

Markov chains on Schur processes

• First we introduce two stochastic matrices, which will be the basis of the construction of Markov chains.

• For any two given Schur-positive specializations $\mathfrak{g}, \mathfrak{g}'$ s.t. $H(\mathfrak{g}; \mathfrak{g}') < \infty$, we define the transition matrices indexed by Young diagrams λ and μ by:

$$(a) \quad P_{\lambda \rightarrow \mu}^{\uparrow}(\mathfrak{g}; \mathfrak{g}') := \frac{1}{H(\mathfrak{g}; \mathfrak{g}')} \frac{S_{\mu}(\mathfrak{g})}{S_{\lambda}(\mathfrak{g})} S_{\mu/\lambda}(\mathfrak{g}')$$

$$(b) \quad P_{\lambda \rightarrow \mu}^{\downarrow}(\mathfrak{g}; \mathfrak{g}') := \frac{S_{\mu}(\mathfrak{g})}{S_{\lambda}(\mathfrak{g}; \mathfrak{g}')} S_{\lambda/\mu}(\mathfrak{g}')$$

Prop 1: $P_{\lambda \rightarrow \mu}^{\uparrow}$ and $P_{\lambda \rightarrow \mu}^{\downarrow}$ are stochastic, i.e., the entries are ≥ 0 and $\forall \lambda \in \mathcal{Y}$,

$$\sum_{\mu \in \mathcal{Y}} P_{\lambda \rightarrow \mu}^{\uparrow}(\mathfrak{g}; \mathfrak{g}') = 1$$

$$\sum_{\mu \in \mathcal{Y}} P_{\lambda \rightarrow \mu}^{\downarrow}(\mathfrak{g}; \mathfrak{g}') = 1$$

For the proof of this and other propositions we will use identities which we recall:

(Skew-Quotient) (A)
$$\sum_{\mu \in \mathcal{Y}} S_{\mu/\lambda}(\mathfrak{g}) S_{\mu/\nu}(\mathfrak{g}') = H(\mathfrak{g}; \mathfrak{g}') \sum_{\chi \in \mathcal{Y}} S_{\lambda/\chi}(\mathfrak{g}') S_{\chi/\nu}(\mathfrak{g})$$

(B)
$$\sum_{\lambda \in \mathcal{Y}} S_{\lambda}(\mathfrak{g}_1) S_{\mu/\lambda}(\mathfrak{g}_2) = S_{\mu}(\mathfrak{g}_1, \mathfrak{g}_2)$$

~~_____~~

(c): (a) with $\lambda = \emptyset$:
$$\sum_{\mu \in \Pi} S_{\mu}(s) S_{\mu, \emptyset}(s') = H(s, s') S_{\emptyset}(s)$$

(112)

the Schur measure
$$\mathbb{D}_{g_1, g_2}(\lambda) := \frac{S_{\lambda}(g_1) S_{\lambda}(g_2)}{H(g_1, g_2)}$$

Proof of Prop 1: Positivity is by definition of Schur-positive specialisations g, g' .

(a)
$$\sum_{\mu} P_{\lambda \rightarrow \mu}^{\uparrow}(g, g') = \sum_{\mu} \frac{1}{H(g, g')} \frac{S_{\mu}(g) S_{\mu, \lambda}(g')}{S_{\lambda}(g)}$$

$$\stackrel{(c)}{=} \frac{1}{H(g, g')} \frac{1}{S_{\lambda}(g)} \cdot H(g, g') S_{\lambda}(g) = 1.$$

(b)
$$\sum_{\mu} P_{\lambda \rightarrow \mu}^{\downarrow}(g, g') = \sum_{\mu} \frac{S_{\mu}(g) S_{\mu, \lambda}(g')}{S_{\lambda}(g, g')}$$

$$\stackrel{(b)}{=} \frac{S_{\lambda}(g, g')}{S_{\lambda}(g, g')} = 1. \quad \#$$

Rem: Since $S_{\mu, \lambda} = 0$ if $\lambda \not\subset \mu$, we have that $P_{\lambda \rightarrow \mu}^{\uparrow} = 0$ unless $\lambda \subset \mu$ (the Young diagram increases) and $P_{\lambda \rightarrow \mu}^{\downarrow} = 0$ unless $\mu \subset \lambda$ (the Young diagram decreases).

Let us see how these stochastic matrices acts as Schur measures:

Prop 2: $\forall \mu \in \Pi$:

(a)
$$\sum_{\lambda \in \Pi} \mathbb{D}_{g_1, g_2}(\lambda) P_{\lambda \rightarrow \mu}^{\uparrow}(g_2, g_3) = \mathbb{D}_{g_1, g_3; g_2}(\mu)$$

(b)
$$\sum_{\lambda \in \Pi} \mathbb{D}_{g_1, g_2, g_3}(\lambda) P_{\lambda \rightarrow \mu}^{\downarrow}(g_2, g_3) = \mathbb{D}_{g_1, g_2}(\mu).$$

Proof: (a)
$$\sum_{\lambda \in \mathbb{I}} \frac{S_{\lambda}(s_1) S_{\lambda}(s_2)}{H(s_1; s_2)} \cdot \frac{1}{H(s_2; s_3)} \cdot \frac{S_{\mu}(s_2) S_{\mu/\lambda}(s_3)}{S_{\lambda}(s_2)}$$

$$= \frac{1}{H(s_1, s_3; s_2)} \cdot S_{\mu}(s_2) \cdot \underbrace{\sum_{\lambda \in \mathbb{I}} S_{\lambda}(s_1) S_{\mu/\lambda}(s_3)}_{\stackrel{(B)}{=} S_{\mu}(s_1, s_3)} \quad \checkmark$$

(b)
$$\sum_{\lambda \in \mathbb{I}} \frac{S_{\lambda}(s_1) S_{\lambda}(s_2, s_3)}{H(s_1; s_2, s_3)} \cdot \frac{S_{\mu}(s_2) P_{\lambda\mu}(s_3)}{S_{\lambda}(s_2, s_3)}$$

(c)
$$\stackrel{(C)}{=} S_{\mu}(s_2) \cdot \frac{H(s_1, s_3) S_{\mu}(s_1)}{H(s_1; s_2) H(s_1, s_3)} \quad \neq \quad \#$$

Remark: The Schur process with distribution $\frac{1}{Z} S_{\lambda^{(0)}}(s_0^+) S_{\lambda^{(2)}/\lambda^{(1)}}(s_1^+) \dots S_{\lambda^{(n)}/\lambda^{(n-1)}}(s_{n-1}^+) \cdot S_{\lambda^{(n)}}(s_-)$

can be rewritten as:

$$\sum_{s_0^+, \dots, s_{n-1}^+; s_-} (\lambda^{(0)}) P_{\lambda^{(0)} \rightarrow \lambda^{(1)}}^{\downarrow}(s_0^+, s_{n-2}^+, s_{n-1}^+) \dots P_{\lambda^{(2)} \rightarrow \lambda^{(1)}}^{\downarrow}(s_0^+, s_1^+).$$

This generalizes to any Schur process, i.e.; it can be viewed as a trajectory of a Markov chain with transition matrices P^{\uparrow} and P^{\downarrow} and an initial distribution given by a Schur measure.

Example: $\frac{1}{Z} S_{\lambda^{(1)}}(s_0^+) S_{\lambda^{(1)}/\mu^{(1)}}(s_1^-) S_{\lambda^{(2)}/\mu^{(1)}}(s_1^+) S_{\lambda^{(2)}}(s_2^-)$ (14)

$$= \sum_{s_0^+, s_1^+, s_2^-} (\lambda^{(1)}) \cdot P_{\lambda^{(2)} \rightarrow \mu^{(1)}}^\downarrow(s_0^+, s_1^+) \cdot P_{\mu^{(1)} \rightarrow \lambda^{(1)}}^\uparrow(s_0^+, s_1^+)$$

Indeed: \downarrow

$$= \frac{S_{\lambda^{(2)}}(s_0^+, s_1^+) S_{\lambda^{(2)}}(s_2^-)}{\text{const}} \cdot \frac{S_{\lambda^{(2)}/\mu^{(1)}}(s_1^+) S_{\mu^{(1)}}(s_0^+)}{S_{\lambda^{(2)}}(s_0^+, s_1^+)}$$

$$\cdot \frac{S_{\lambda^{(1)}/\mu^{(1)}}(s_1^-) S_{\lambda^{(1)}}(s_0^+)}{\text{const} \cdot S_{\mu^{(1)}}(s_0^+)}$$

$$= \text{const} \cdot S_{\lambda^{(2)}}(s_2^-) S_{\lambda^{(2)}/\mu^{(1)}}(s_1^+) S_{\lambda^{(1)}/\mu^{(1)}}(s_1^-) S_{\lambda^{(1)}}(s_0^+)$$

• The key property is the following commutation relation:

Prop. 3: $\forall \lambda, \nu \in \mathcal{Y}$, it holds:

$$\sum_{\mu \in \mathcal{Y}} P_{\lambda \rightarrow \mu}^\uparrow(s_1, s_2; s_3) P_{\mu \rightarrow \nu}^\downarrow(s_1, s_2) = \sum_{\mu \in \mathcal{Y}} P_{\lambda \rightarrow \mu}^\downarrow(s_1, s_2) P_{\mu \rightarrow \nu}^\uparrow(s_1, s_3)$$

Proof: l.h.s. = $\sum_{\mu} \frac{1}{H(s_1, s_2; s_3)} \frac{S_{\mu}(s_1, s_2)}{S_{\lambda}(s_1, s_2)} S_{\mu/\lambda}(s_3) \cdot \frac{S_{\nu}(s_1) S_{\mu/\nu}(s_2)}{S_{\mu}(s_1, s_2)}$

$$\stackrel{(A)}{=} \frac{H(s_2; s_3)}{H(s_1, s_2; s_3)} \frac{S_{\nu}(s_1)}{S_{\lambda}(s_1, s_2)} \sum_{\mu} S_{\lambda/\mu}(s_2) S_{\nu/\mu}(s_3)$$

$L = \frac{1}{H(s_1; s_3)}$

$$\text{r.h.s.} = \sum_{\mu} \frac{S_{\lambda}(s_1)}{S_{\lambda}(s_1, s_2)} S_{\lambda/\mu}(s_2) \cdot \frac{1}{H(s_1; s_3)} \frac{S_{\nu}(s_1) S_{\nu/\mu}(s_3)}{S_{\mu}(s_1)}$$

$$= \text{l.h.s.}$$

#

Remark: As acting as Schur measures, the commutation relation says that adding s_3 and then removing s_2 is the same as first removing s_2 and then adding s_3 :

$$\sum_{s_4, s_{11}, s_2} P^\uparrow(s_{11}, s_2; s_3) = \sum_{s_3, s_4, s_{11}, s_2}$$

followed by $\sum_{s_3, s_4, s_{11}, s_2} P^\downarrow(s_{11}, s_2) = \sum_{s_3, s_4, s_1}$

is the same as:

$$\sum_{s_4, s_{11}, s_2} P^\downarrow(s_{11}, s_2) = \sum_{s_4, s_1}$$

followed by $\sum_{s_4, s_1} P^\uparrow(s_{11}, s_3) = \sum_{s_3, s_4, s_1}$.

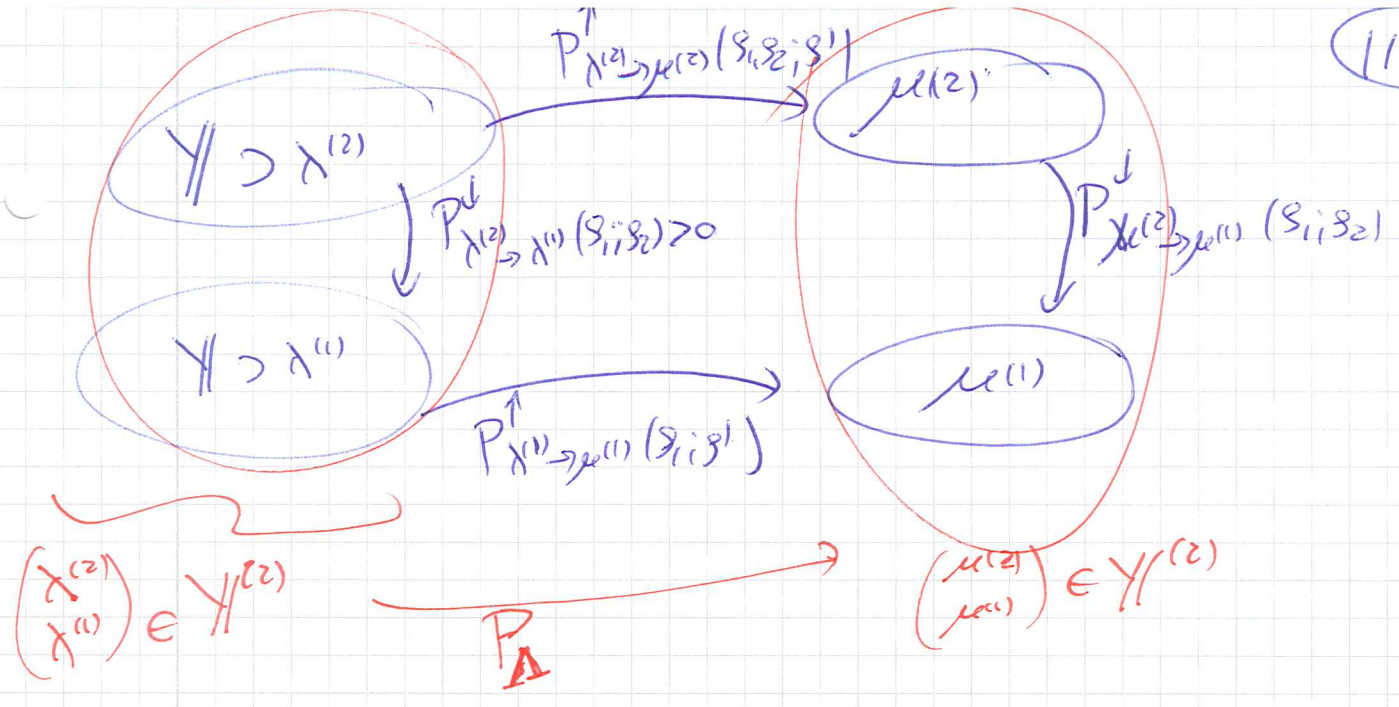
• So far we have two types of transition matrices, one adding and one removing blocs from one Young diagram.

• Now we want to construct (and then apply to special cases) Markov chains on pairs of Young diagrams.

Def. 4 let $\mathcal{Y}^{(2)}$ be the state space of pairs of Young diagrams $\begin{pmatrix} \lambda^{(2)} \\ \lambda^{(1)} \end{pmatrix}$ and s_1, s_2 Schur-positive spec. s.t. $P_{\lambda^{(2)} \rightarrow \lambda^{(1)}}^\downarrow(s_1, s_2) > 0$. Then we define the (sequential) transition probabilities:

$$\mathbb{P}_\Lambda \left(\begin{pmatrix} \lambda^{(2)} \\ \lambda^{(1)} \end{pmatrix} \rightarrow \begin{pmatrix} \mu^{(2)} \\ \mu^{(1)} \end{pmatrix} \right) := P_{\lambda^{(1)} \rightarrow \mu^{(1)}}^\uparrow(s_1, s_1) \cdot$$

$$\cdot \frac{P_{\lambda^{(2)} \rightarrow \mu^{(2)}}^\uparrow(s_1, s_2; s_1) \cdot P_{\mu^{(2)} \rightarrow \mu^{(1)}}^\downarrow(s_1, s_2)}{\sum_{\mu \in \Lambda} P_{\lambda^{(2)} \rightarrow \mu}^\uparrow(s_1, s_2; s_1) \cdot P_{\mu \rightarrow \mu^{(1)}}^\downarrow(s_1, s_2)}$$



Remark: P_Δ does the following:

- (1) $\lambda^{(1)}$ evolves to $\mu^{(1)}$ according to $P_{\lambda^{(1)} \rightarrow \mu^{(1)}}^\uparrow(s_1, s')$
- (2) Given $\lambda^{(2)}, \mu^{(1)}$, the distribution of $\mu^{(2)}$ is the one of the middle point in the 2-step M.C. with transitions $P_{\lambda^{(2)} \rightarrow \mu}^\uparrow(s_1, s_2, s')$ and $P_{\mu \rightarrow \mu^{(1)}}^\downarrow(s_1, s_2)$

The transition P_Δ has the nice property that, due to the commutativity of Prop 3, the following form of measures is preserved:

Prop 5: We have

$$\sum_{(\lambda^{(1)}, \lambda^{(2)}) \in \mathcal{Y}^2} \sum_{s_1, s_2, s} S_{s_1, s_2, s}^{-1} (\lambda^{(2)}) P_{\lambda^{(2)} \rightarrow \lambda^{(1)}}^\downarrow(s_1, s_2) \cdot P_\Delta \left(\begin{pmatrix} \lambda^{(2)} \\ \lambda^{(1)} \end{pmatrix} \rightarrow \begin{pmatrix} \mu^{(2)} \\ \mu^{(1)} \end{pmatrix} \right)$$

$$= \sum_{s_1, s_2, s} S_{s_1, s_2, s}^{-1} (\mu^{(2)}) P_{\mu^{(2)} \rightarrow \mu^{(1)}}^\downarrow(s_1, s_2)$$

~~Proof: l.h.s. = $\sum_{\lambda^{(2)} \in \mathcal{Y}} \sum_{\lambda^{(1)} \in \mathcal{Y}} \sum_{s_1, s_2, s} S_{\lambda^{(2)} \rightarrow \lambda^{(1)}}^\downarrow(s_1, s_2) S_{\lambda^{(2)} \rightarrow \lambda^{(1)}}^\uparrow(s_1, s_2) \cdot S_{\lambda^{(1)} \rightarrow \mu^{(1)}}^\downarrow(s_1, s_2) S_{\lambda^{(1)} \rightarrow \mu^{(1)}}^\uparrow(s_1, s_2)$~~

Proof: l.h.s. = $\sum_{\lambda^{(2)} \in \mathcal{Y}} \sum_{\lambda^{(1)} \in \mathcal{Y}} \sum_{s_1, s_2, s} S_{s_1, s_2, s}^{-1} (\lambda^{(2)}) P_{\lambda^{(2)} \rightarrow \lambda^{(1)}}^\downarrow(s_1, s_2)$

$\cdot P_{\lambda^{(1)} \rightarrow \mu^{(1)}}^\uparrow(s_1, s')$

$\frac{P_{\lambda^{(2)} \rightarrow \mu^{(2)}}^\uparrow(s_1, s_2, s') P_{\mu^{(2)} \rightarrow \mu^{(1)}}^\downarrow(s_1, s_2)}{\sum_{\mu \in \mathcal{Y}} P_{\lambda^{(2)} \rightarrow \mu}^\uparrow(s_1, s_2, s') P_{\mu \rightarrow \mu^{(1)}}^\downarrow(s_1, s_2)}$

Using Prop 3 we have:

$$\sum_{\lambda^{(2)} \in \Pi} P_{\lambda^{(2)} \rightarrow \lambda^{(1)}}^{\downarrow}(s_1, s_2) P_{\lambda^{(1)} \rightarrow \mu^{(1)}}^{\uparrow}(s_1, s'_1)$$

$$= \sum_{\mu \in \Pi} P_{\lambda^{(2)} \rightarrow \mu}^{\uparrow}(s_1, s_2; s'_1) \cdot P_{\mu \rightarrow \mu^{(1)}}^{\downarrow}(s_1, s_2)$$

⇒ the denominator simplifies leading to:

$$\sum_{\lambda^{(2)} \in \Pi} \underbrace{S_{s_1, s_2, s'_1}^{-1}(\lambda^{(2)}) P_{\lambda^{(2)} \rightarrow \mu^{(2)}}^{\uparrow}(s_1, s_2; s'_1) P_{\mu^{(2)} \rightarrow \mu^{(1)}}^{\downarrow}(s_1, s_2)}_{= S_{s_1, s_2, s'_1}(\mu^{(2)})} \quad \#$$

Plan:
 { → Generalize to N-tuples of Yang diagrams.
 { → Look at a concrete example.

Markov chain of N-tuples of Yang ~~tables~~ diagrams, $\mathcal{Y}^{(N)}$.

Def 6: let $\mathcal{Y}^{(N)}$ the space of N-tuples of Yang diagrams

let s_1, \dots, s_N be Schur-positive specializations ~~and~~ and $(\lambda^{(1)}, \dots, \lambda^{(N)}) \in \mathcal{Y}^{(N)}$.

Assume, $P_{\lambda^{(k)} \rightarrow \lambda^{(k-1)}}^{\downarrow}(s_1, \dots, s_{k-1}, s_k) > 0$, $k=2, \dots, N$, then define

$$P_{\lambda}((\lambda^{(1)}, \dots, \lambda^{(N)}) \rightarrow (\mu^{(1)}, \dots, \mu^{(N)})) :=$$

$$= P_{\lambda^{(1)} \rightarrow \mu^{(1)}}^{\uparrow}(s_1, s'_1) \cdot \prod_{k=2}^N \frac{P_{\lambda^{(k)} \rightarrow \mu^{(k)}}^{\uparrow}(s_1, \dots, s_k; s'_1) P_{\mu^{(k)} \rightarrow \mu^{(k-1)}}^{\downarrow}(s_1, \dots, s_{k-1}, s_k)}{\sum_{\mu \in \Pi} P_{\lambda^{(k)} \rightarrow \mu}^{\uparrow}(s_1, \dots, s_k; s'_1) P_{\mu \rightarrow \mu^{(k-1)}}^{\downarrow}(s_1, \dots, s_{k-1}, s_k)}$$

defines a Markov chain on $\mathcal{Y}^{(N)}$ (with $\textcircled{118}$)
 sequential update: first $\mu^{(1)}$, then $\mu^{(2)}, \mu^{(3)}, \dots, \mu^{(N)}$.

The generalisation of Prop 5 is immediate.

Prop. 7: ~~We have~~ Define

$$\mathcal{M}_{\mathcal{S}_1 - \mathcal{S}_N | \mathcal{S}^-}(\vec{\lambda}) := \int_{\mathcal{S}_1 - \mathcal{S}_N | \mathcal{S}^-} (\lambda^{(N)}) \cdot P_{\lambda^{(N)} \rightarrow \lambda^{(N-1)}}(\mathcal{S}_1 - \mathcal{S}_{N-1} | \mathcal{S}^-) \cdots P_{\lambda^{(2)} \rightarrow \lambda^{(1)}}(\mathcal{S}_1 | \mathcal{S}^-)$$

Then,

$$\sum_{(\vec{\lambda}) \in \mathcal{Y}^{(N)}} \mathcal{M}_{\mathcal{S}_1 - \mathcal{S}_N | \mathcal{S}^-}(\vec{\lambda}) \cdot \mathbb{I}_1(\vec{\lambda} \rightarrow \vec{\mu}) = \mathcal{M}_{\mathcal{S}_1 - \mathcal{S}_N | \mathcal{S}^-}(\vec{\mu})$$

Proof: An easy generalisation of the one of Prop. 5. #

Remark: The measure $\mathcal{M}_{\mathcal{S}_1 - \mathcal{S}_N | \mathcal{S}^-}$ is the one of a Schur process and thus we know ~~that~~ that it has determinantal correlation functions (and we know ~~in fact~~ how to compute its correlation kernel).

Application:

• let us consider the simple case where each $g_k = (1, 0, \dots; 0; 0)$ and $g' = (0; (b, 0, \dots); 0)$. $(b \in (0, 1))$

• Consider the discrete time (homogeneous) Markov chain $\vec{\lambda}(t) = (\lambda^{(1)}(t), \dots, \lambda^{(n)}(t))$ starting from the Schur process $\mathcal{M}_{g_1, \dots, g_n; g^-}(\vec{\lambda}(0))$ with $g^- = (0; 0; 0)$.

Q1 What is the measure at $t=0$?

~~$$\mathcal{M}_{g_1, \dots, g_n; 0}(\vec{\lambda}) = \int \prod_{k=1}^n \delta_{(\lambda^{(k)}(0); 0; 0)}(\lambda^{(k)}) P_{g_1, \dots, g_n}^{\downarrow}(\vec{\lambda}(0), (\lambda^{(k)}(0), (\lambda^{(k)}(0), \dots))$$~~

• Since $\int \delta_{(\lambda^{(k)}(0); 0; 0)}(\lambda^{(k)}) = \int \delta_{\lambda^{(k)}(0)}(0; 0; 0) \delta_{\lambda^{(k)}(0)}(\lambda^{(k)}; 0; 0)$
 $= \delta_{\lambda^{(k)}(0), \phi}$

(this can be easily seen from the line ensemble representation)

• Then $P_{\phi \rightarrow \lambda^{(n-1)}(\ast; \ast)}$ implies that $\lambda^{(n-1)} = \phi$ and so on.

\Rightarrow at $t=0$, the measure is all concentrated on the configuration $\vec{\lambda}(0) = (\phi, \dots, \phi)$.

Q: Measure at time t ?

By Proposition 7, the measure at time t is given by

$$\begin{aligned} & \mathcal{M}_{\left(\frac{a_1-a}{k}; 0; 0\right), \left(0; \frac{b_1-b}{t}; 0\right)}(\vec{\lambda}(t)) = \\ & = \int_{\left(\frac{a_1-a}{k}; 0; 0\right), \left(0; \frac{b_1-b}{t}; 0\right)} \lambda^{(k)}(t) \cdot \prod_{k=2}^n P_{\lambda^{(k)} \rightarrow \lambda^{(k-1)}} \left(\left(\frac{a_1-a}{k-1}; 0; 0\right); \left(1; 0; 0\right) \right) \end{aligned}$$

Consequence: ~~The last product implies that~~

$\lambda^{(k)}(t)$ has at most k non-empty rows and their coordinates satisfy the following interlacing conditions:

$$\lambda_1^{(k)} \geq \lambda_1^{(k-1)} \geq \lambda_2^{(k)} \geq \dots \geq \lambda_{k-1}^{(k-1)} \geq \lambda_k^{(k)}$$

Indeed: one can see by iteration that the measure on $\lambda^{(k)}(t)$ is (using Prop 2 (b))

$$\begin{aligned} & \int_{\left(\frac{a_1-a}{k}; 0; 0\right); \left(0; \frac{b_1-b}{t}; 0\right)} \lambda^{(k)}(t) \cdot \prod_{k=2}^n P_{\lambda^{(k)} \rightarrow \lambda^{(k-1)}} \\ & = \int_{\lambda^{(k)}(t)} \left(\frac{a_1-a}{k}; 0; 0\right) \cdot t \dots \\ & = 0 \text{ if } \lambda_{k+1}^{(k)}(t) \neq 0. \end{aligned}$$

Interlacing comes from the factors $P_{\lambda^{(k)} \rightarrow \lambda^{(k-1)}} \dots$

Q: Transition probabilities.

• $\lambda^{(k)}$ has a single row with transition probabilities:

$$\begin{aligned}
 P_{\lambda^{(k)} \rightarrow \mu^{(k)}}^{\uparrow}((i; 0; 0); (a; b; 0)) &= \\
 &= \frac{1}{1+b} \cdot \frac{S_{\mu^{(k)}}((i; 0; 0))}{S_{\lambda^{(k)}}((i; 0; 0))} \cdot \boxed{S_{\mu^{(k)}/\lambda^{(k)}}((a; b; 0))} \\
 &= \begin{cases} \frac{b}{b+1}, & \text{if } \mu^{(k)} = \lambda^{(k)} + 1, \\ \frac{1}{b+1}, & \text{if } \mu^{(k)} = \lambda^{(k)}, \\ 0, & \text{otherwise.} \end{cases}
 \end{aligned}$$

$= \begin{cases} b, & \text{if } \mu^{(k)} = \lambda^{(k)} + 1 \\ 1, & \text{if } \mu^{(k)} = \lambda^{(k)} \\ 0, & \text{otherwise} \end{cases}$

• More generally,

$$\mathbb{P}(\lambda^{(k)}(t+1) = \nu \mid \lambda^{(k)}(t) = \lambda, \lambda^{(k-1)}(t+1) = \mu) =$$

$$= \frac{S_{\nu/\lambda}(a; b; 0) S_{\nu/\mu}(1; 0; 0)}{\sum_{\eta \in \mathcal{Y}} S_{\eta/\lambda}(a; b; 0) S_{\eta/\mu}(1; 0; 0)} \cdot b^{|\nu| - |\lambda|}$$

given that $0 \leq \nu_i - \lambda_i \leq 1$
and μ, ν are interlacing.

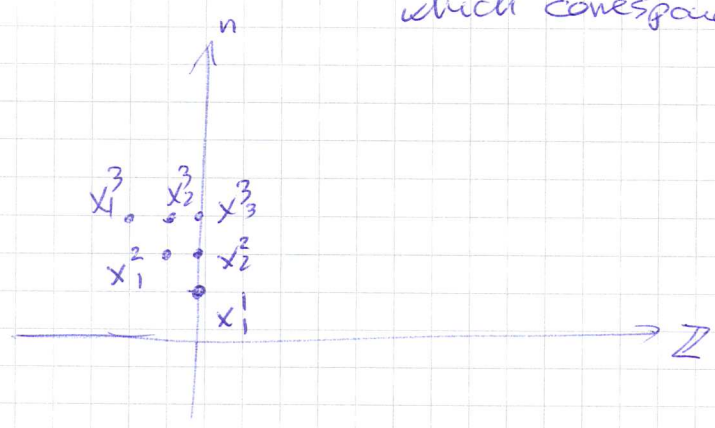
• This means that the length of each row of $\lambda^{(k)}$ indep. increases by 1 with proba $\frac{b}{b+1}$ unless this contradicts interlacing. In the latter case, ~~the~~ the length either stays the same or increases by 1 with proba 1.

Visualization as an interacting particle system.

• Let us introduce the ~~$N(N+1)$~~ $\frac{N(N+1)}{2}$ particles with integer coordinates

$$X_i^n := \sum_{k=1}^n \lambda_{n+1-k} - b + i, \quad n=1, \dots, N, \quad i=1, \dots, n$$

• In particular if all $\lambda_k^{(n)}$ are equal to 0, which corresponds to the initial condition.



• The interlacing for the particle system becomes:

$$x_1^n < x_1^{n-1} \leq x_2^n < x_2^{n-1} \leq \dots \leq x_n^n, \quad n=2, \dots, N.$$

Dynamics: At each time t , each particles ~~flips a coin with bias $\frac{b}{b+1}$ and jumps to its right with proba $\frac{b}{1+b}$~~ ^{would like to} jumps to its right with proba $\frac{b}{1+b}$.

$$(a) \begin{cases} x_i^1(t+1) = x_i^1(t) + 1 & \text{with proba } \frac{b}{b+1} \\ x_i^1(t) & \text{with proba } \frac{1}{b+1} \end{cases}$$

(b) Recursively from bottom to top:

→ If $x_k^{n-1}(t+1)$, $1 \leq k \leq n-1$ have updated, then

$$(1) \text{ If } k \geq 1 \text{ and } x_k^{n-1}(t) = x_{k-1}^{n-1}(t+1) - 1 \Rightarrow x_k^n(t+1) = x_k^n(t) + 1$$

(pushed)

otherwise: (2) If $x_k^{n-1}(t+1) = x_k^{n-1}(t) + 1 \Rightarrow x_k^n(t+1) = x_k^n(t)$

(blocked)

otherwise: (3) $X_k^u(t+1) = \begin{cases} X_k^u(t) + 1 & \text{with prob } \frac{b}{b+1} \\ X_k^u(t) & \text{with prob } \frac{1}{b+1} \end{cases}$ (123)

Remark 1 One can easily take the continuous limit ($b \rightarrow 0$ and $t = \tau/b$)

In this case the dynamics is simpler:

• each particle ~~tries~~ to jump to its right with rate 1 and

(a) If $X_k^u(t)$ tries to jump and

" X_{k-1}^{u-1} block X_k^u " $X_k^u(t) = X_{k-1}^{u-1}(t) - 1 \Rightarrow$ jump suppressed

(b) If $X_k^u(t)$ jumps and ~~after~~ before the jump $X_k^u(t) = X_{k+1}^{u+1}(t) = \dots = X_{k+c}^{u+c}(t)$

for some $c \Rightarrow$ all these particles are moved to the right by 1

(" X_k^u pushes X_{k+1}^{u+1} , which pushes X_{k+2}^{u+2} ...")

• One can also take the diffusive scaling limit. The result is a system of reflected Brownian motions.

Projection onto $(X_1^{(1)}(t), \dots, X_1^{(N)}(t))$.

• The projection to $(X_1^{(1)}(t), \dots, X_1^{(N)}(t))$ is called TASEP with sequential update (in discrete time).

↑
Totally Asymmetric Simple Exclusion Process

TASEP in continuous time.

- The TASEP = Totally Asymmetric Simple Exclusion in continuous time is an interacting particle system on \mathbb{Z} :

- State space: $\Omega = \{0, 1\}^{\mathbb{Z}}$, where

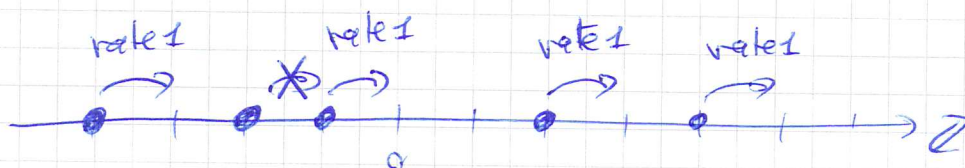
$$\eta(x) = \begin{cases} 1, & \text{if } \exists \text{ particle at } x \\ 0, & \text{if } x \text{ is empty.} \end{cases}$$

- Dynamics: In words, each particle tries to jump to its right with rate 1, provided that the site is empty.

- Mathematically, it is a Markov process with generator

$$(L f)(\eta) = \sum_{x \in \mathbb{Z}} \eta(x)(1 - \eta(x+1)) [f(\eta^{x, x+1}) - f(\eta)]$$

for f local functions; $\eta^{x, x+1}(z) = \begin{cases} \eta(x), & \text{if } z = x+1 \\ \eta(x+1), & \text{if } z = x \\ \eta(z), & \text{otherwise} \end{cases}$



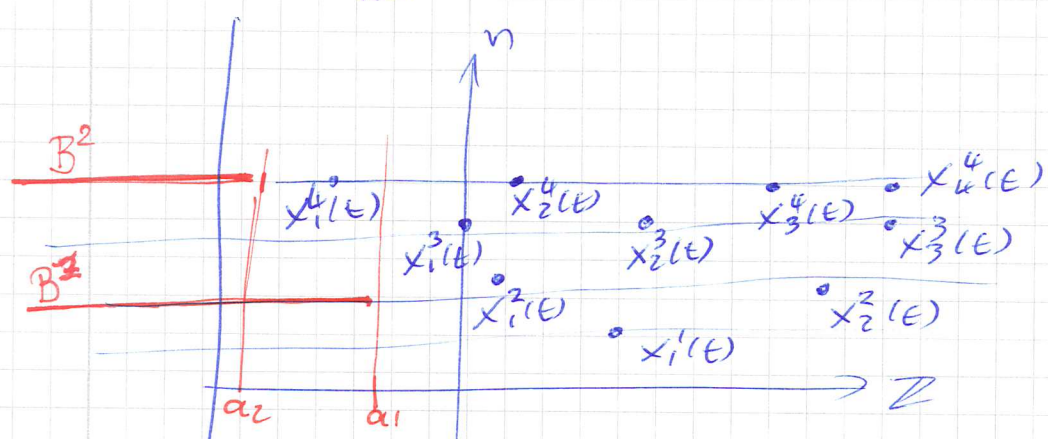
Consider the initial conditions corresponding to $\gamma^{(n)} = \phi, \forall n$:

$$x_i^n(0) = -n+i, 1 \leq i \leq n \leq N.$$

TASEP particles are $(x_1^1(t), x_1^2(t), \dots, x_1^N(t))$.

Q: Can we determine the joint distributions of particles? For any $1 \leq n_1 < n_2 < \dots < n_m$, TASEP

what is $\mathbb{P} \left(\bigcap_{k=1}^m \{x_{i_k}^{n_k}(t) \geq a_k\} \right) = ?$



Ex: $m=2; n_1=2; n_2=4$

$$= \mathbb{P} \left(\bigcap_{k=1}^m \{ \text{set } \{x_i^{n_k}, x < a_k\} \text{ is empty} \} \right)$$

Since the measure on the point process

$$\mu = \sum_{n \geq 1} \sum_{k=1}^n \delta_{(x_k^n(t), n)}$$

is determinantal, the probability we are looking for is a Fredholm determinant.

• Before going into computations, remark that this model is equivalent to the growth model

described in the introduction (page 3), see also Thm 1.

• Indeed, one can define a height function

$$h(x, t) = \begin{cases} 2N(t) + \sum_{y=1}^x (1 - 2\eta_y(t)), & \text{if } x \geq 1, \\ 2N(t) & \text{if } x = 0, \\ 2N(t) - \sum_{y=-x}^0 (1 - 2\eta_y(t)), & \text{if } x \leq -1. \end{cases}$$

where $N(t) = \#$ of jumps from site 0 to site 1 during the time-span $[0, t]$.

• In particular,

$$\mathbb{P} \left(\bigcap_{k=1}^m \{X_{n_k}(t) \geq m_k - n_k\} \right) = \mathbb{P} \left(\bigcap_{k=1}^m \{h(n_k - n_k, t) \geq m_k + n_k\} \right)$$

$\underbrace{\qquad\qquad\qquad}_{\equiv X_1^{n_k}(t)}$

• Correlation kernel of the measure at time t :

• In the discrete time, the measure at time t is given by

$$\int \prod_{i=1}^N (1 - \lambda_i) \lambda_i \rho_i; \rho_i \prod_{i=1}^N (1 - \lambda_i) \lambda_i \rho_i \quad (\lambda^{(t)})$$

$$\prod_{k=2}^N P_{\lambda^{(k)}} \downarrow \lambda^{(k-1)} \left(\prod_{i=1}^N (1 - \lambda_i) \lambda_i \rho_i \right)$$

See page

(113)
$$= \frac{1}{z} S_{\lambda^{(1)}}(s_0^+) S_{\lambda^{(2)} / \lambda^{(1)}}(s_1^+) \dots S_{\lambda^{(n)} / \lambda^{(n-1)}}(s_{n-1}^+) \cdot S_{\lambda^{(n)} / \beta}$$

with $s_0^+ = \dots = s_{n-1}^+ = (1; 0; 0)$, for which $H(s_k^+) = \frac{1}{1-z}$
~~and $s_{-1}^- = (0; 1; 0)$~~ and $s_{-1}^- = (0; \underbrace{b_{1-1}, b}_{t}; 0)$, for which
 $H(s_{-1}^-) = (1 + bz)^N$.

• The continuous limit is obtained ~~as~~ as the limit $b \rightarrow 0$ and $t \rightarrow \frac{t}{b}$.

⇒ Measure at time t is given by

$$\mathcal{M}_{(\underbrace{(1, \dots, 1)}_N; 0; 0); (0; 0; t)}(\lambda^{(1)}, \dots, \lambda^{(n)}) =$$

see page (113)

$$= \frac{1}{z} S_{\lambda^{(1)}}((1; 0; 0)) \dots S_{\lambda^{(n)} / \lambda^{(n-1)}}((1; 0; 0)) \cdot S_{\lambda^{(n)}}((0; 0; t))$$

• We already computed the correlation kernel of this Schur process, see page (10).

• In the general formula, we need to specialize as follows:

$$H(s_{k-1}^+, s_k^+)(v) = \left(\frac{1}{1-av} \right)^k$$

$$H(\bar{s}_{k-1}^-, \bar{s}_N^-)(N) = e^{-Lv}$$

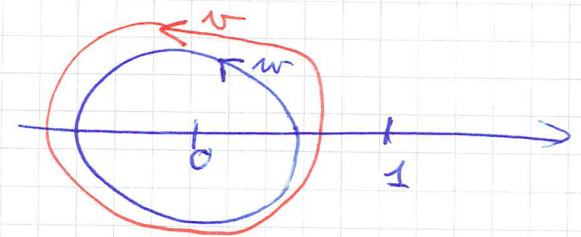
• the result of the three specialized reads:

Thm: Let $\xi := \sum_{n=1}^{\infty} \sum_{k=1}^n \delta_{(n, x_k^n(t))}$. ξ is a determinantal point process on $\mathbb{Z}_{>0} \times \mathbb{Z}$ with correlation kernel:

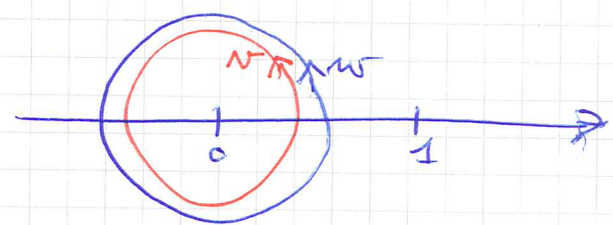
$$K(n_1, x_1; n_2, x_2) = \frac{1}{(2\pi i)^2} \oint_{\Gamma_0} \oint_{\Gamma_1} \frac{(1-w)^{n_1}}{(1-v)^{n_2}} \frac{e^{t/v} w^{x_1-1}}{e^{t/v} v^{x_2} w} \frac{1}{w-v}$$

where the contours are as follows:

For $n_1 > n_2$:



For $n_1 < n_2$:



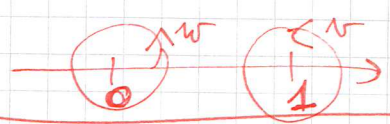
Remark: The poles of K for $n_1 > n_2$ are at $v=0$ & $w=v$.

\Rightarrow we can write as $\oint_{\Gamma_0} \oint_{\Gamma_1}$

For $n_1 < n_2$, we can ~~also~~ exchange the contours and get the pole at $w=v$ as well.

This leads to the following formula:

$$K(n_1, x_1; n_2, x_2) = \frac{-1}{2\pi i} \oint_{\Gamma_0} \frac{1}{(1-w)^{n_2-n_1}} \cdot \frac{1}{w^{x_2-x_1+1}} \mathbb{1}_{[n_1 < n_2]} + \frac{1}{(2\pi i)^2} \oint_{\Gamma_0} \oint_{\Gamma_1} \frac{e^{t/v}}{e^{t/v}} \cdot \frac{(1-w)^{n_1}}{(1-v)^{n_2}} \cdot \frac{w^{x_1-1}}{v^{x_2}} \cdot \frac{1}{w-v}$$



Large time asymptotics:

- We want to determine the large time asymptotics of $X_n(t)$ for $n = O(t)$.
- Let $j(x,t) = \mathbb{E}[\eta_x(t)(1-\eta_{x+1}(t))]$ and $\rho(x,t) := \mathbb{E}[\eta_x(t)]$.
 \uparrow average current of particles from x to $x+1$ \uparrow particle density at x .

~~Lemma 9~~

Lemma 9 The conservation of particles implies:

$$\frac{d}{dt} \rho(x,t) + \nabla_x j(x,t) = 0$$

$$\text{where } \nabla_x j(x,t) := j(x,t) - j(x-1,t).$$

Proof: Let $T(t)$ be the semigroup generated by the TASEP generator \mathcal{L} .

The forward eq. is: $\frac{d}{dt} T(t)f = T(t)\mathcal{L}f$

Taking $f(y) = \eta(x)$ and integrating wrt. the initial condition we get ($\rho_t := \mathcal{L} T(t)$)

$$\frac{d}{dt} \rho_t f = \frac{d}{dt} \rho(x,t).$$

$$\text{Further: } \mathcal{L}f(y) = \sum_{x \in \mathbb{Z}} \eta_x (1 - \eta_{x+1}) [f(y^{\leftarrow x, x+1}) - f(y)]$$

$$= -\eta_x (1 - \eta_{x+1}) + \eta_{x-1} (1 - \eta_x)$$

$$\begin{aligned} \Rightarrow \rho_t \mathcal{L}f &= \mathbb{E}[\eta_{x-1}(t)(1-\eta_x(t)) - \mathbb{E}[\eta_x(t)(1-\eta_{x+1}(t))] \\ &= j(x-1,t) - j(x,t). \quad \# \end{aligned}$$

Large scale: Now consider $X = \varepsilon x, x \in \mathbb{Z}$

and set $\tilde{\delta}(X, t) := \delta(\lfloor \varepsilon^{-1} X \rfloor, t)$.

$$\Rightarrow \nabla_x \delta(x, t) = \varepsilon \frac{\partial}{\partial X} \tilde{\delta}(X, t) + O(\varepsilon^2)$$

\Rightarrow To have a non-trivial limit we need to take $t = \varepsilon^{-1} T$.

$$(x, t) \mapsto (\varepsilon^{-1} X, \varepsilon^{-1} T)$$

is called the hydrodynamic scaling.

let $\mathcal{J}(X, T) := \lim_{\varepsilon \rightarrow 0} \tilde{\delta}(\lfloor X \varepsilon^{-1} \rfloor, T \varepsilon^{-1})$ and

$S_{\text{inv}}(X, T) := \lim_{\varepsilon \rightarrow 0} \delta(\lfloor X \varepsilon^{-1} \rfloor, T \varepsilon^{-1})$. Then

one can show (heuristically follows from the discrete version of the eq. in Lemma 9):

$$\partial_T S_{\text{inv}}(X, T) + \partial_X \mathcal{J}(X, T) = 0$$

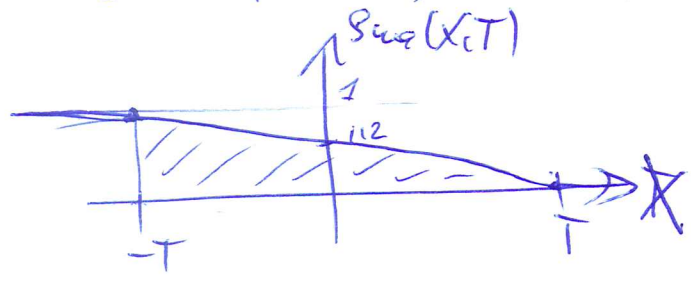
In our case $\mathcal{J}(X, T) = S_{\text{inv}}(X, T) (1 - S_{\text{inv}}(X, T))$ *

* is also known as Burgers equation.

Solution of * in our case:

We have $S_{\text{inv}}(X, 0) = \begin{cases} 1, & X < 0, \\ 0, & X > 0. \end{cases}$

One can get (see ^{also} any PDE lectures, method of characteristics) $S_{\text{inv}}(X, T) = \begin{cases} 1, & X < -T, \\ \frac{T-X}{2}, & X \in [-T, 0], \\ 0, & X > T. \end{cases}$



From this we can estimate which particles are around the origin at time T , namely particle # $\approx \frac{T}{4}$, since the # of particles which jumped over the origin is $\approx \int_0^{\infty} dx \delta_{\text{wa}}(x|T) = T/4$.

Scaling limit:

Let us consider $n_i = \frac{t}{4} + u_i \left(\frac{t}{2}\right)^{2/3}$

From the macroscopic picture $\left(\int_{\xi_i}^{\infty} dx \delta_{\text{wa}}(x,t) = n_i \Rightarrow \xi_i = \dots \right)$

we expect $X_{n_i}(t)$ to be roughly around

$$\xi_i = -2u_i \left(\frac{t}{2}\right)^{2/3} + u_i^2 \left(\frac{t}{2}\right)^{1/3}$$

Due to the $(\frac{2}{3}, \frac{1}{3})$ KPZ scaling, we set

$$a_i = \xi_i - s_i \left(\frac{t}{2}\right)^{1/3}$$

Then, we can prove the following result:

Thm. 10: \forall fixed $u_1 < u_2 < \dots < u_M, s_1, s_2, \dots, s_M \in \mathbb{R}$,

$$\lim_{t \rightarrow \infty} \mathbb{P} \left(\bigcap_{k=1}^M \{X_{n_k}(t) > a_k\} \right) = \mathbb{P} \left(\bigcap_{k=1}^M \{A_2(u_k) \leq s_k\} \right)$$

Let us explain some of the steps to prove Thm. 10. By the formula of page (108) (Thm 9):

$$\mathbb{P} \left(\bigcap_{k=1}^M \{X_{n_k}(t) > a_k\} \right) = \det \left(\mathbb{1} - \mathcal{K}_t \right) e^{\sum_{k=1}^M (n_k - u_k)} \left(\sum_{k=1}^M \mathbb{1}_{\{n_k - u_k\}} \right)$$

with $A_2(n_k, x) = \mathbb{1}(x < a_k)$.

Thus we need to consider the rescaled kernel:

$$\begin{aligned}
 & \left(\frac{t}{2}\right)^{113} K_{\frac{t}{2}} \left(\frac{t}{4} + u_1 \left(\frac{t}{2}\right)^{213}, -2u_1 \left(\frac{t}{2}\right)^{213} + u_1^2 \left(\frac{t}{2}\right)^{113} - s_1 \left(\frac{t}{2}\right)^{113}; \right. \\
 & \left. \frac{t}{4} + u_2 \left(\frac{t}{2}\right)^{213}, -2u_2 \left(\frac{t}{2}\right)^{213} + u_2^2 \left(\frac{t}{2}\right)^{113} - s_2 \left(\frac{t}{2}\right)^{113} \right) =: K_{\frac{t}{2}}^{\text{resc}}(u_1, s_1; u_2, s_2).
 \end{aligned}$$

The ~~main part~~ of the kernel (~~the part with s_1, s_2~~) is given by:

$$K_{\frac{t}{2}}^{\text{resc}}(u_1, s_1; u_2, s_2) = \left(\frac{t}{2}\right)^{113} \int_{\mathbb{R}} \int_{\mathbb{R}} d\omega \int_{\mathbb{R}} d\nu \frac{e^{-t\phi(\omega)}}{e^{-t\phi(\nu)}} \frac{e^{\left(\frac{t}{2}\right)^{213} f_1(u_1, \omega)}}{e^{\left(\frac{t}{2}\right)^{213} f_1(u_2, \nu)}} \frac{e^{\left(\frac{t}{2}\right)^{113} f_2(u_1, s_1, \omega)}}{e^{\left(\frac{t}{2}\right)^{113} f_2(u_2, s_2, \nu)}} \cdot \frac{\omega^{-1}}{\omega - \nu}.$$

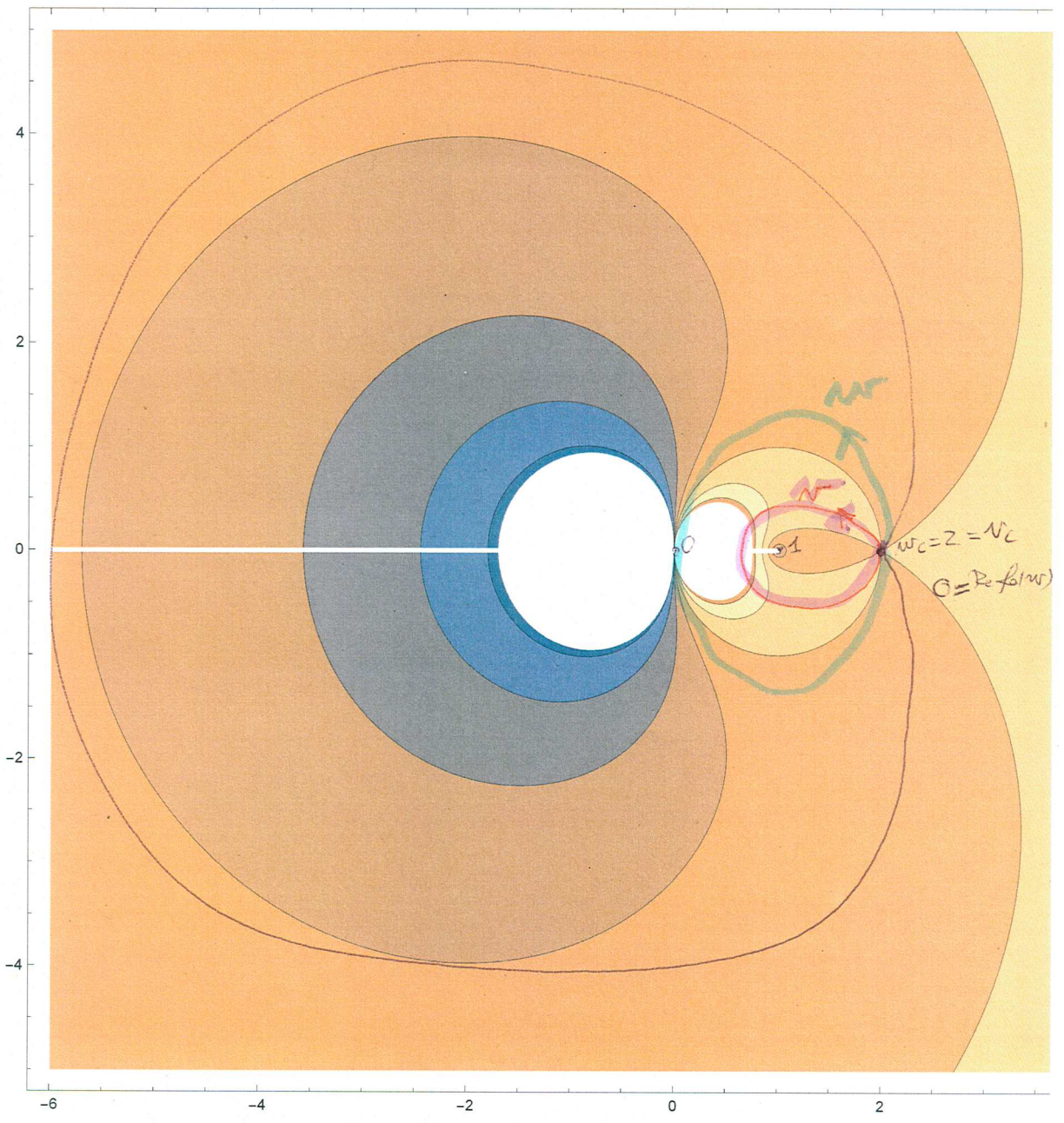
$$\begin{cases}
 \phi(\omega) = \frac{1}{\omega} + \frac{1}{4} \ln(\omega - 1), \\
 f_1(u_i, \omega) = u_i \ln(\omega - 1) - 2u_i \ln(\omega), \\
 f_2(u_i, s_i, \omega) = (u_i^2 - s_i) \ln(\omega)
 \end{cases}$$

Step 1: Understand from which regime the integral gets the dominant contribution. consider only ϕ

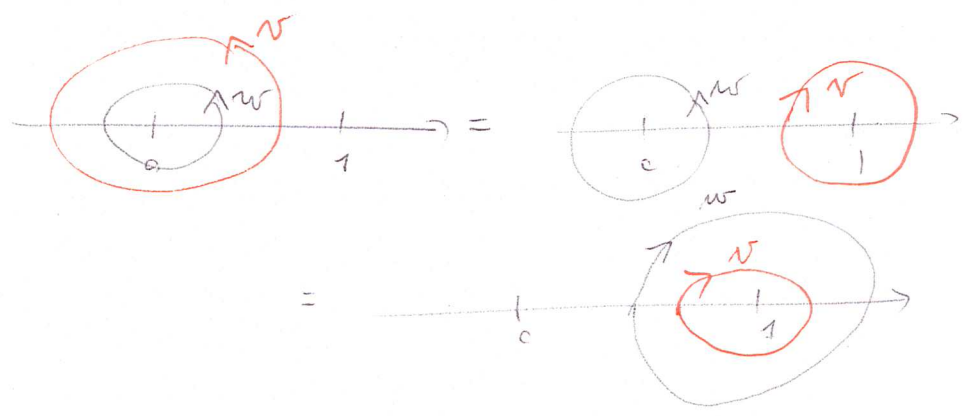
(a) Critical points: $\frac{d\phi}{d\omega} = -\frac{1}{\omega^2} + \frac{1}{4(\omega-1)} = \frac{-4 + 4\omega - \omega^2}{4\omega^2(\omega-1)} = -\frac{(2-\omega)^2}{4\omega^2(\omega-1)}$

$\Rightarrow \frac{d\phi(\omega)}{d\omega} = 0$ for $\omega = 2 = \omega_c$.

\Rightarrow Close to $\omega_c = 2$, $\phi(\omega) = \frac{1}{2} + \frac{1}{48}(\omega-2)^3 + O((\omega-2)^4)$,
 $f_1(u_i, \omega) = f_1(u_i, 2) - \frac{1}{4}u_i(\omega-2)^2 + O((\omega-2)^3)$
 $f_2(u_i, s_i, \omega) = f_2(u_i, s_i, 2) + (u_i^2 - s_i)(\omega-2) + O((\omega-2)^2)$.



$\text{Re } f(w) = \text{constant}$ are the lines
 On the path for w , $\text{Re}(f(w)) < \text{Re}(f(w_c))$ except at $w=w_c=2$
 " " v , $-\text{Re}(f(w)) < -\text{Re}(f(w_c))$ " " $v = v_c = 2$



(b) One shows that the leading contribution comes from a neighborhood of the critical point $w_c = v_c = 2$, by so-called steep descent analysis.

Step 2: Contribution around the critical point:

Using Taylor expansions, define the new variables

$$w = 2 + 2W \left(\frac{t}{2}\right)^{-1/3}, \quad v = 2 + 2V \left(\frac{t}{2}\right)^{-1/3}$$

$$\Rightarrow K_t^{N_{\text{eff}}} (u_i, s_i; \epsilon_i, \xi_i) \approx \left(\frac{t}{2}\right)^{1/3} \int dW \int dV \frac{1}{(2\pi i)^2} \cdot e^{\frac{t f_0(2) + \left(\frac{t}{2}\right)^{2/3} f_1(u_1, 2) + \left(\frac{t}{2}\right)^{1/3} f_2}{e^{t f_0(2) + \left(\frac{t}{2}\right)^{2/3} f_1(u_2, 2) + \left(\frac{t}{2}\right)^{1/3} f_2}}$$

it is a conjugation

$$\cdot e^{\frac{1}{48} \frac{2}{t} \frac{8W^3}{3} + O(W^4/t^{1/3})} \cdot e^{-\left(\frac{t}{2}\right)^{2/3} \frac{u_1}{4} \frac{2W^2}{t^{2/3}} + O\left(\frac{W^3}{t^{1/3}}\right)}$$

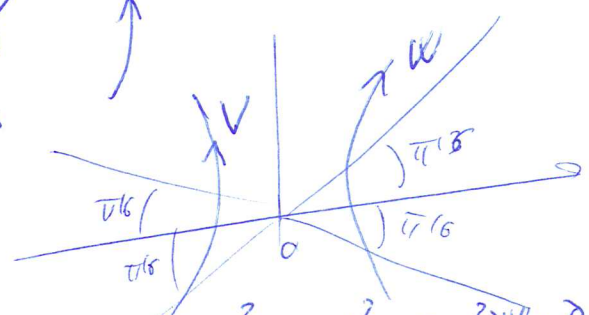
$$\cdot e^{(u_1^2 - s_1) \left(\frac{t}{2}\right)^{1/3} \frac{2W}{t^{1/3}} + O\left(\frac{W^2}{t^{1/3}}\right)}$$

$$\frac{e^{W^3/3 + O(W^4/t^{1/3})} e^{-u_2 V^2 + O(V^3/t^{1/3})}}{e^{(u_2^2 - s_2) W + O(W^2/t^{1/3})}}$$

$$\cdot \frac{1}{2} \frac{1}{2(W-V) \left(\frac{t}{2}\right)^{-1/3}}$$

$$\approx \frac{1}{(2\pi i)^2 (2\pi i)^2} \int dW \int dV \frac{e^{W^3/3 - u_1 W^2 - (s_1 - u_1^2)W}}{e^{V^3/3 - u_2 V^2 - (s_2 - u_2^2)V}} \frac{1}{W-V}$$

One shows that $O(\dots)$ are irrelevant
 ⊕ Conjugation



$$\frac{1}{W-V} = \int_0^\infty d\lambda e^{-\lambda(W-V)} = \int_0^\infty d\lambda \left[\frac{1}{2\pi i} \int dW e^{\frac{W^3}{3} - u_1 W^2 - (s_1 - u_1^2)W - \lambda W} \right] \left[\frac{1}{2\pi i} \int dV e^{-\left[\frac{V^3}{3} - u_2 V^2 - (s_2 - u_2^2)V - \lambda V\right]} \right]$$

Change of variables:

$$\begin{cases} W := \lambda w + u_1 \\ V := \lambda v + u_2 \end{cases} \Rightarrow = \int_0^\infty d\lambda \int_{\mathcal{F}} \frac{1}{2\pi i} \left[d\omega e^{\frac{\omega^3}{3} - s_1 \omega - \lambda \omega} \right]$$

conjugate pair

$$\frac{e^{\frac{u_1^3}{3} - s_1 u_1}}{e^{\frac{u_2^3}{3} - s_2 u_2}} \cdot \frac{e^{-\lambda u_1}}{e^{-\lambda u_2}} \cdot \left(\frac{1}{2\pi i} \int d\omega e^{-[\frac{\omega^3}{3} - (s_2 - \lambda)\omega]} \right)$$

$$\stackrel{(cont)}{\equiv} \int_0^\infty d\lambda e^{-\lambda(u_1 - u_2)} Ai(s_1 + \lambda) Ai(s_2 + \lambda),$$

which is the extended Airy kernel for u_1, u_2 .

By working out the details one proves that

$$\lim_{t \rightarrow \infty} K_t^{vesc}(u_1, s_1; u_2, s_2) \stackrel{(cont)}{=} KA_2(u_1, s_1; u_2, s_2)$$

and also obtains with a little bit more work also

$$\left| K_t^{vesc}(u_1, s_1; u_2, s_2) \right|_{(cont)} \leq C e^{-(s_1 + s_2)t} \mathbb{1}_{(u_1 < u_2)} \cdot e^{-|s_1 - s_2|t},$$

for some C, \tilde{C} indep. of t .

This bounds are then enough to prove Thm. 10.

Using the correlation kernel, and doing asymptotic analysis we can obtain other results.

Here is a short description of the most important ones, obtained in my paper with A. Barodin "Anisotropic growth of random surfaces in 2+1 dimensions".

First we define a height function:

~~$h(x, n, t)$~~
 $h(x, n, t) =$ # of particles at level n on the right of position x at time t .

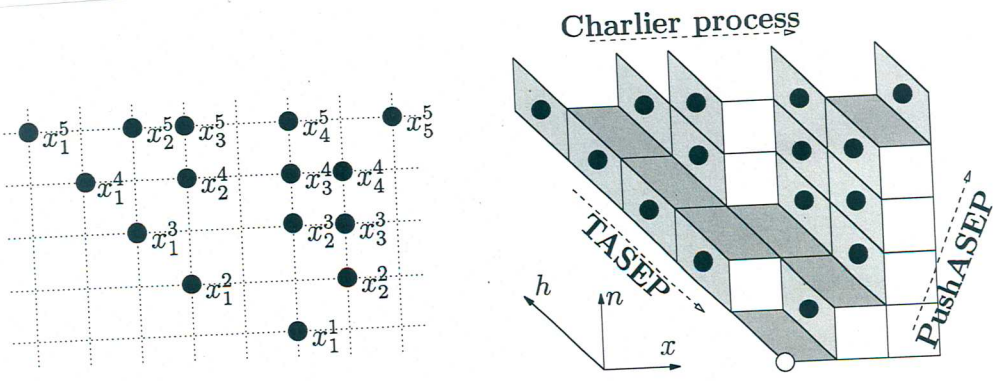


Figure 1.2: From particle configurations (left) to 3d visualization via lozenge tilings (right). The corner with the white circle has coordinates $(x, n, h) = (-1/2, 0, 0)$.



Figure 1.3: A configuration of the model analyzed with $N = 100$ particles at time $t = 25$, using the same representation as in Figure 1.2. In [38] there is a Java animation of the model.

(a) Description of the limit shape border:

Let $n_i = \eta_i L$, $x_i = -\eta_i L + \nu_i L$, $t_i = z_i L$.
We want to describe the $L \rightarrow \infty$ limit.

The random region, where there is not only one type of color/lozenge, is the following:

$$\mathcal{D} := \left\{ (\nu, \eta, z) \in \mathbb{R}_+^3 \mid (\sqrt{\eta} - \sqrt{z})^2 < \nu < (\sqrt{\eta} + \sqrt{z})^2 \right\}$$

This is obtained by computing the density of particle, which is given by $K_t(x_i, x_i, n_i, x_i)$ and see what this equals to 0 or 1.




(b) Fluctuations in the disordered phase:

Thm 12: $\forall (\nu, \eta, z) \in \mathcal{D}$, with $\kappa_0 := (2\pi^2)^{-1}$

$$\lim_{L \rightarrow \infty} \frac{h((\nu - \eta)L, \eta L, zL) - \mathbb{E}(h((\nu - \eta)L, \eta L, zL))}{\sqrt{\kappa_0 \ln L}} = \sum \nu W(\rho_1)$$

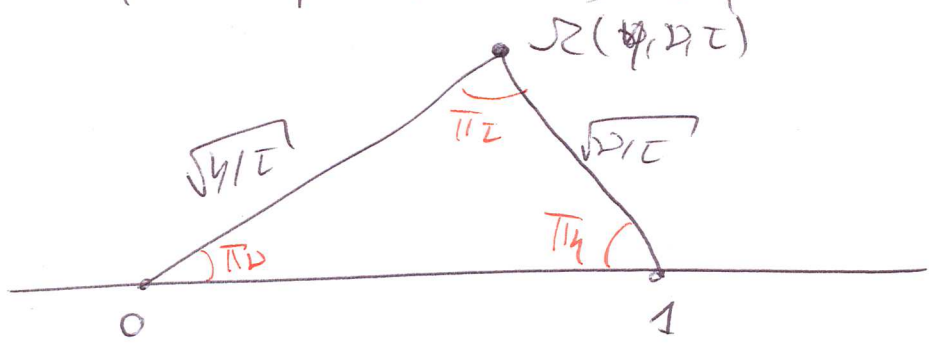
This means that the fluctuations of the height functions are asymptotically Gaussian in the $\sqrt{\ln L}$ scale.

(c) Densities of the three types of lozenges

-  = type I \leftrightarrow angle $\pi/4 \Rightarrow$ frequency $\frac{\pi/4}{\pi}$
-  = type II \leftrightarrow angle $\pi/2 \Rightarrow$ frequency $\frac{\pi/2}{\pi}$
-  = type III \leftrightarrow angle $\pi/3 \Rightarrow$ frequency $\frac{\pi/3}{\pi}$

Given $(\eta, \nu, \tau) \in D$, define the map $\Omega: D \rightarrow H$,

where $H = \{z \in \mathbb{C} \mid \text{Im}(z) > 0\}$ as follows:



Prop. 13. (Limit shape)

$$\lim_{L \rightarrow \infty} \frac{\mathbb{E}(h((\nu-\eta)L, \nu L, \tau L))}{L} = h_{\text{asy}}(\nu, \eta, \tau)$$

$$= \frac{1}{\pi} \left\{ -\nu \pi \eta + \eta (\pi - \pi \nu) + \tau \cdot \frac{\sin(\pi \nu) \sin(\pi \eta)}{\sin(\pi \tau)} \right\}$$

Furthermore: Slopes: $\frac{\partial h_{\text{asy}}(\nu, \eta, \tau)}{\partial \nu} = -\frac{\pi \eta}{\pi}$

$$\frac{\partial h_{\text{asy}}(\nu, \eta, \tau)}{\partial \eta} = 1 - \frac{\pi \nu}{\pi}$$

Speed of growth: $\frac{\partial h_{\text{asy}}(\nu, \eta, \tau)}{\partial \tau} = \frac{1}{\pi} \frac{\sin(\pi \nu) \sin(\pi \eta)}{\sin(\pi \tau)} = \frac{\text{Im}(\Omega)}{\pi}$

(d) Random field in the "bulk":

Let us introduce the notation

$$G(z, w) := \frac{-1}{2\pi} \log \left| \frac{z-w}{z-\bar{w}} \right|$$

This is the Green function of the Laplace operator on H with Dirichlet boundary condition on ∂H .

Thm 14: let $x_i = (x_i, y_i, z=1) \in D$ be N distinct tuples.

let $H_L(x_i, y_i) = \sqrt{\pi} [h((x-y)L, yL, L) - \mathbb{E}(\dots)]$

and $R_k = R(x_k, y_k, 1)$.

Then,

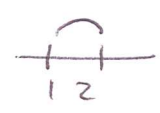
$\lim_{L \rightarrow \infty} \mathbb{E}(H_L(x_1) \dots H_L(x_N)) =$

$$= \begin{cases} \sum_{\sigma \in \mathcal{F}_N} \prod_{j=1}^{N/2} g(R_{\sigma(2j-1)}, R_{\sigma(2j)}) & \text{if } N \text{ even} \\ 0 & \text{if } N \text{ odd,} \end{cases}$$

where \mathcal{F}_N is the set of point free involutions on $\{1, \dots, N\}$, also known as pairings.

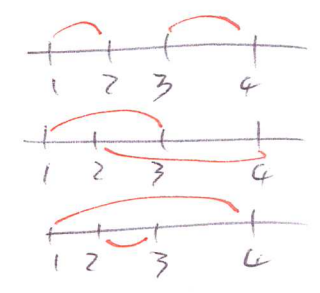
Example:

For $N=2$: ~~we have~~ we have $g(R_1, R_2)$



For $N=4$: we have:

$$g(R_1, R_2) g(R_3, R_4) + g(R_1, R_3) g(R_2, R_4) + g(R_1, R_4) g(R_2, R_3)$$



Remarks: Thm 12 & Thm 14 uses different normalisations!

In Thm 12 we divide by $\sqrt{\pi}L$, in Thm 14 we do not divide!

The reason is that the limit of H_L is not a smooth random field, but a singular one. In particular, H_L ~~converges to~~ converges to a distribution, not to a function.

The correlators in Thm 14 are the ones of the so-called Gaussian Free Field \mathcal{GFF} .