure** of continuous diagram

$$\frac{1}{z} \exp\left\{ \int_{\mathbb{R}} \frac{1}{x-z} \left( \frac{\omega(x) - |x|}{2} \right)' dx \right\} = \int_{\mathbb{R}} \frac{1}{z-x} \mathfrak{m}_\omega(dx), \quad z \in \mathbb{C}^+$$

**Remark** Add a box at the  $i$ th valley  $x_i$  of  $\lambda \in \mathbb{Y}$  to make  $\mu^{(i)}$ , then

$$\mathfrak{m}_\lambda(x_i) = \frac{\dim \mu^{(i)}}{(|\lambda| + 1) \dim \lambda} = p^\uparrow(\lambda, \mu^{(i)})$$

(transition probability for Plancherel growth process)

**Freeness** is a notion for describing relation between random variables.

Free structure often appears in **large** random matrices/permutations.

In several mathematical contexts,

**independence** vs **freeness** for random variables

results in/from interesting contrasts such as

- direct product vs free product (as group or algebra structure)
- lattice vs tree (as Laplacian)
- Gauss vs Wigner (as central limit theorem)
- Boson Fock vs full Fock (as creation and annihilation)                      etc.

Let  $a, b$  be real random variables (typically, self-adjoint elements in function or operator algebra) with distributions  $\mu, \nu$  respectively

$$\mathbb{E}[a^n] = \int_{\mathbb{R}} x^n \mu(dx), \quad \mathbb{E}[b^n] = \int_{\mathbb{R}} x^n \nu(dx) \implies \mathbb{E}[(a+b)^n] = \int_{\mathbb{R}} x^n ?(dx)$$

$$\begin{array}{lll} a + b \longrightarrow \mu * \nu & \text{convolution} & \text{if } a, b \text{ are independent} \\ \longrightarrow \mu \boxplus \nu & \text{free convolution} & \text{if } a, b \text{ are free} \end{array}$$

$p$  : projection free to  $a \longrightarrow pap$  : free compression

$c$  = expectation of  $p \in (0, 1)$  i.e.  $\mathbb{E}[p] = \mathbb{E}[p^2] = c$

$\mu_c$  : distribution of  $pap$  (no commutative analogue)

$$\mathbb{E}[(pap)^n] = \int_{\mathbb{R}} x^n \mu_c(dx)$$

## §6 Characterization of the macroscopic profile at time $t$

**Theorem** (recall) [Publ. RIMS 2015, SpringerBriefs Math-Phys. 2016]

The concentration property is propagated as time goes by.

If initial distributions  $\mathbb{M}_0^{(n)}$  satisfy the concentration property with  $\omega_0 \in \mathbb{D}$ , then for  $\forall t > 0$   $\mathbb{M}_t^{(n)}$  also satisfy the concentration property, hence there exists  $\omega_t \in \mathbb{D}$  s.t. LLN

$$\mathbb{M}_t^{(n)} \left( \left\{ \lambda \in \mathbb{Y}_n \mid \|\lambda^{\sqrt{n}} - \omega_t\|_{\text{sup}} \geq \epsilon \right\} \right) \xrightarrow[n \rightarrow \infty]{} 0 \quad (\forall \epsilon > 0).$$

Here  $\omega_t$  is determined by

$$\mathbf{m}_{\omega_t} = (\mathbf{m}_{\omega_0})_{e^{-t}} \boxplus (\mathbf{m}_{\Omega})_{1-e^{-t}}$$

(free convolution of free compressions of transition measures).

Furthermore time evolution of the distributions is described through its

Stieltjes transform:  $G(t, z) = \int_{\mathbb{R}} \frac{1}{z-x} \mathbf{m}_{\omega_t}(dx)$ . ■

► PDE describing time evolution of transition measure  $\mathfrak{m}_{\omega_t}$

$$\frac{\partial G}{\partial t} = -G \frac{\partial G}{\partial z} + \frac{1}{G} \frac{\partial G}{\partial z} + G, \quad t > 0, z \in \mathbb{C}^+$$

**Remark** Transition measure of  $\Omega_t$  (limit shape of Plancherel growth process at time  $t$ ) is semicircle distribution of mean 0 and variance  $t$ ,

$$g(t, z) = \int_{\mathbb{R}} \frac{1}{z - x} \mathfrak{m}_{\Omega_t}(dx) = \frac{z - \sqrt{z^2 - 4t}}{2t}$$

satisfying PDE :

$$\frac{\partial g}{\partial t} = -g \frac{\partial g}{\partial z}$$

- Equation for  $\omega(t, x) = \omega_t(x)$  is still open.
- 1 step transition of Res-Ind chain is non-local.

## §7 Global fluctuation

Dynamic model : initial  $\rightarrow\rightarrow\rightarrow$  Plancherel

Fluctuation for other (non-Plancherel) ensembles

Śniady (2005) “character factorization property”

►  $(Y_n, \mathbb{M}^{(n)})$  or  $(Z(\mathbb{C}[\mathfrak{S}_n]), \phi^{(n)})$ ,

$C$  : cumulant functional w.r.t.  $E_{\mathbb{M}^{(n)}}$  or  $\phi^{(n)}$

Assume

$$C[\Sigma_{j_1}, \dots, \Sigma_{j_k}] = O\left(n^{\frac{j_1 + \dots + j_k - k + 2}{2}}\right).$$

Then

$$\left\{ \sqrt{n} \left( n^{-\frac{j+1}{2}} \Sigma_j - E_{\mathbb{M}^{(n)}} \left[ n^{-\frac{j+1}{2}} \Sigma_j \right] \right) \right\}_{j \geq 2} \xrightarrow[n \rightarrow \infty]{} \{X_j\} : \text{Gaussian, mean 0.} \quad (\star)$$

## Theorem (not satisfactory)

In our model, character factorization property is propagated at any macroscopic time  $t$ .

Hence  $\sqrt{n}(\mathbf{m}_{\lambda\sqrt{n}} - \mathbf{m}_{\omega_t})$  on  $(\mathbb{Y}_n, \mathbb{M}_t^{(n)})$  converges as  $n \rightarrow \infty$  to the fluctuation at  $t$ , i.e.

- ▶  $\left\{ \langle x^j, \sqrt{n}(\mathbf{m}_{\lambda\sqrt{n}} - \mathbf{m}_{\omega_t}) \rangle \right\}_j \xrightarrow[n \rightarrow \infty]{} \text{Gaussian system with mean 0}$
- ▶ Covariance of  $(X_j)$  in  $(\star)$  for  $\mathbb{M}^{(n)} = \mathbb{M}_t^{(n)}$  has complicated  $t$ -dependence, vanishes as  $t \rightarrow \infty$ . ■

Grand canonical setting  $\mathbb{Y} = \bigsqcup_{n=0}^{\infty} \mathbb{Y}_n$

Poissonization of the Plancherel measure

$$\mathbb{M}_{\text{PP}}^{(\xi)} = \sum_{n=0}^{\infty} \frac{e^{-\xi} \xi^n}{n!} \mathbb{M}_{\text{Pl}}^{(n)}, \quad \xi > 0$$

is kept invariant under transition probability  $P^{(\xi)}$  on  $\mathbb{Y}$  :

$$P^{(\xi)} = \alpha_{\xi}(n) P^{\uparrow(n)} + (1 - \alpha_{\xi}(n)) P^{\downarrow(n)},$$

$$\alpha_{\xi}(n) = \int_0^1 \xi e^{-\xi x} (1-x)^n dx$$

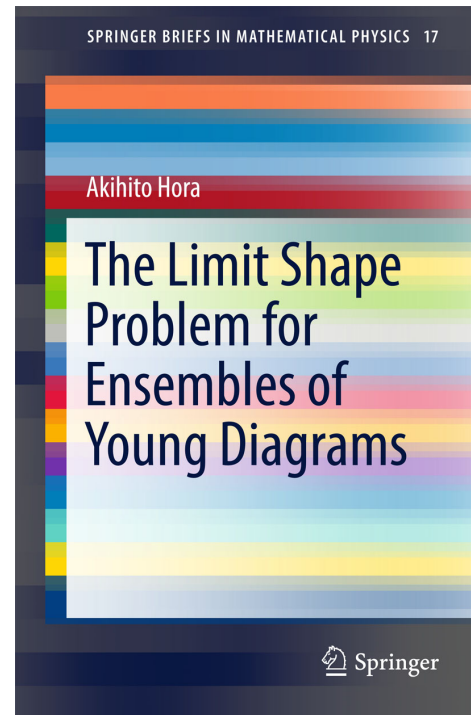
Continuous time Markov chain  $(X_s^{(\xi)})_{s \geq 0}$

► Rescale for time  $t\xi$ , for space  $\frac{1}{\sqrt{\xi}} \lambda(\sqrt{\xi}x)$  ( $\lambda \in \mathbb{Y}$ )

Behavior as  $\xi \rightarrow \infty$  .....



## Reference



A. Hora: The Limit Shape Problem for Ensembles of Young Diagrams, SpringerBriefs in Mathematical Physics 17, Springer, 2016

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