#### MUCCICONI MATTEO based on a collaboration with A. BUFETOV and L. PETROV

#### Stochastic Analysis, Random Fields and Integrable Probability

令和1年08月5日



► We discuss a random algorithm whose output is a random "field" of Young Diagrams  $\lambda = \{\lambda^{(x,y)} | x, y \in \mathbb{Z}_{\geq 0}\}.$ 





► We discuss a random algorithm whose output is a random "field" of Young Diagrams  $\lambda = \{\lambda^{(x,y)} | x, y \in \mathbb{Z}_{>0}\}.$ 



► The algorithm consists in a sequence of local moves defined through a "bijectivization" of the Yang-Baxter Equation





► We discuss a random algorithm whose output is a random "field" of Young Diagrams  $\lambda = \{\lambda^{(x,y)} | x, y \in \mathbb{Z}_{\geq 0}\}.$ 



► The algorithm consists in a sequence of local moves defined through a "bijectivization" of the Yang-Baxter Equation



► A bijectivization [Bufetov-Petrov '17] is a way to assign transition probabilities

$$\mathbb{P}(a_i \rightarrow b_j).$$



Random fields of Young diagrams are popular objects in Integrable Probability because they allow the description of random tilings, stochastic interacting particle systems, stochastic vertex models, etc.



- Random fields of Young diagrams are popular objects in Integrable Probability because they allow the description of random tilings, stochastic interacting particle systems, stochastic vertex models, etc.
- In our case, the random field inherits its integrability from the Yang-Baxter Equation. The joint probability distribution along down-right paths π assume the form

$$\sum_{u_{1} \neq 1}^{\mathfrak{F}} \sum_{\substack{(i_{1}, j_{2}) \neq 1 \\ \tau_{1} \neq 1 \\ v_{2} \neq 1 \\ \tau_{1} \neq 1 \\ \tau_{1$$

where  $\mathfrak{F},\mathfrak{G}$  are special symmetric functions (multi-parameter generalizations of the Schur polynomials).



Results we obtain considering this simple procedure:

From marginal observables (e.g. λ<sup>(x,y)</sup> → length(λ<sup>(x,y)</sup>)) we recover the Stochastic Six Vertex Model [Gwa-Spohn '92], the Stochastic Higher Spin Six Vertex Model [Corwin-Petrov '15] and also more general vertex models



Results we obtain considering this simple procedure:

- From marginal observables (e.g. λ<sup>(x,y)</sup> → length(λ<sup>(x,y)</sup>)) we recover the Stochastic Six Vertex Model [Gwa-Spohn '92], the Stochastic Higher Spin Six Vertex Model [Corwin-Petrov '15] and also more general vertex models
- We are able to construct "MacDonald operators" for symmetric functions δ, 6. These are guessed from known results about stochastic vertex models



Results we obtain considering this simple procedure:

- From marginal observables (e.g. λ<sup>(x,y)</sup> → length(λ<sup>(x,y)</sup>)) we recover the Stochastic Six Vertex Model [Gwa-Spohn '92], the Stochastic Higher Spin Six Vertex Model [Corwin-Petrov '15] and also more general vertex models
- We are able to construct "MacDonald operators" for symmetric functions &, &. These are guessed from known results about stochastic vertex models
- We describe statistics of the random field using these new operators (like in MacDonald Processes [Borodin-Corwin '11])

