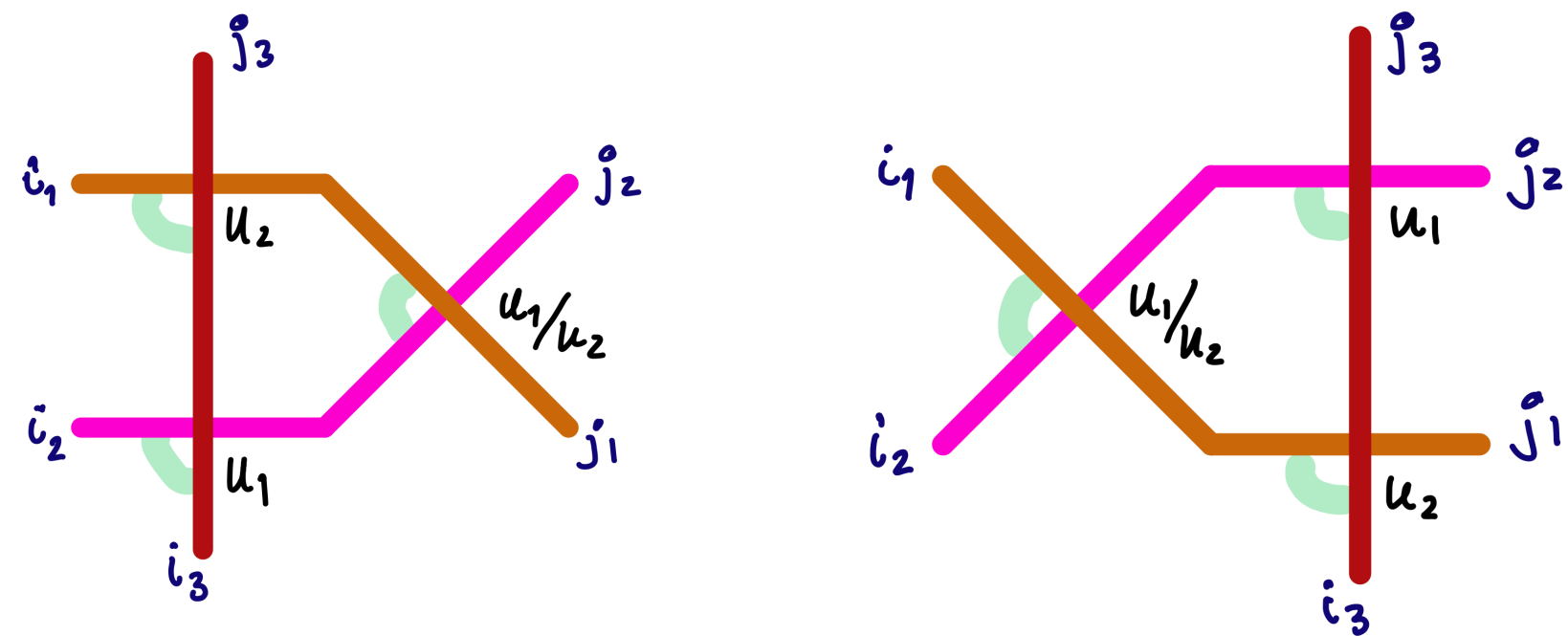


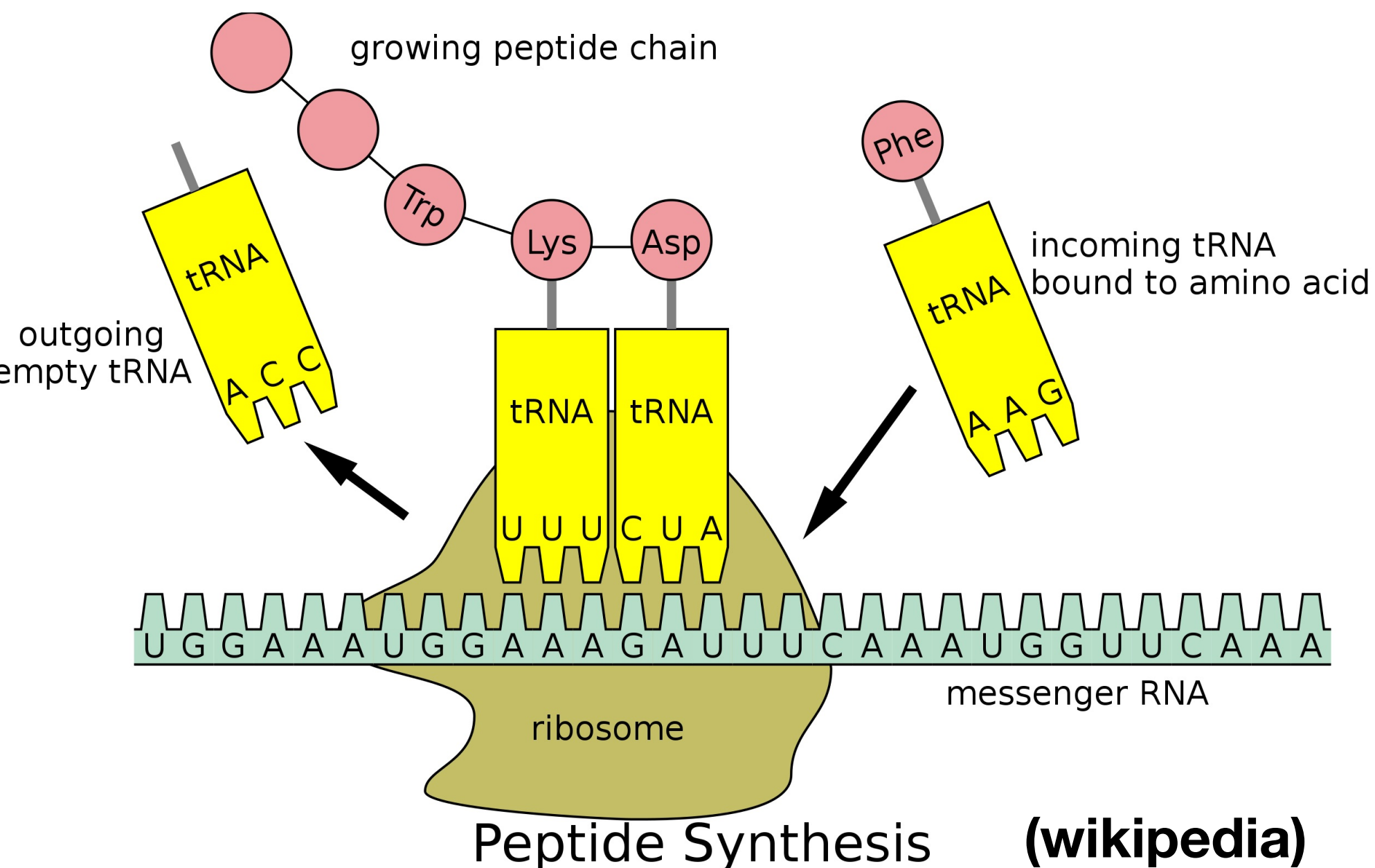
Vertex model integrability for stochastic particle systems



Leonid Petrov
(University of Virginia)

May 20, 2024

IPAM Workshop IV: Vertex Models: Algebraic and Probabilistic Aspects of Universality



- P.-Saenz
arXiv:2212.01643
- Aggarwal-Nicoletti-P.
arXiv:2309.11865

TL;DR

Goal:

Apply the Yang-Baxter equation to stochastic particle systems. **Graphical manipulations** lead to interesting **probabilistic consequences**

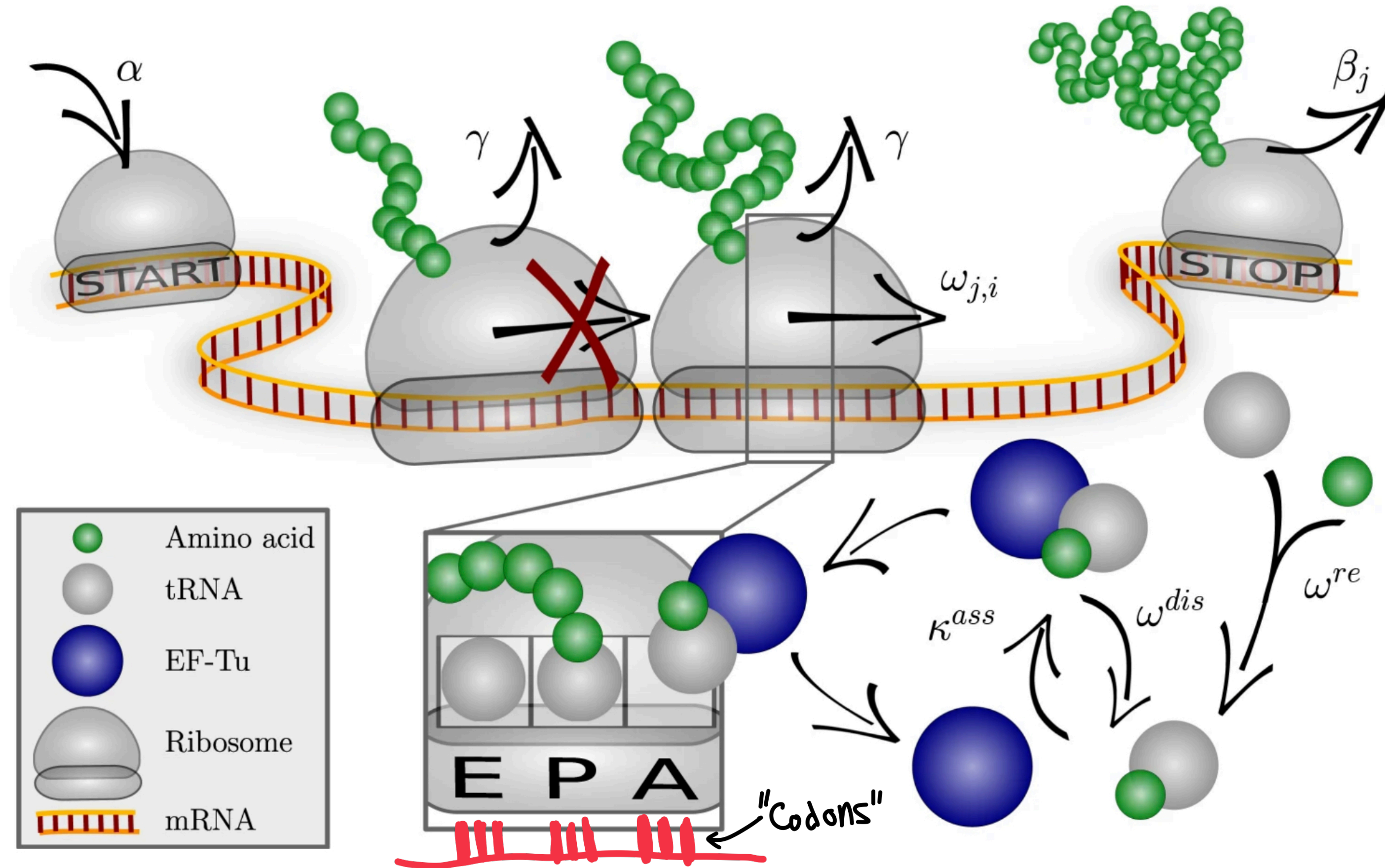
Corollaries:

- Lax-type equations for $(q-)$ TASEP
- Description of stationary measures for ASEP

I. TASEP with inhomogeneous speeds and symmetry on the line

- [C. MacDonald, J. Gibbs, A. Pipkin 1969]
- [Spitzer 1970]
- [Rost 1981]
- [Johansson 2000]
- [Matetski, Quastel, Remenik 2017]
- [Dauvergne, Ortmann, Virag 2018]
- [Busani, Seppäläinen, Sorensen 2022+]
- ...

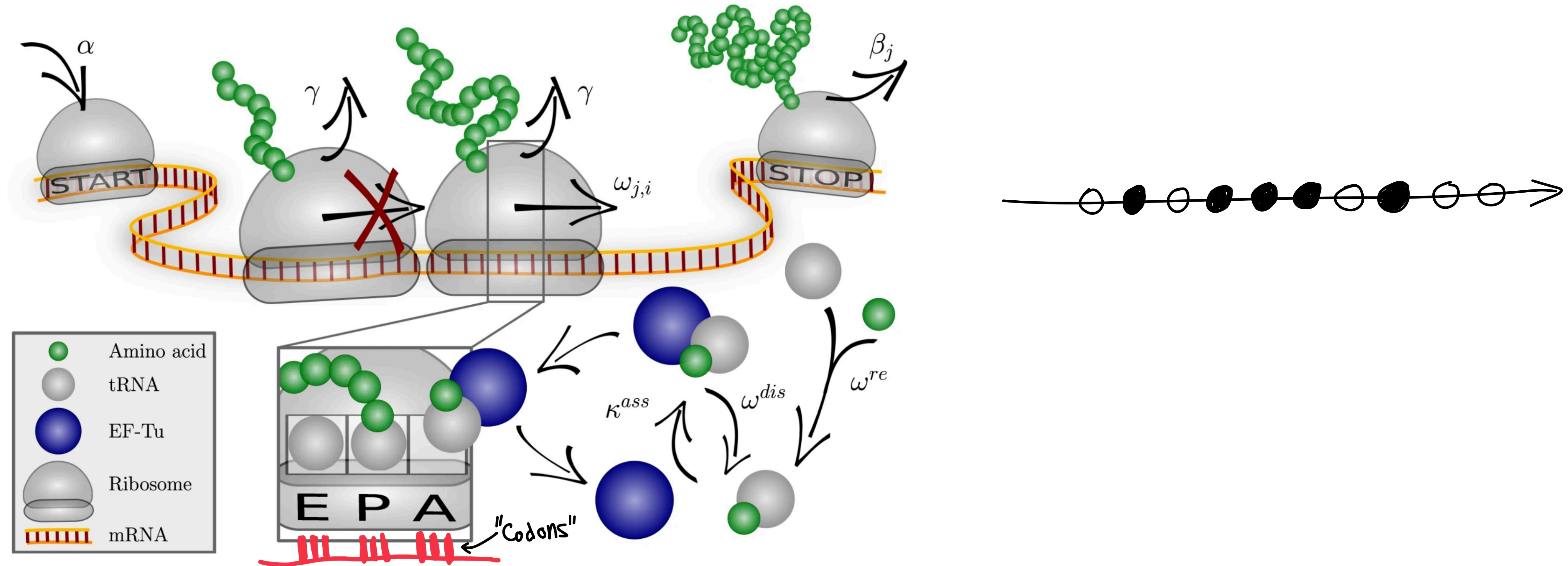
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Sketch of the codon-specific elongation model (COSEM). Ribosomes attach to a codon sequence labeled by j with initiation rate α , which is determined by the ribosome concentration if the initiation site is not occupied, and move to the next position with the elongation rate $\omega_{j,i}$ specific to the codon at position i in the sequence j as well as to the organism under consideration.

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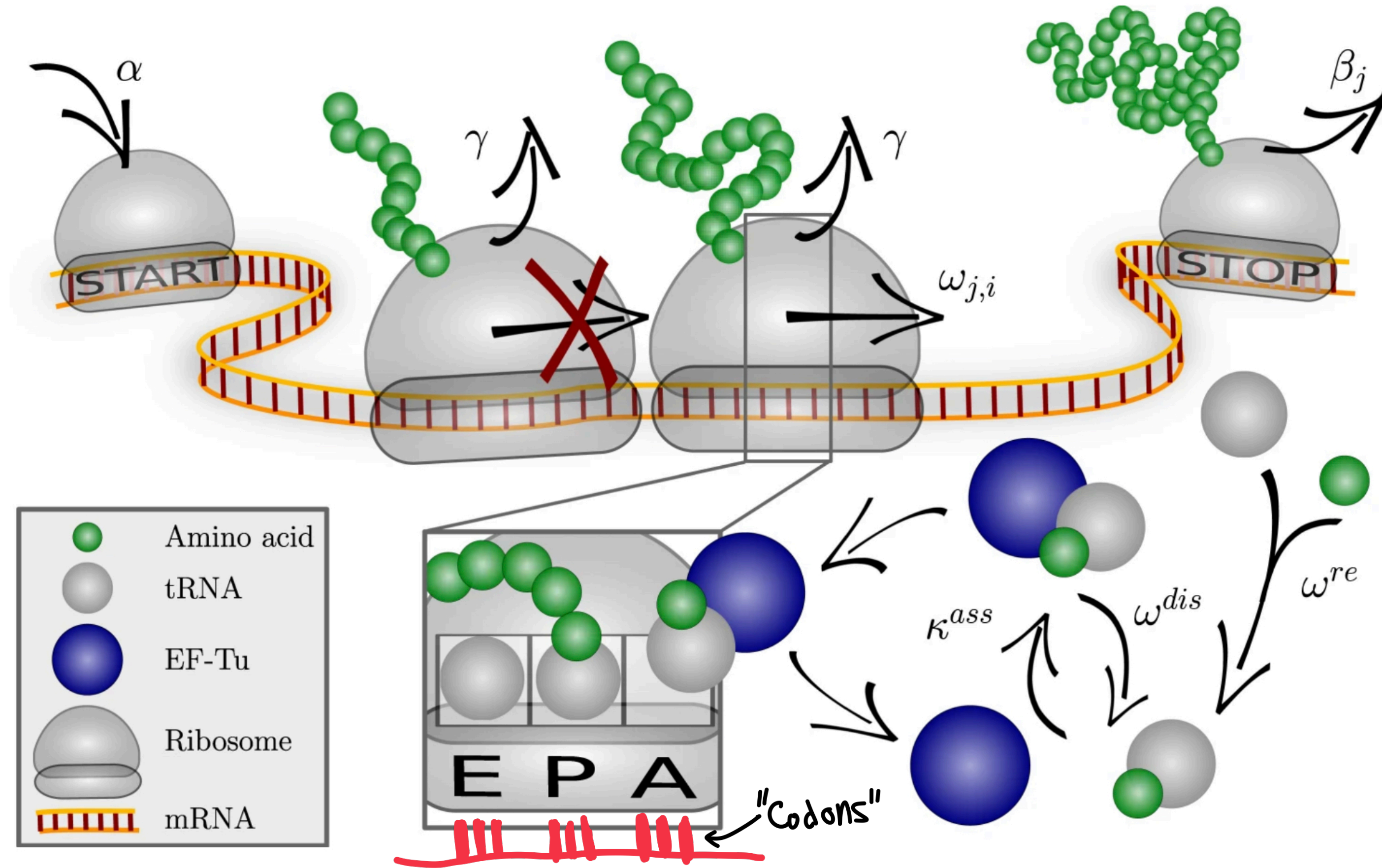
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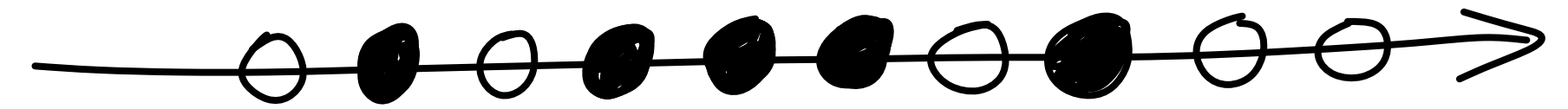
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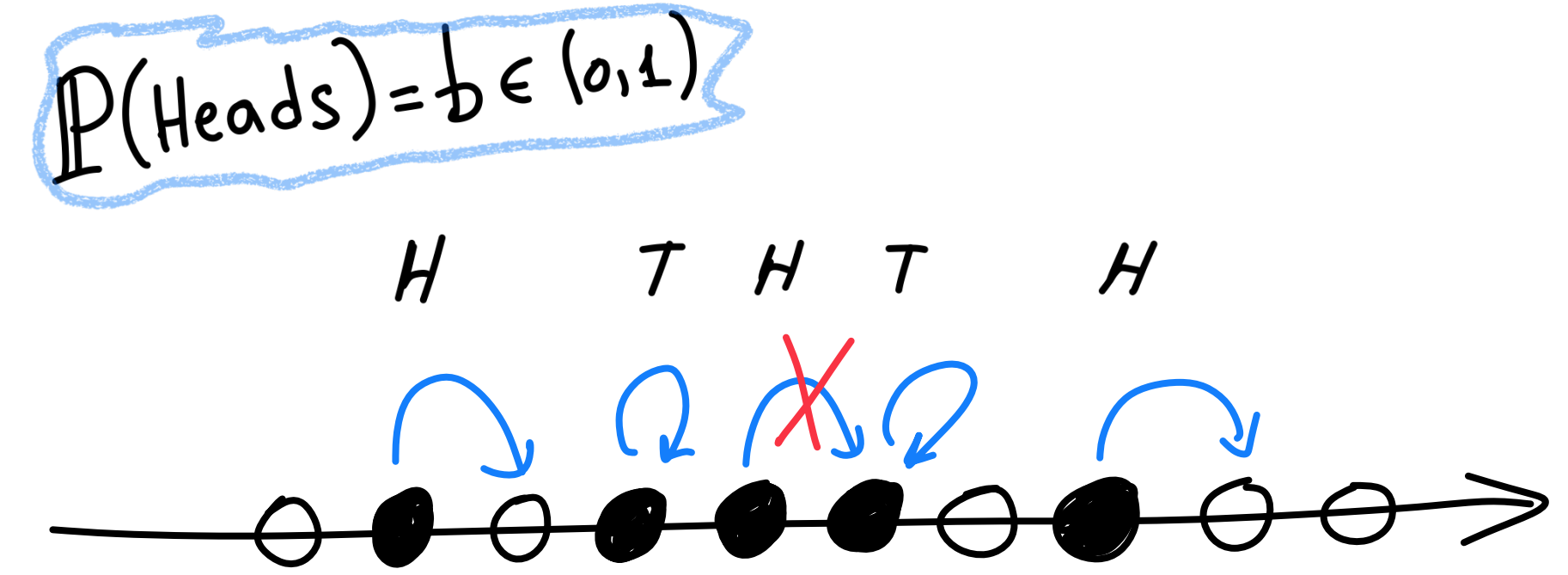
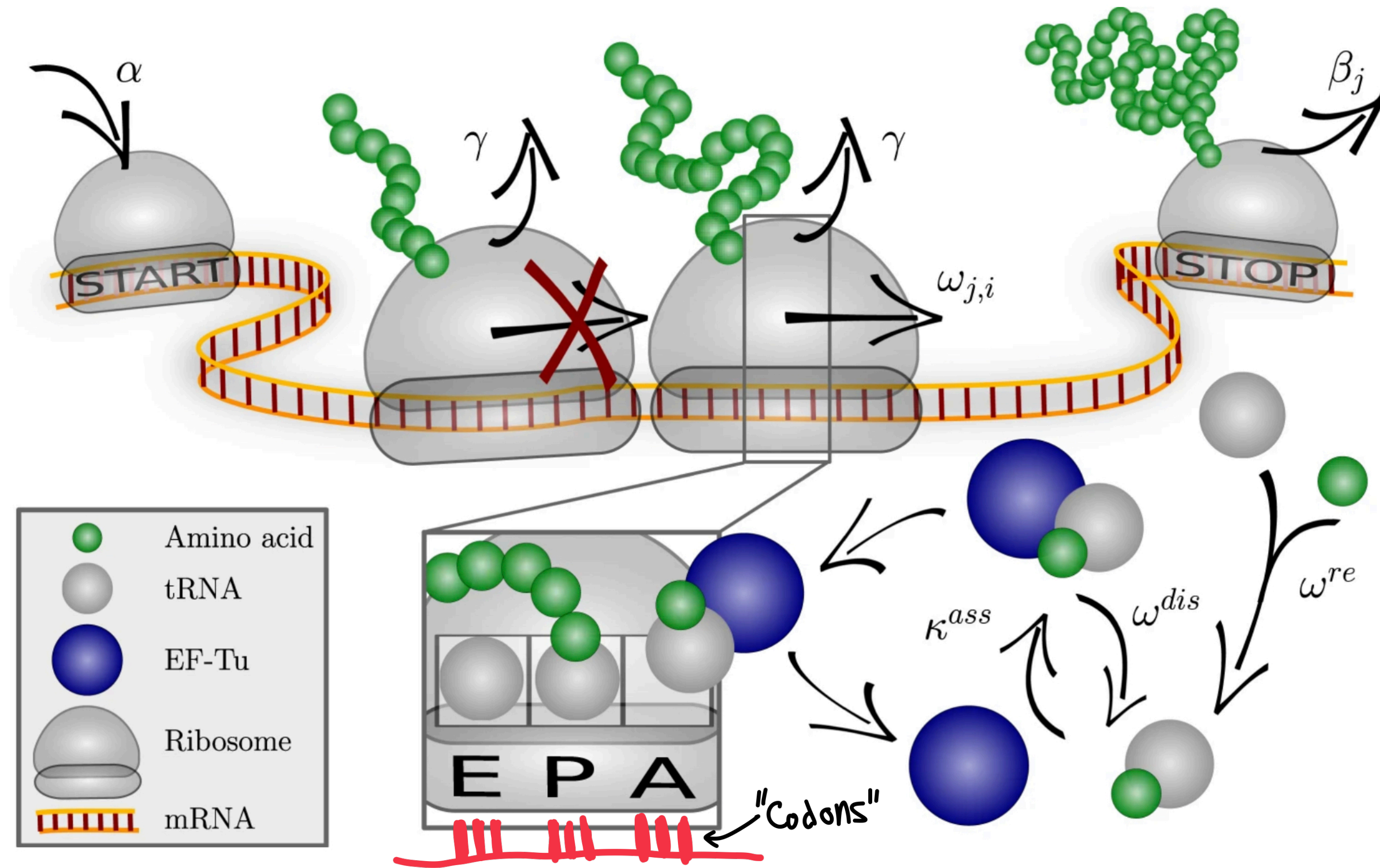
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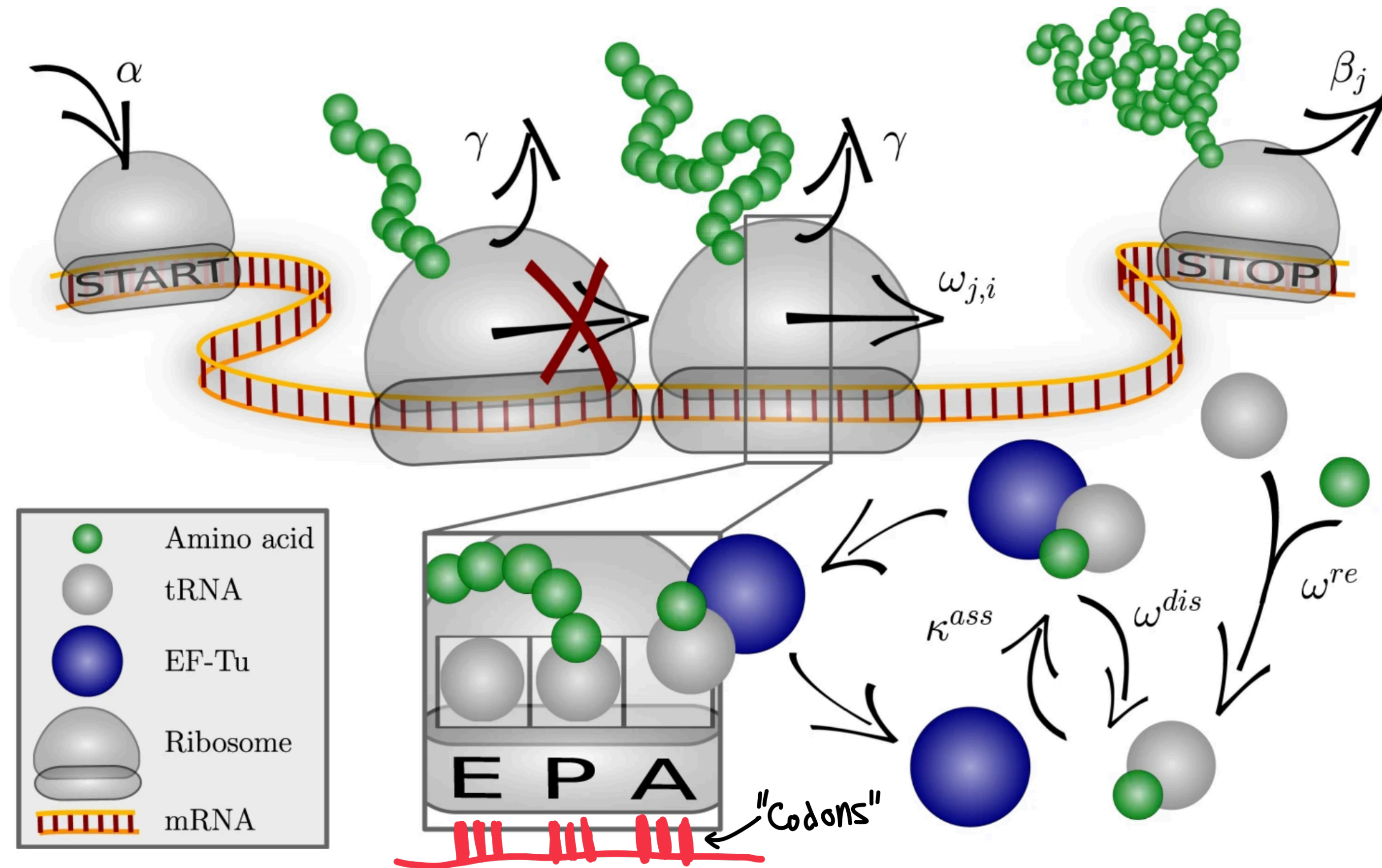
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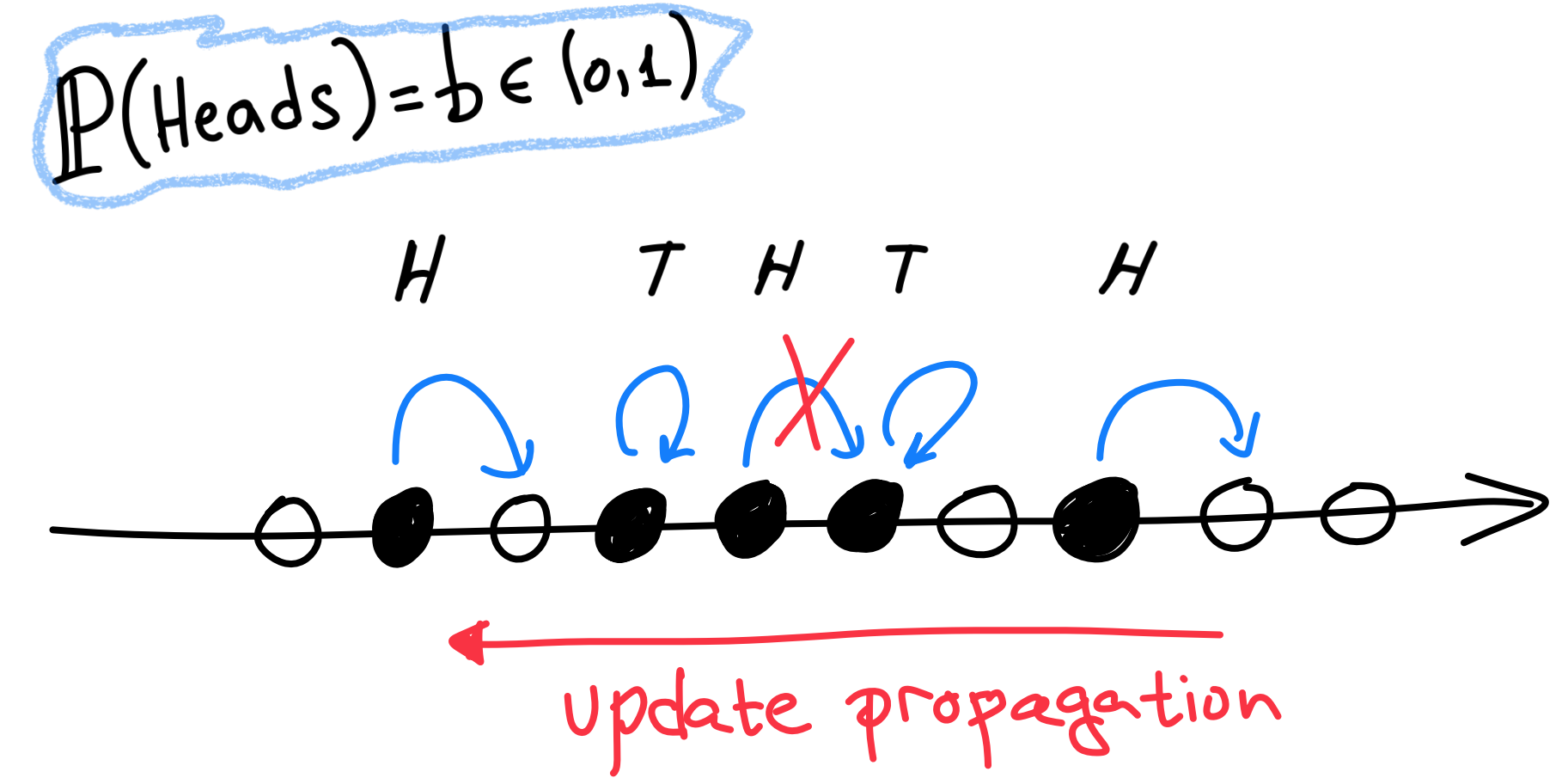
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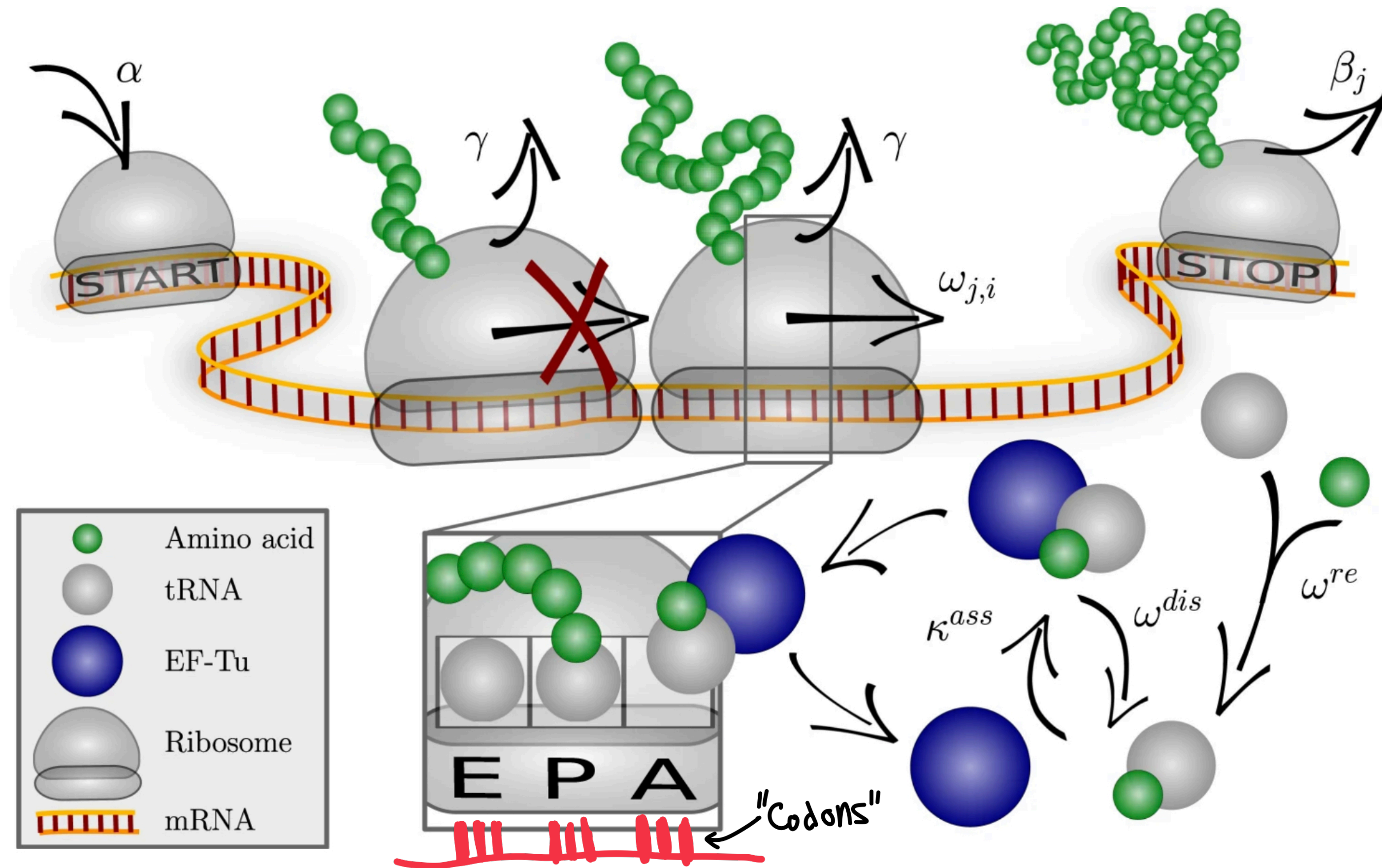


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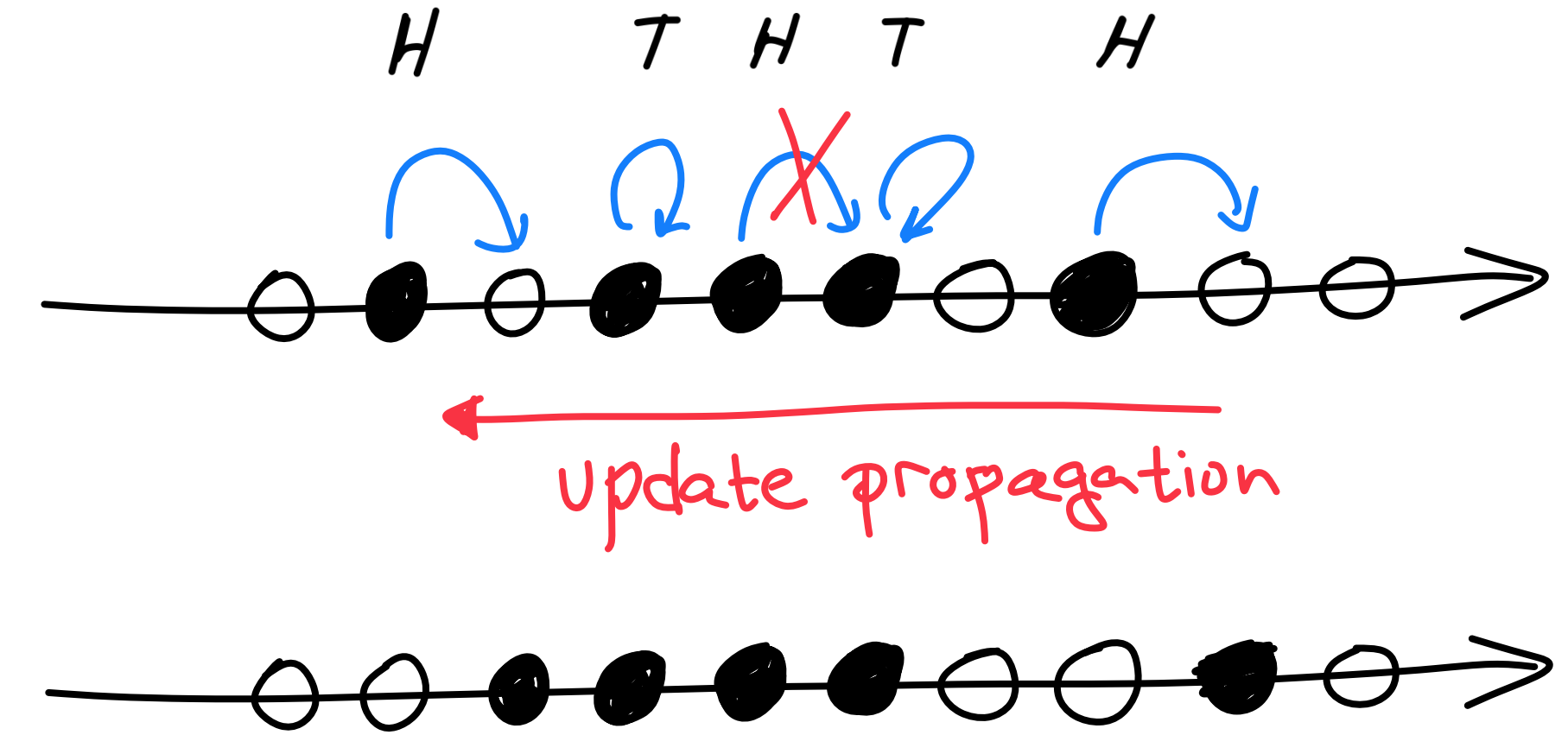
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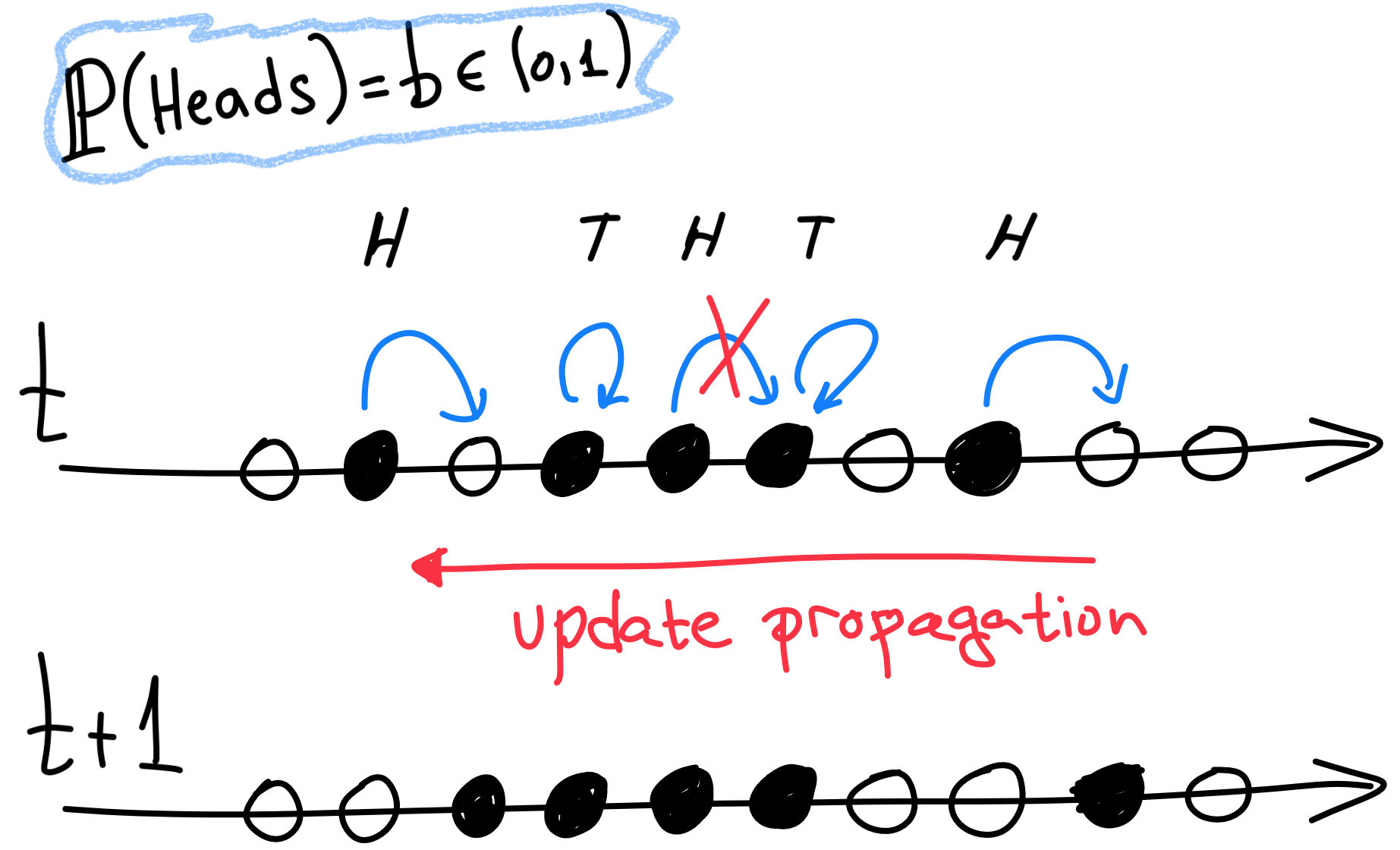
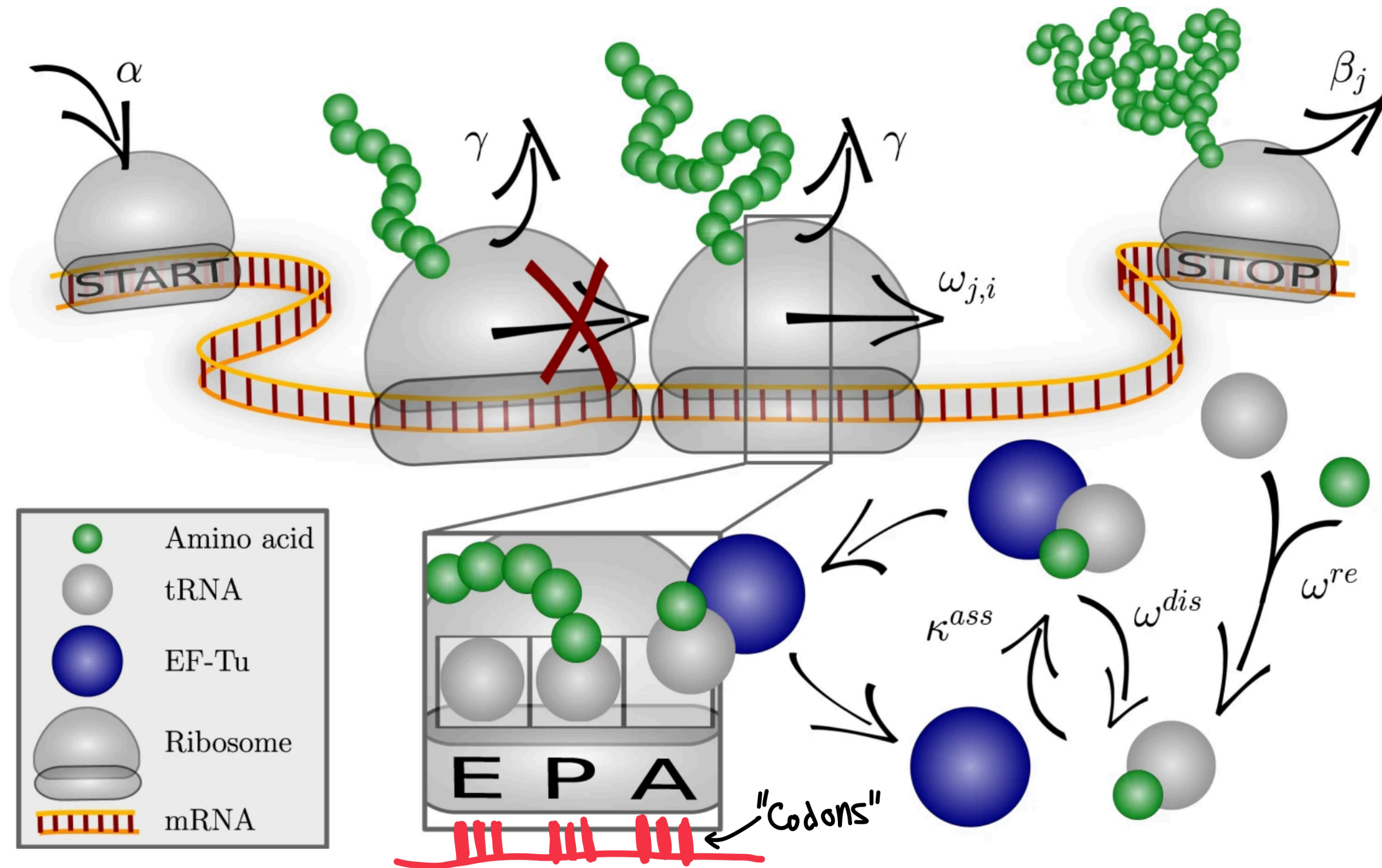
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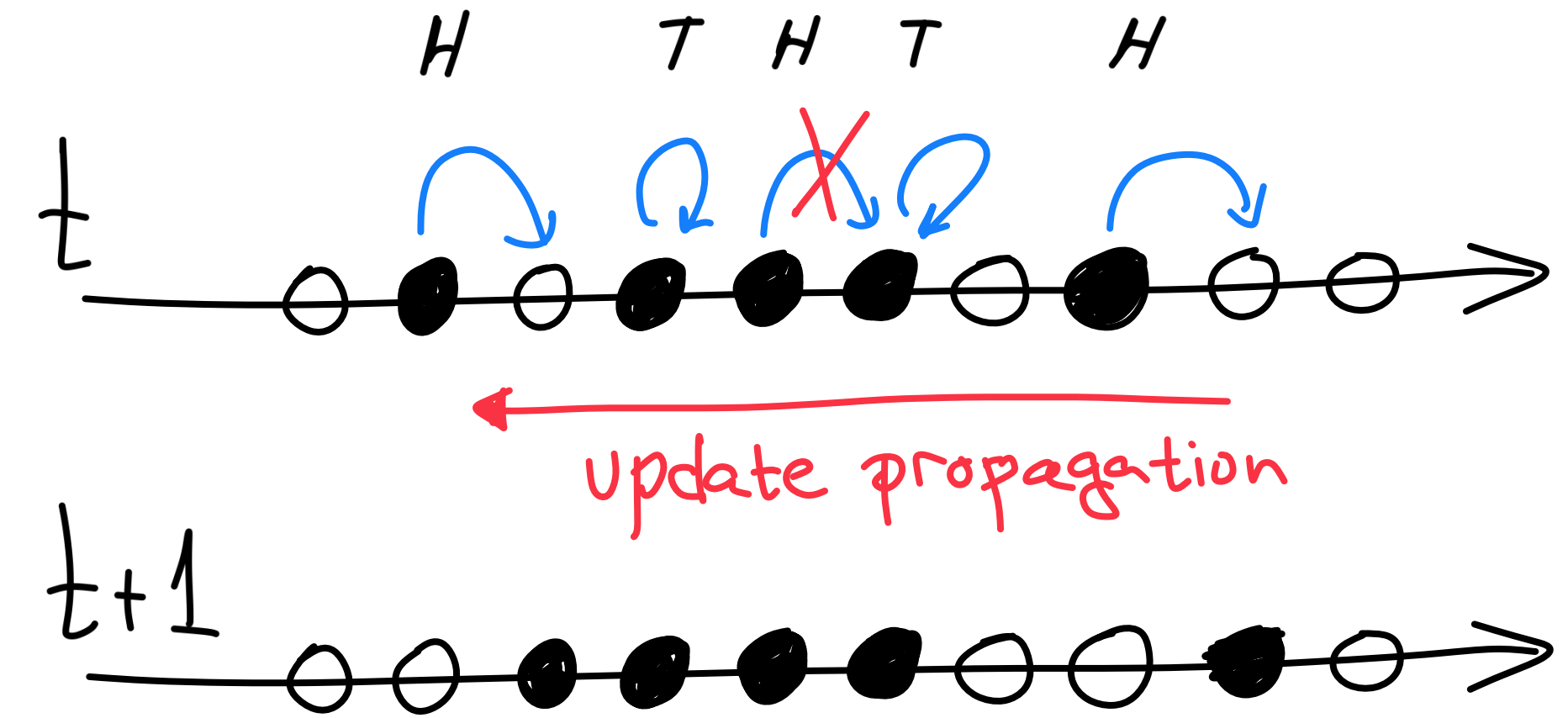


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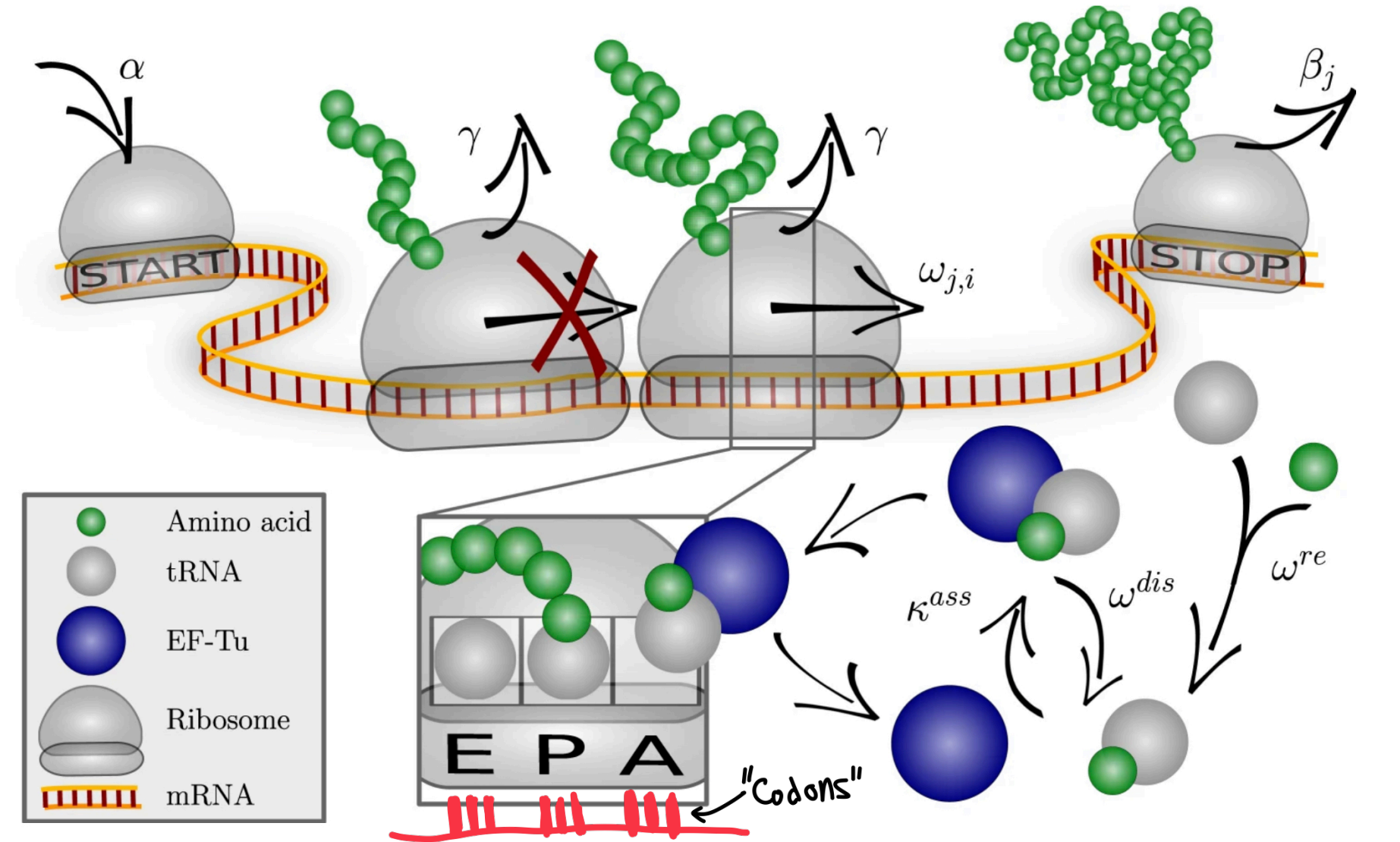
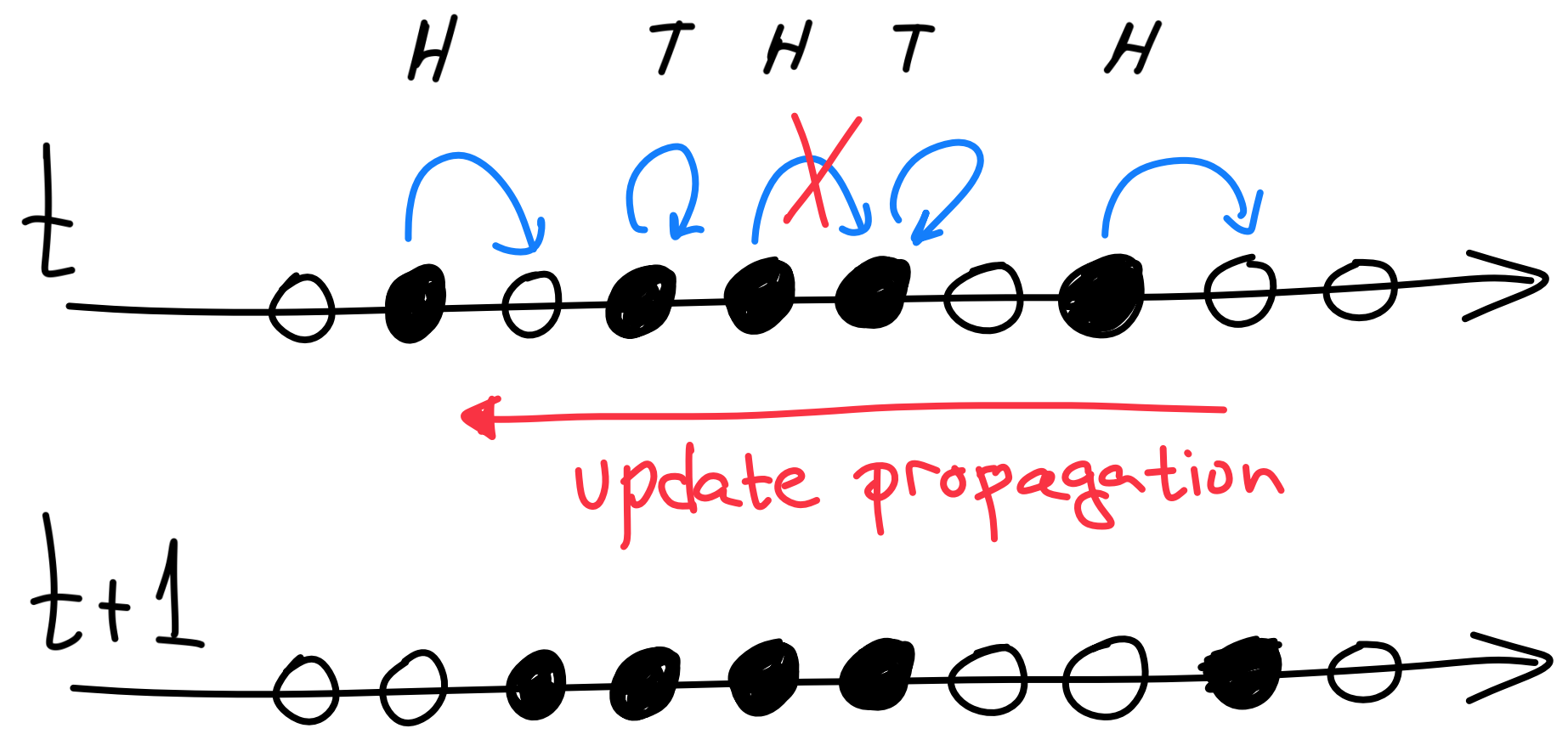
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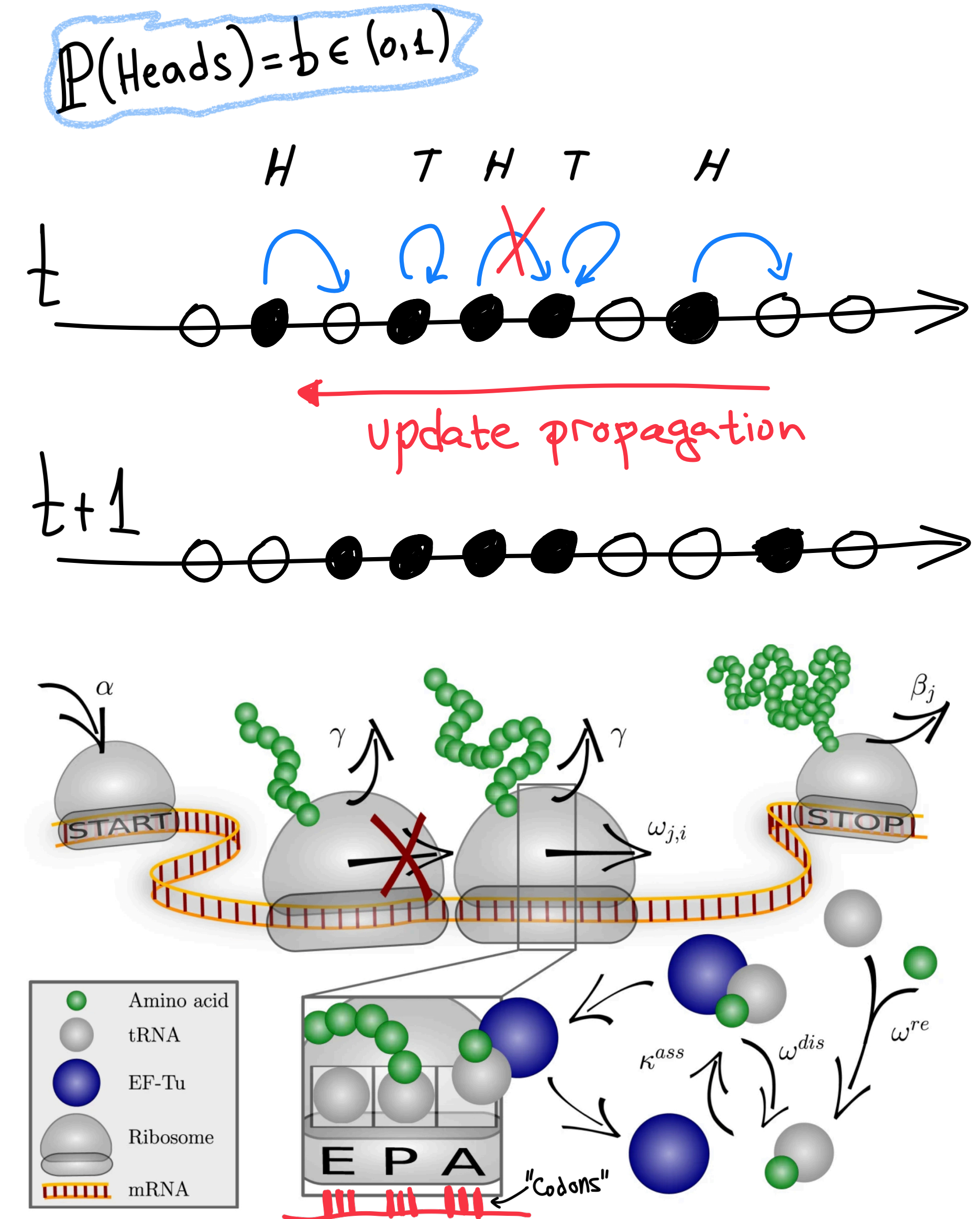


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TASEP (Totally Asymmetric Simple Exclusion Process), with discrete time, Bernoulli jumps, and sequential update

- mRNA tells us that speed b depends on the *particle's location* (and particles randomly change type)
- Mathematically, this is **challenging**
- More tractable (**integrable**) if the speeds are the same, or may depend on the *particles* (leads to **symmetric** dependence on particle's speeds)

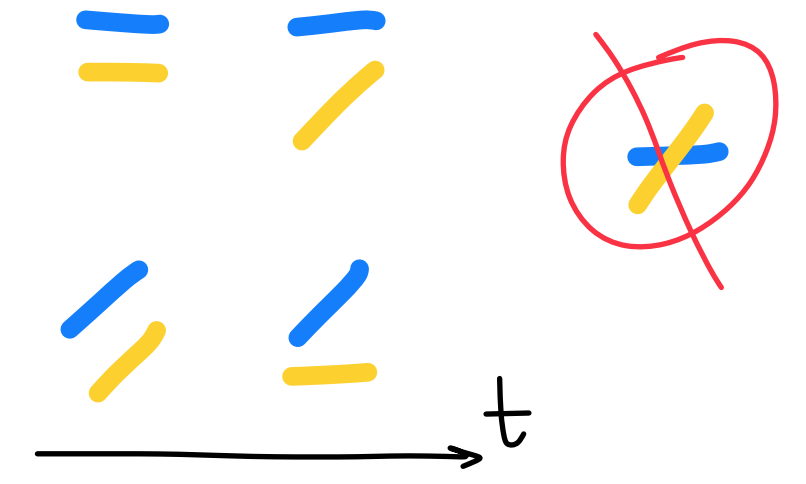


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Two cars (two-particle discrete time TASEP)

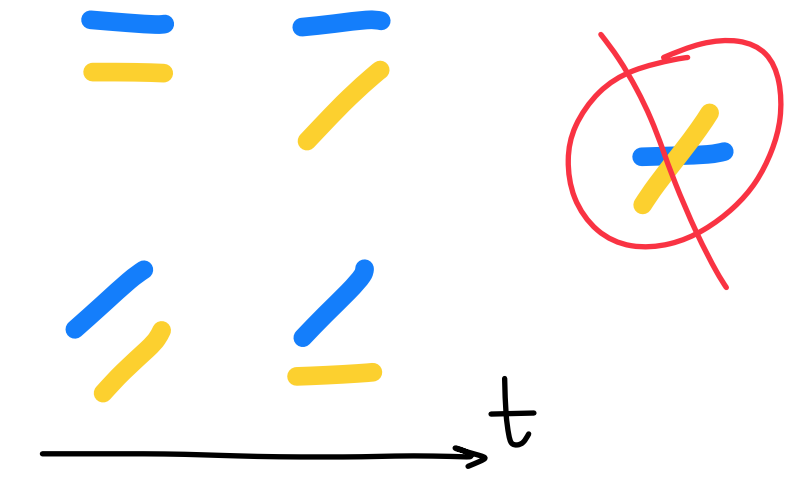
Time $t \in \mathbb{Z}_{\geq 0}$, 2 cars with speeds $a_1 > a_2 > 0$, probabilities of jumps $b_i = \frac{a_i}{1 + a_i}$

One-lane highway: no passing. Consider two systems: FS and SF

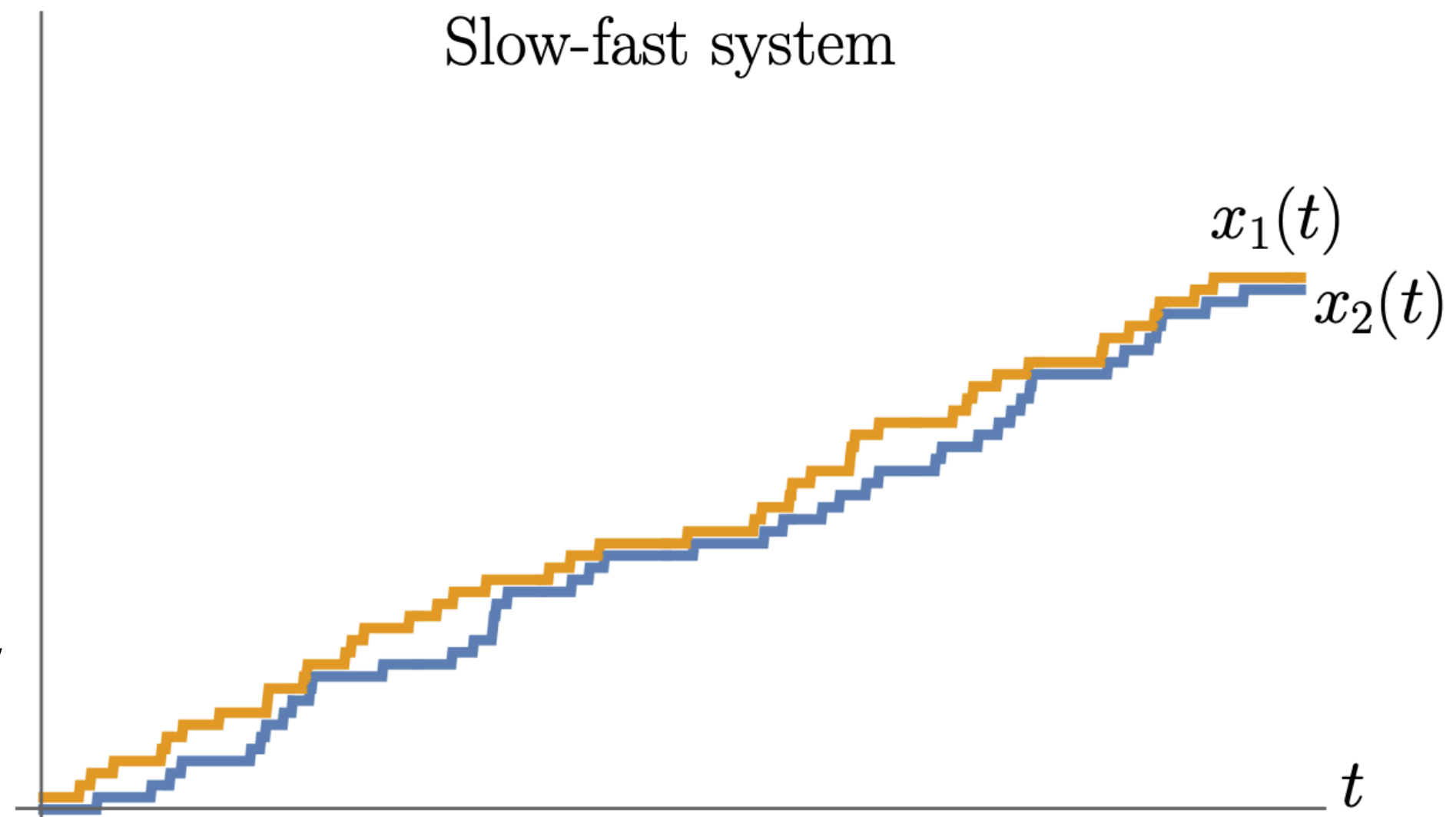
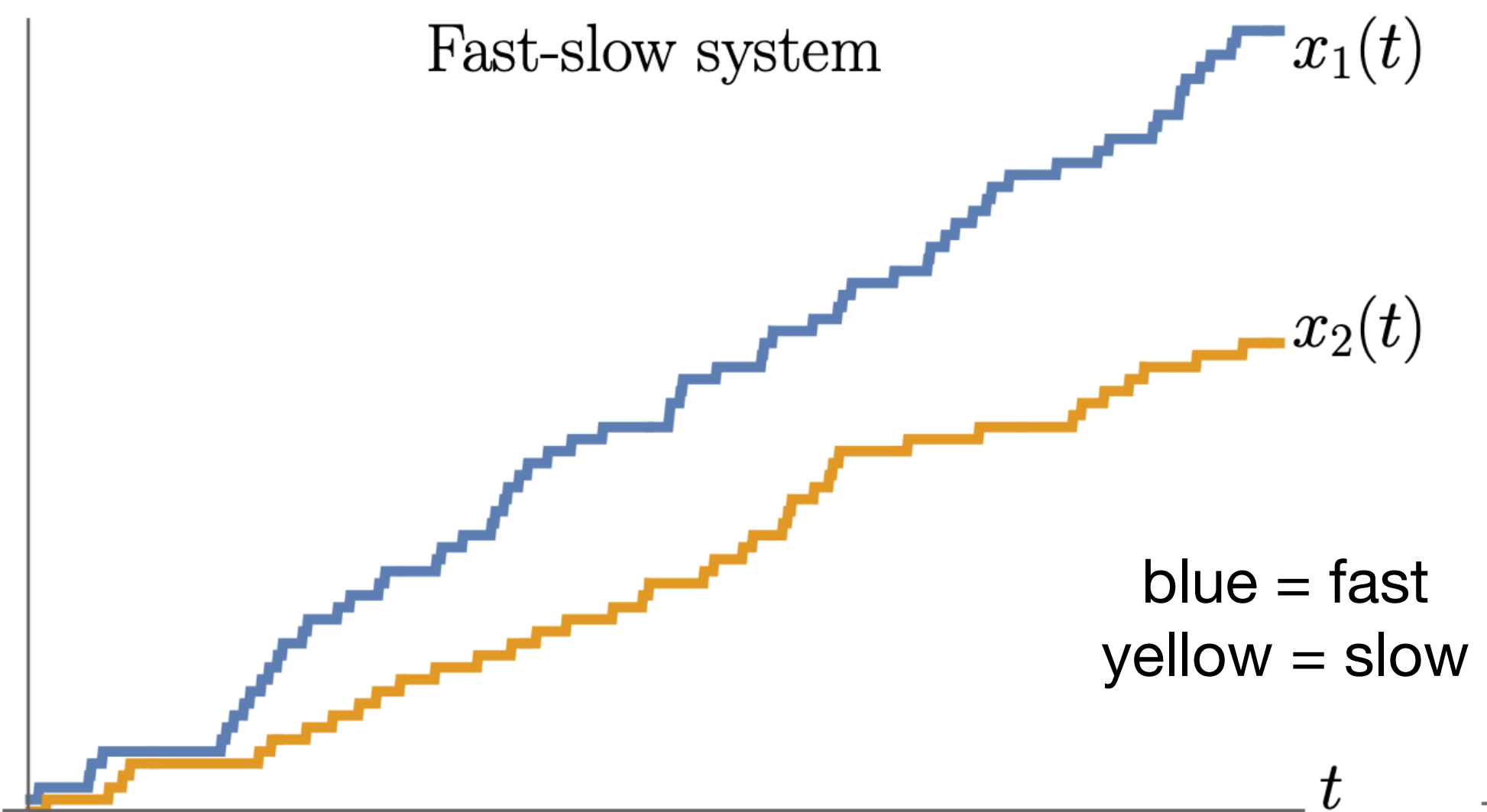


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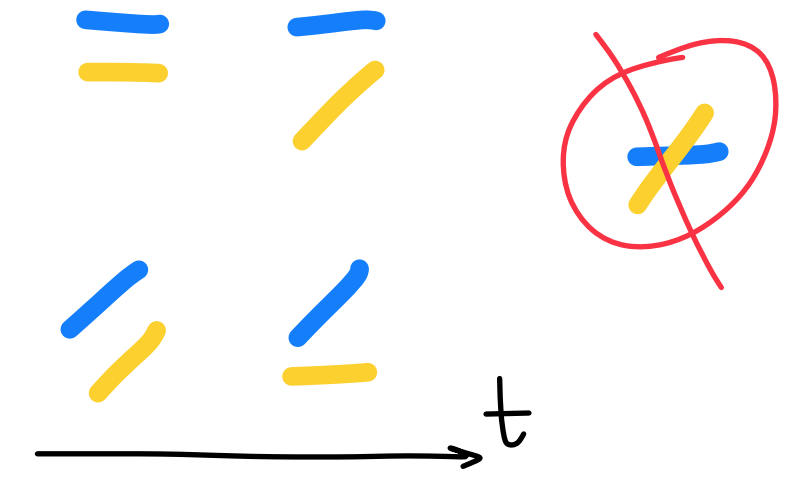


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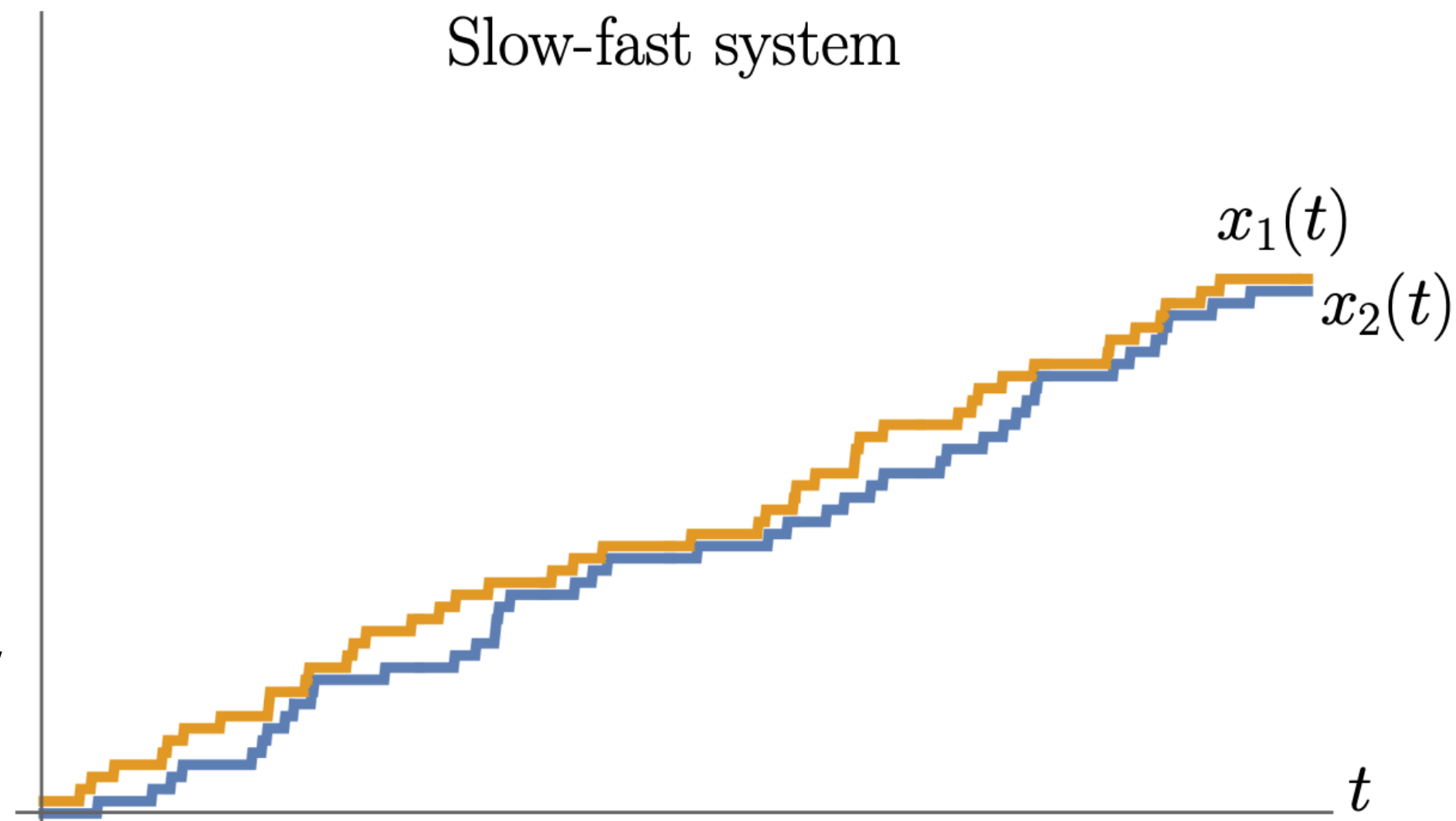
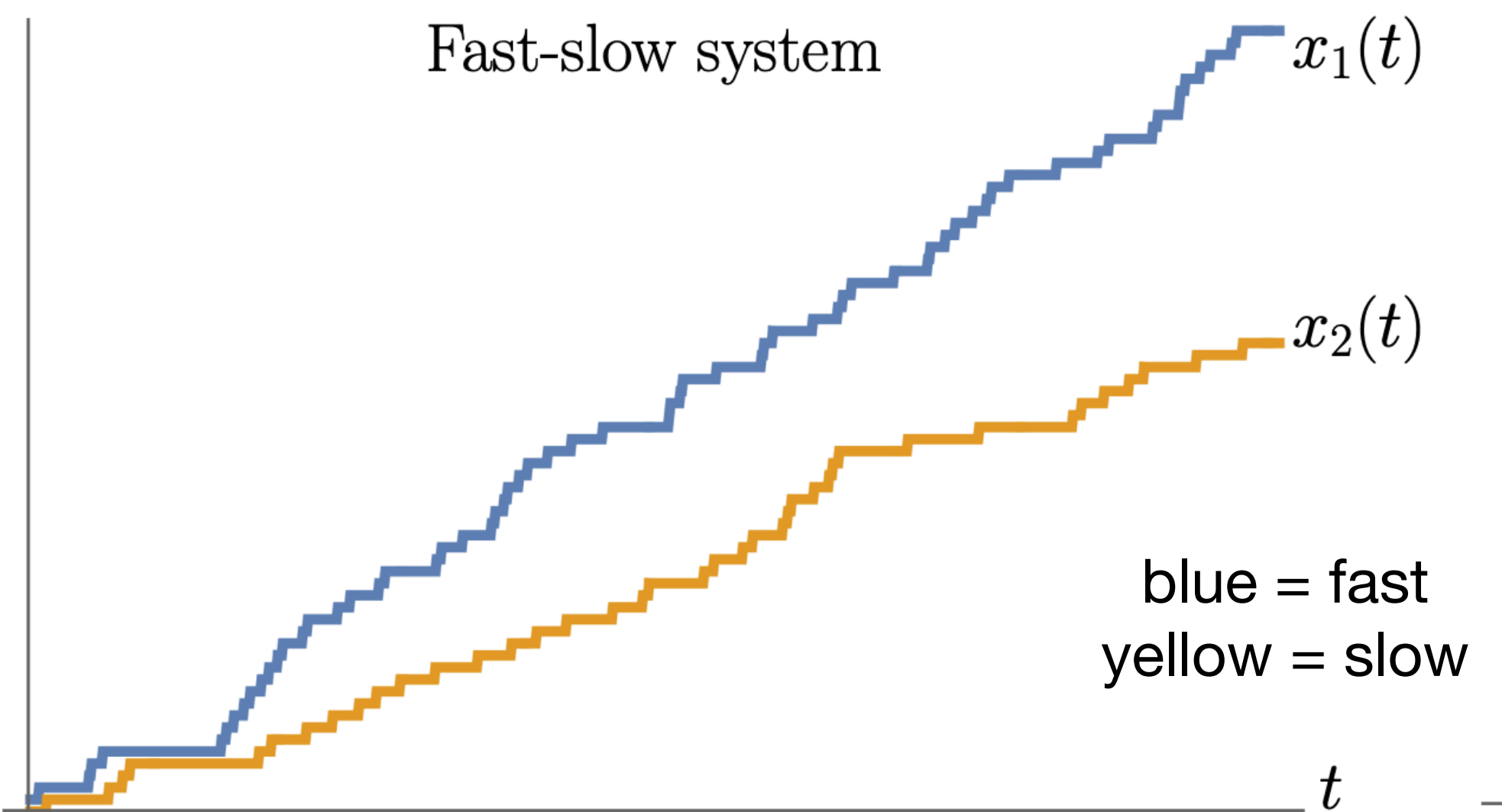


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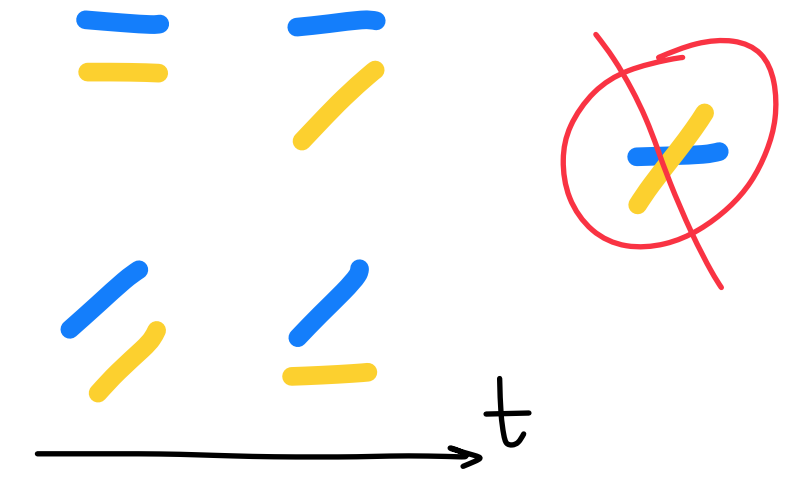
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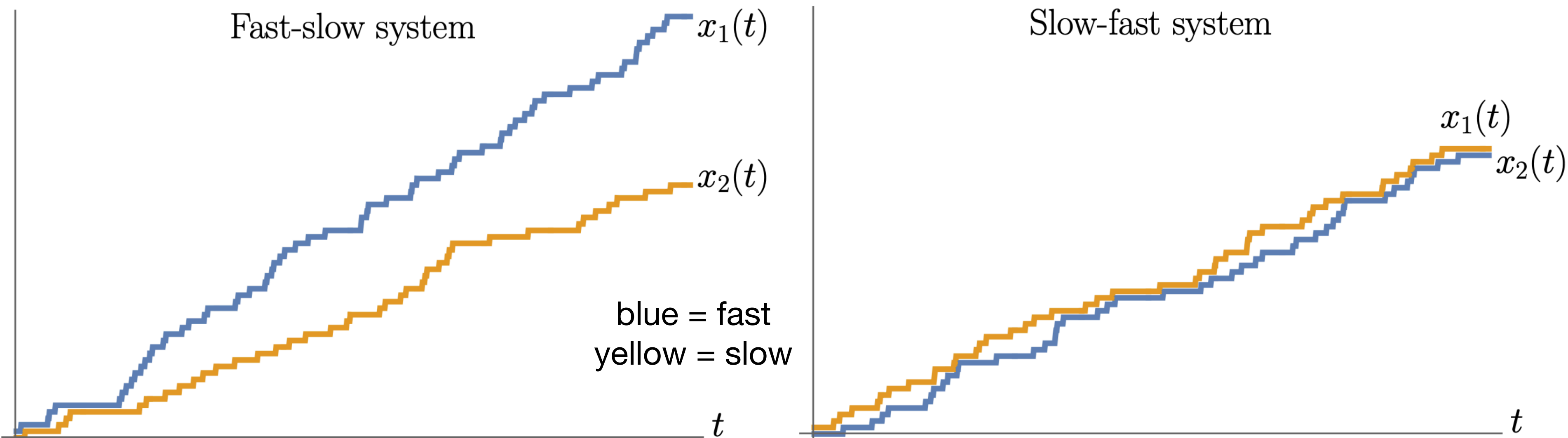
The long-time speed of the car ahead depends on which car is first; for the car behind it **does not** depend on the order

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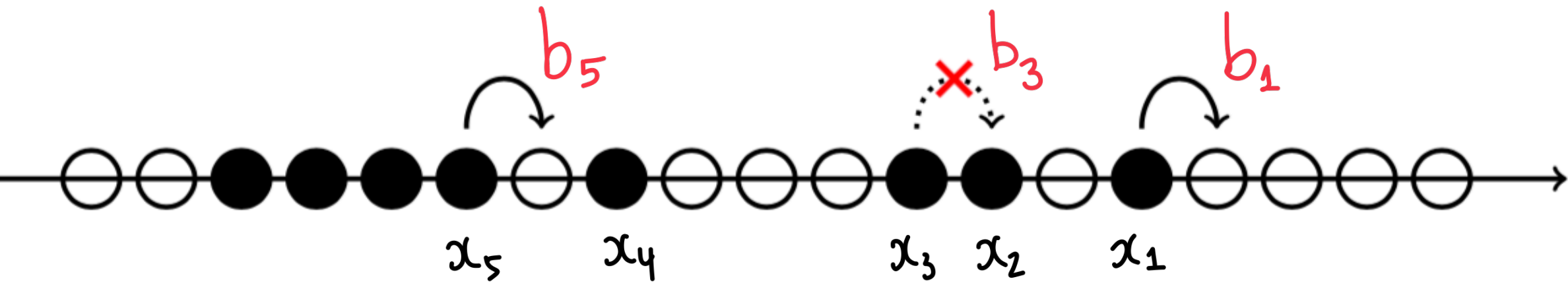
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Fact 0 - symmetry of trajectory. (Vershik-Kerov ~1981; O'Connell 2003)

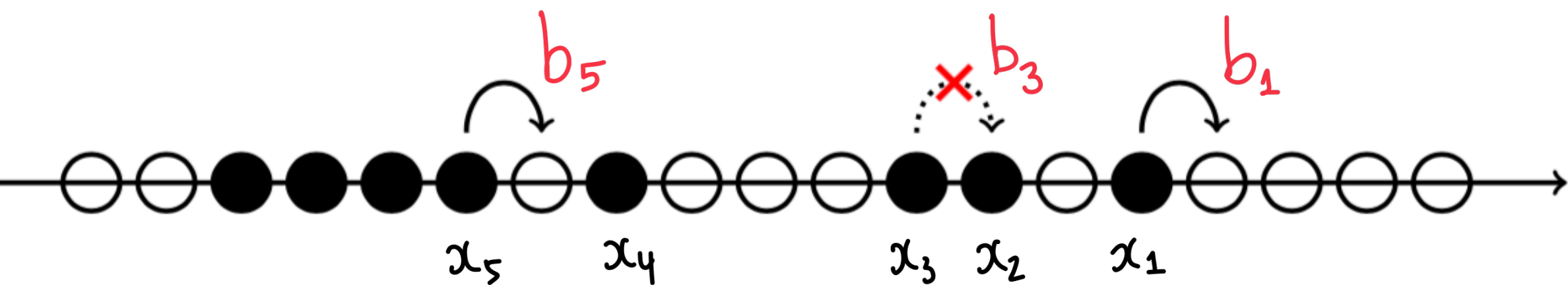
Cars start at 0,1 (*step initial configuration*)

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Why symmetry is nice?

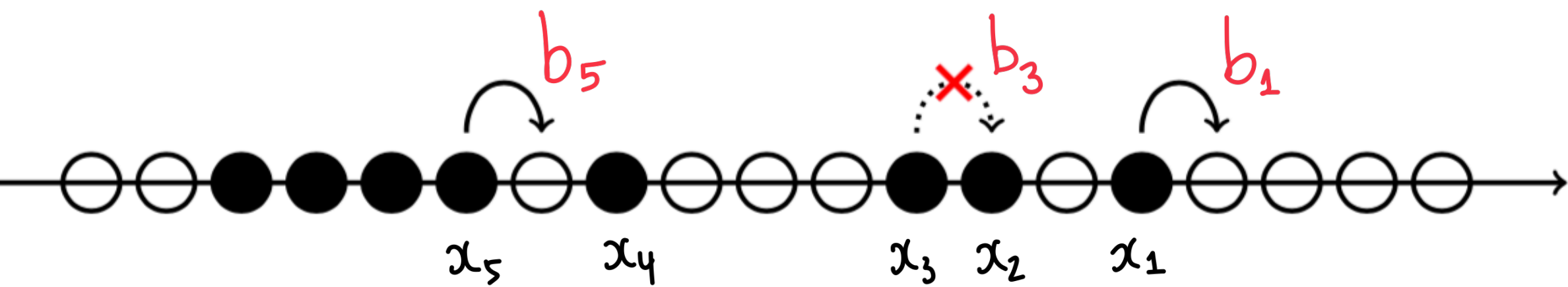


Why symmetry is nice?



- Add parameters $b_i > 0$, where b_i is the jumping probability / rate of particle x_i
- If $x_i(0) = -i$ (**step**), then the trajectory of the particle $x_n(t)$ depends on parameters b_1, b_2, \dots, b_n **symmetrically**
- We can use **symmetric polynomials** to study this trajectory. Expanding probabilities in **symmetric function bases** yields exact formulas suitable for asymptotic analysis

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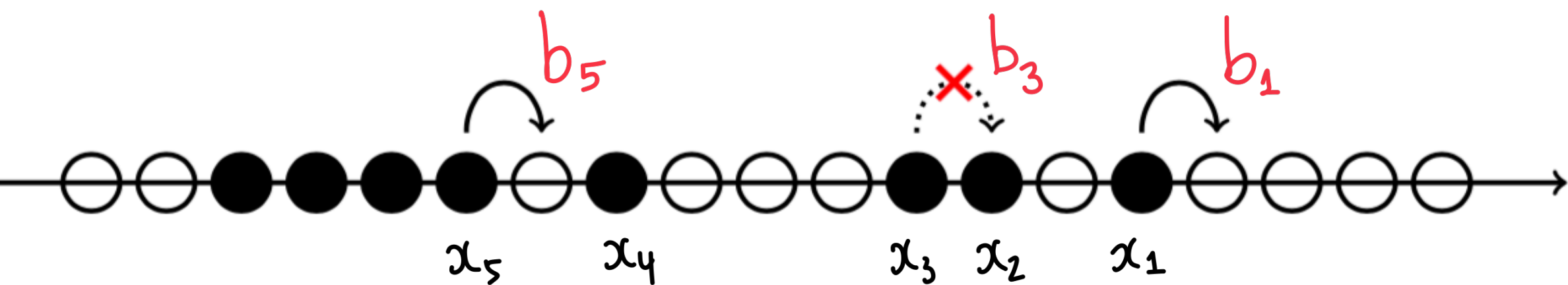
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- The linear space of **symmetric polynomials** in n variables has numerous interesting bases, like Schur polynomials $\lambda = (\lambda_1 \geq \dots \geq \lambda_n \geq 0)$:

$$s_\lambda(u_1, \dots, u_n) = \frac{\det[u_i^{\lambda_j + n - j}]_{i,j=1}^n}{\prod_{i < j} (u_i - u_j)}$$

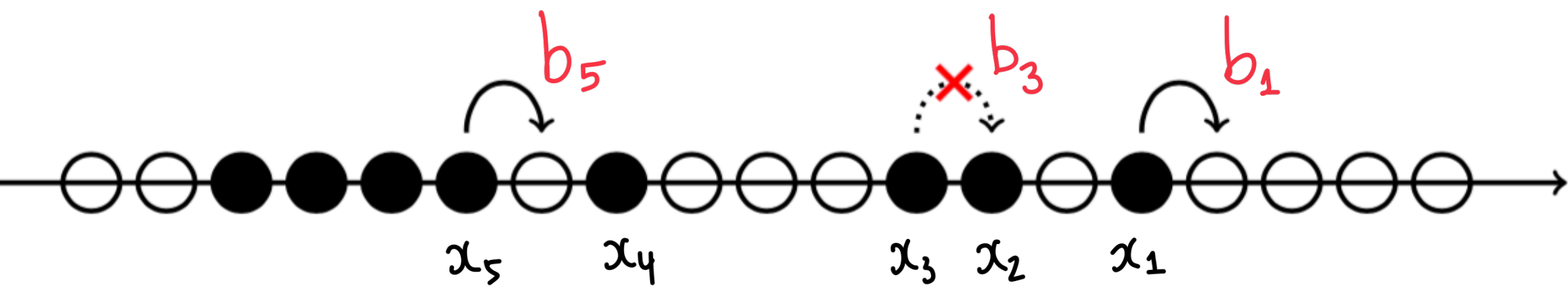
- Enumerative / algebraic combinatorics
- Representation theory / \mathbb{C} (of S_n, GL_N)
- Geometry (Hilbert schemes, ...)
- Random matrices, particle systems, statistical mechanics, ...

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- What if we swap $b_{n-1} \leftrightarrow b_n$?
- Then the trajectories of x_n, x_{n-2}, \dots, x_1 do not change in distribution, but the **trajectory of x_{n-1} changes**
- We constructed a **coupling** between two particle systems that moves only x_{n-1} **[P.-Saenz 2019, 2022]**
- Also extended this to **arbitrary initial conditions** **[P.-Saenz 2022]**
- Next, I discuss the latter setup for two particles, and show how it follows from the **Yang-Baxter equation**

Randomized initial conditions

Fact 0. Cars start at $0,1$ (*step initial configuration*) \Rightarrow the distribution of the trajectory of the car behind is **independent** of the order of the speeds

Randomized initial conditions

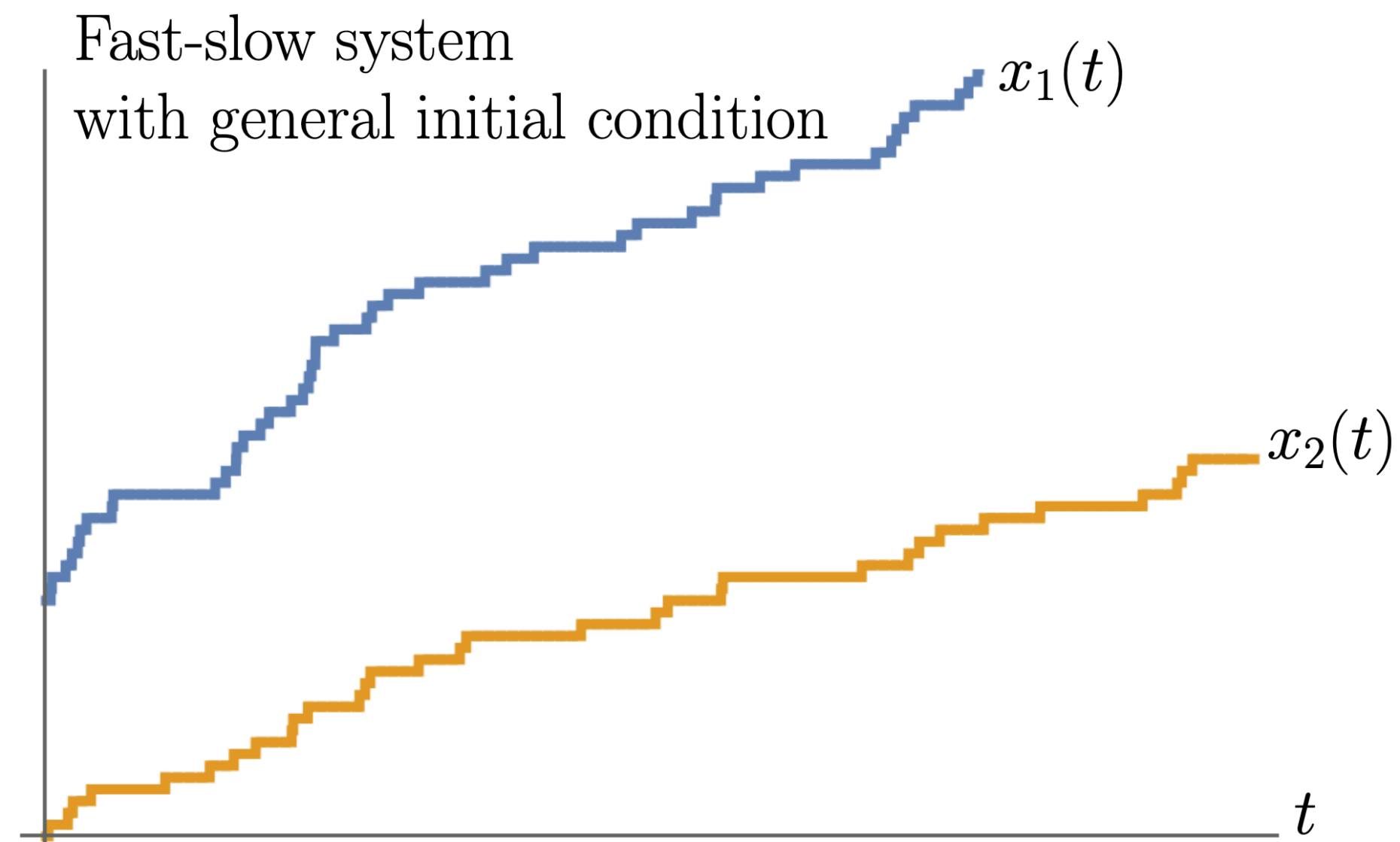
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This **fails** when cars are not initially neighbors, $x_1(0) - x_2(0) - 1 > 0$

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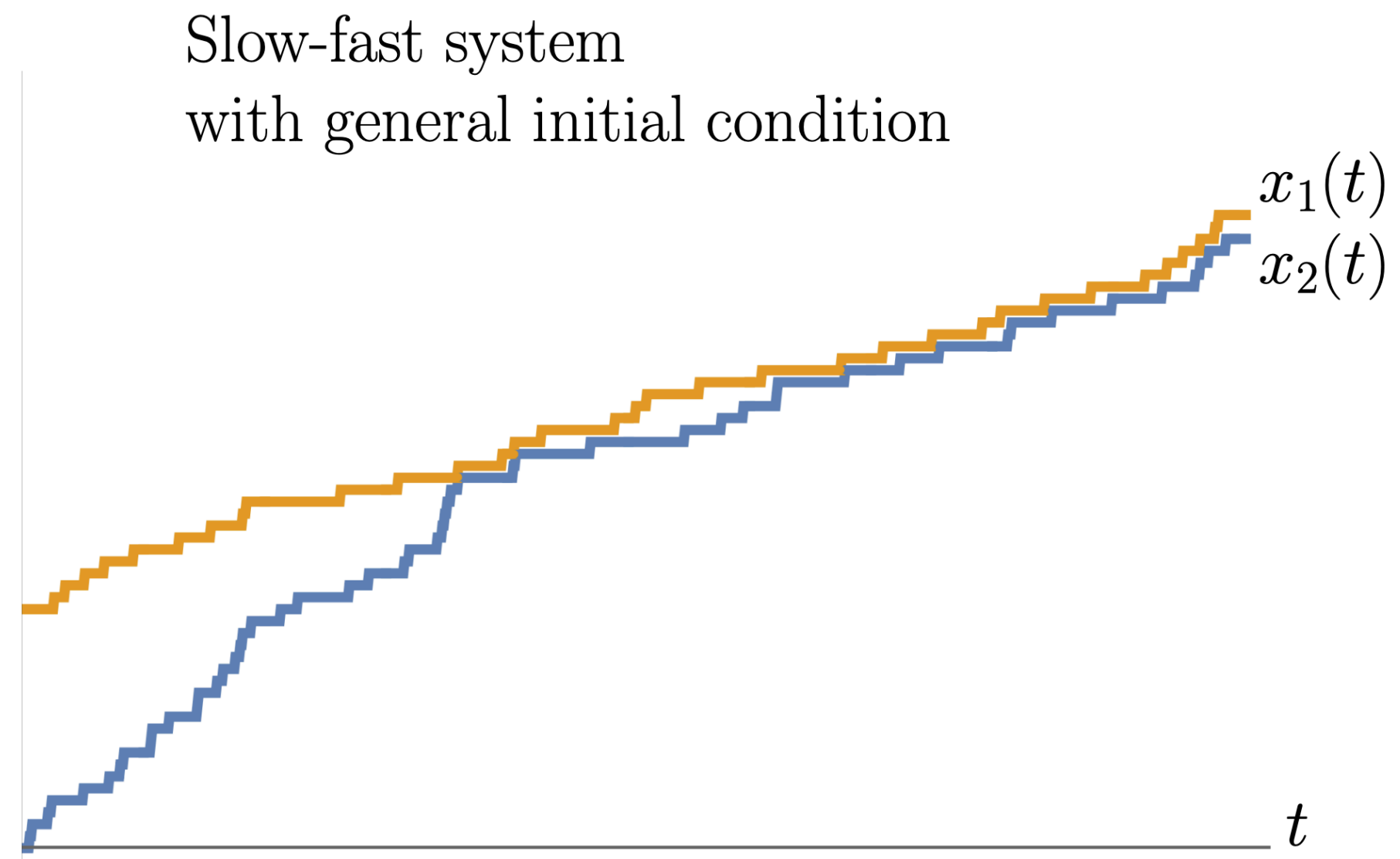
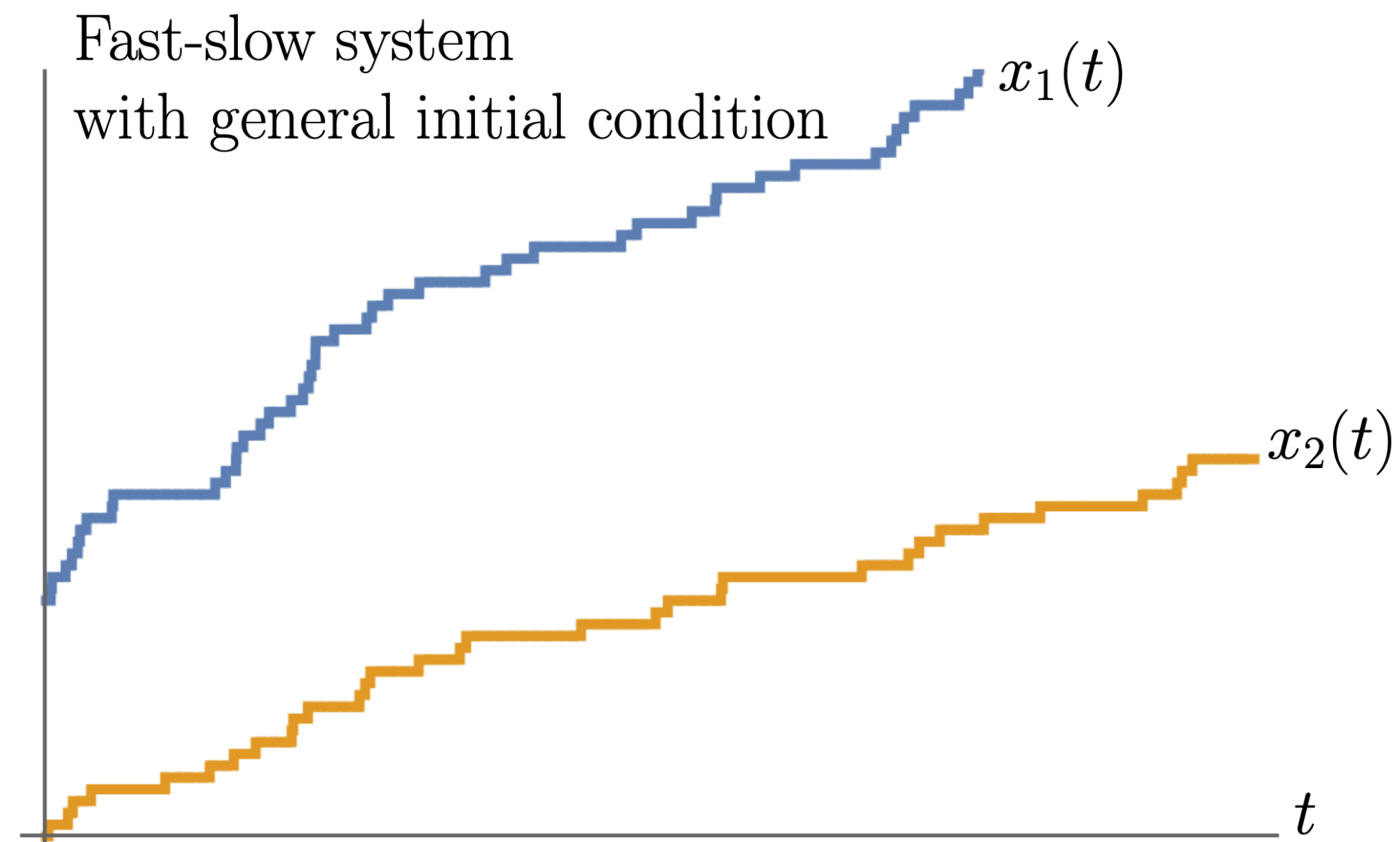
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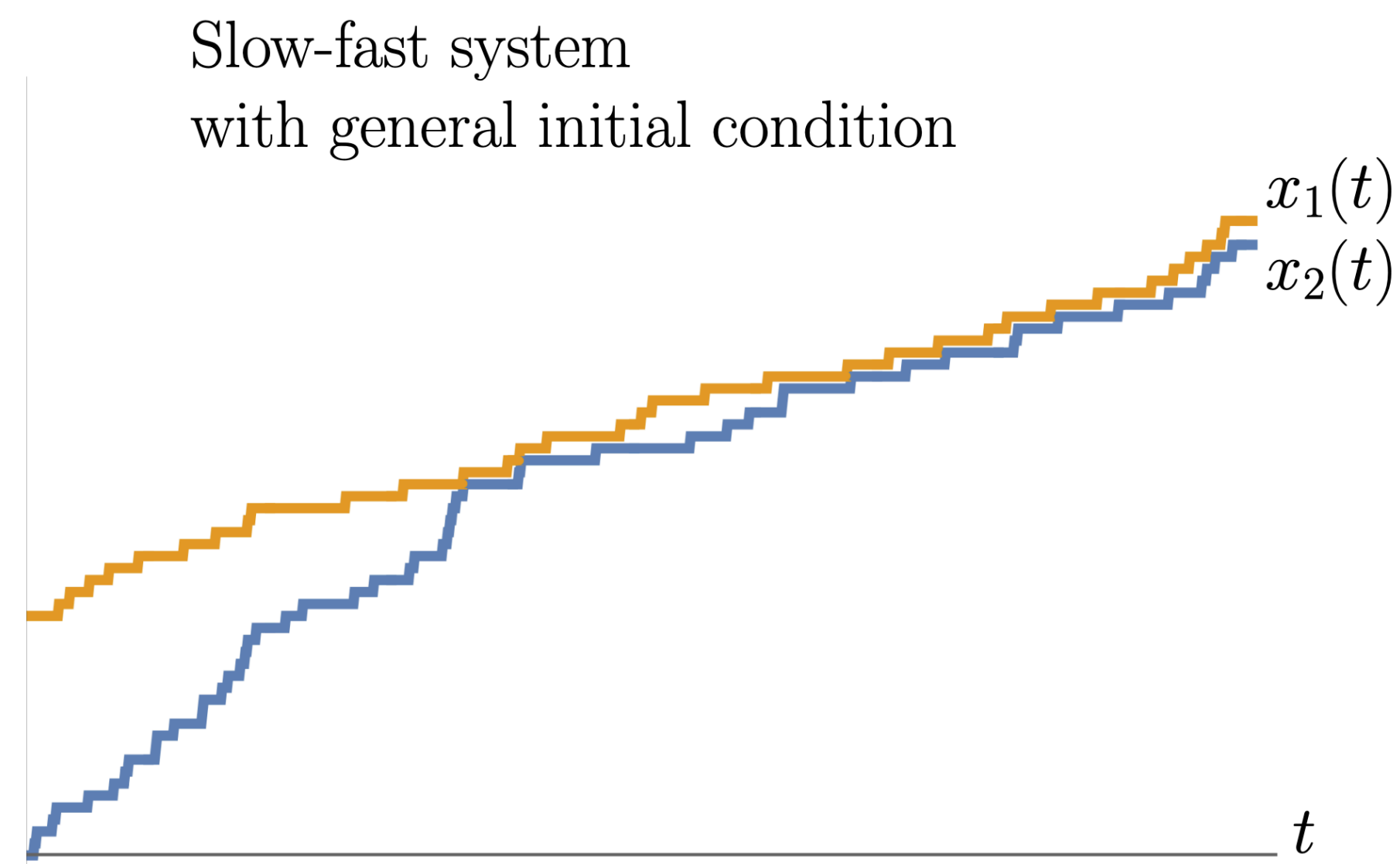
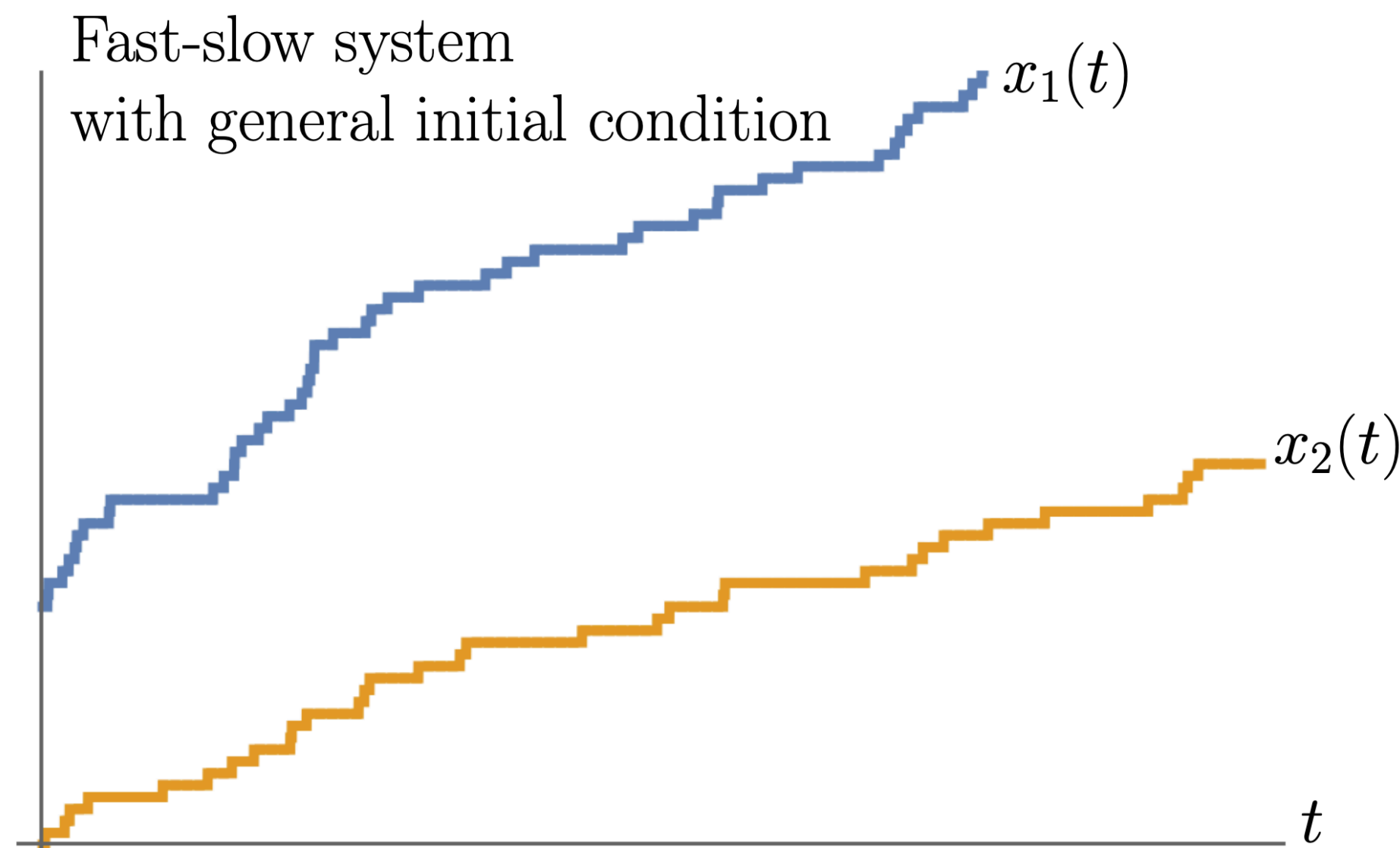
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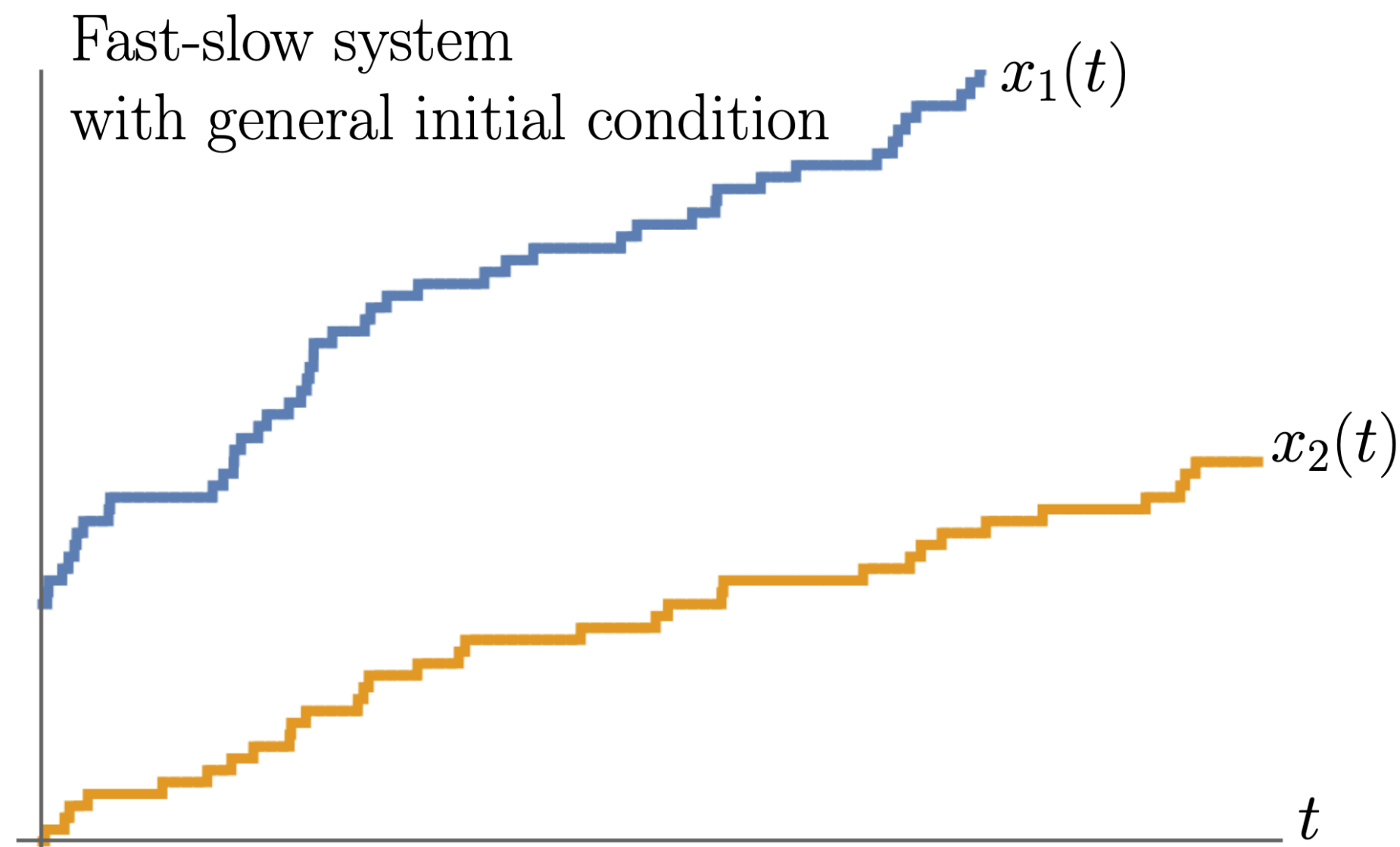
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Then the trajectories of the second particle become **the same in distribution**.

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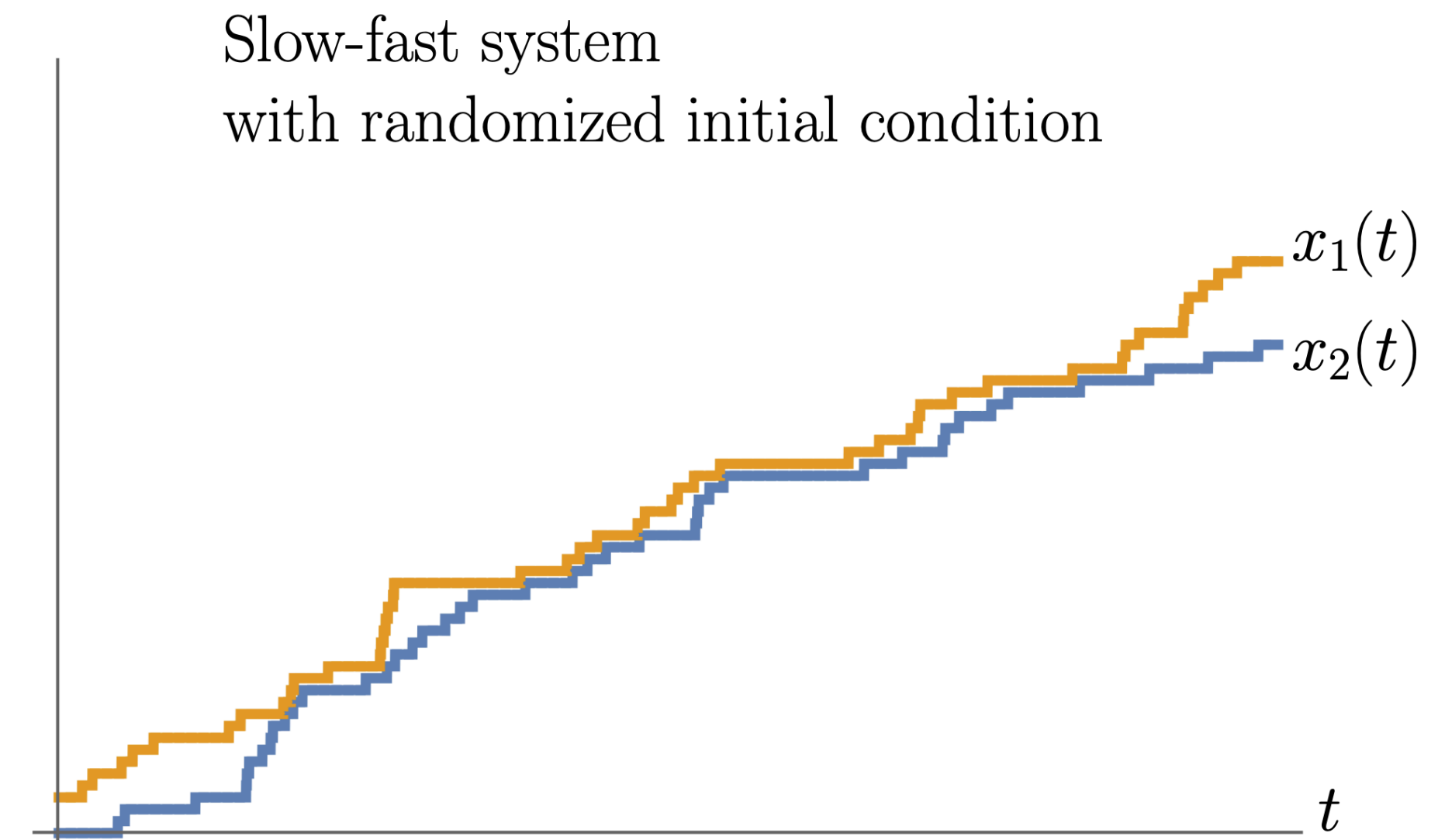
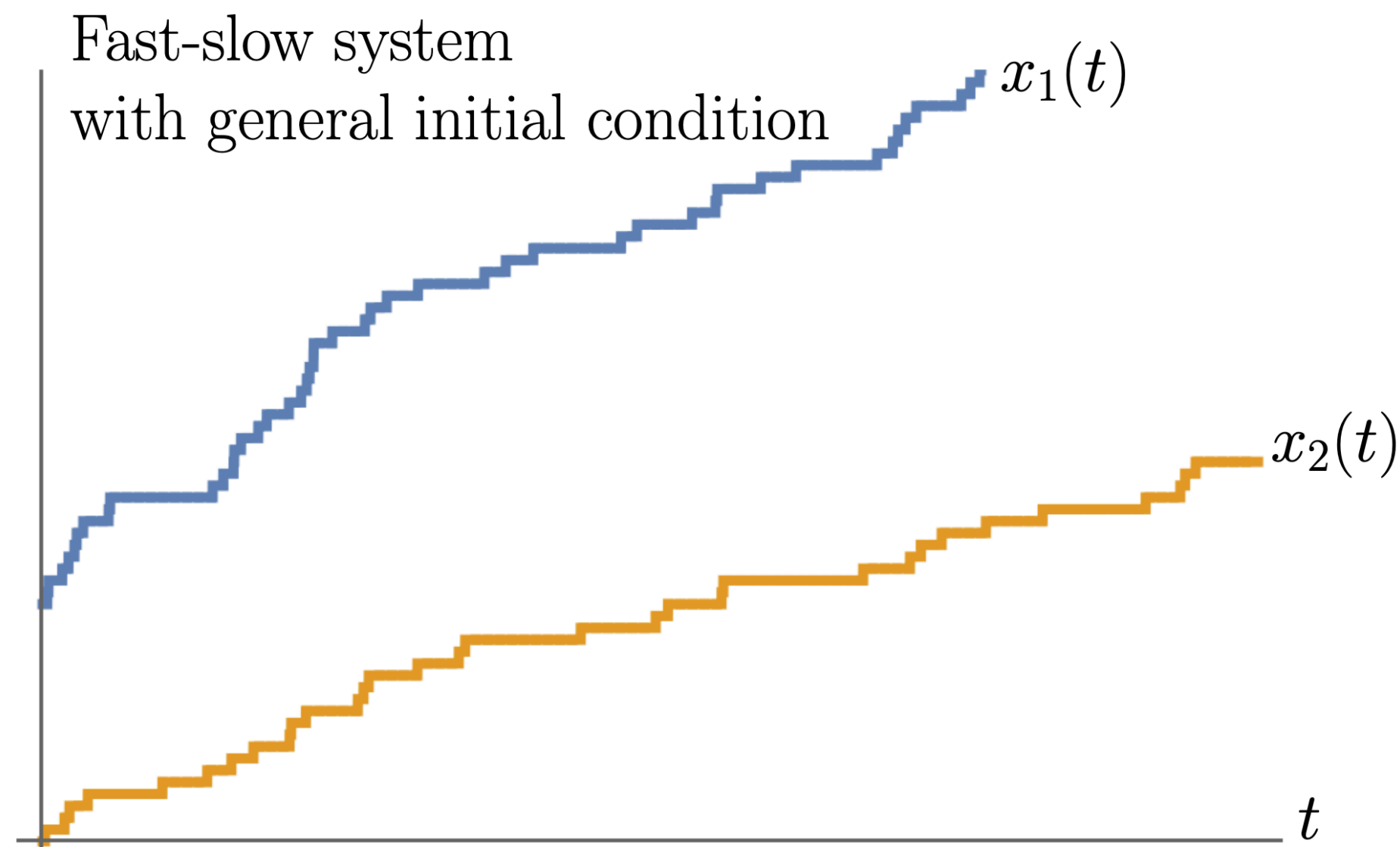
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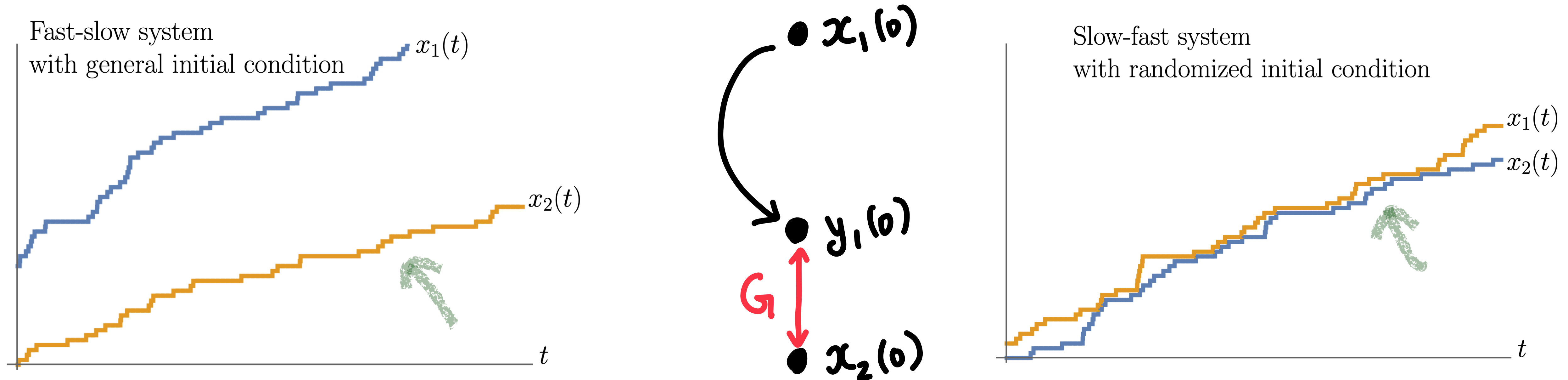
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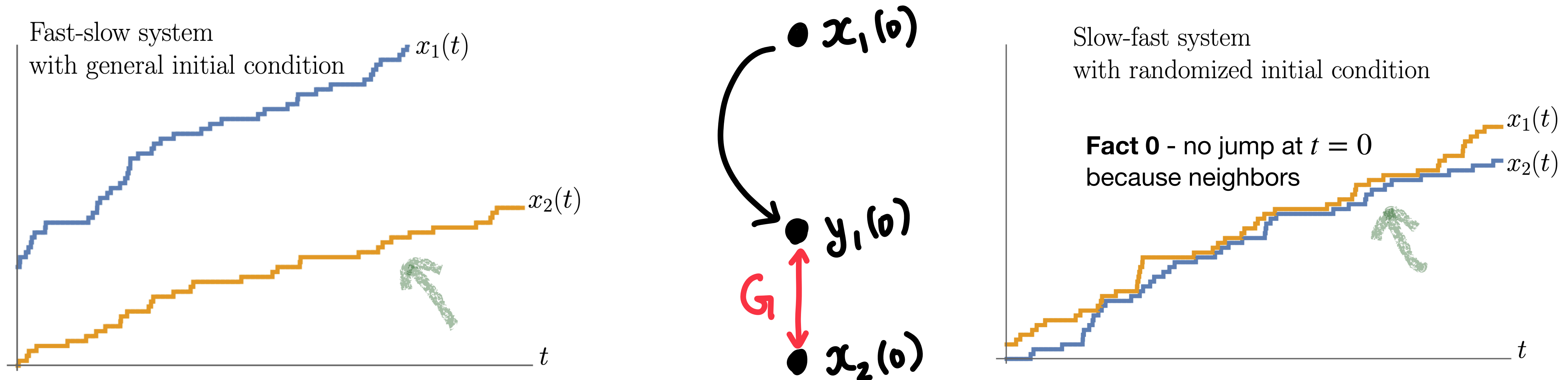
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Randomized initial conditions

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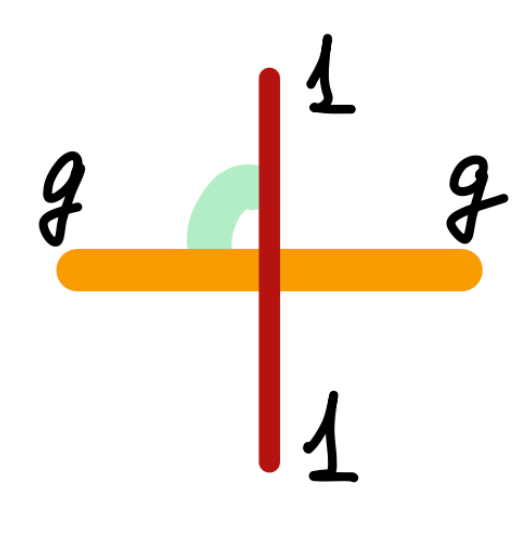
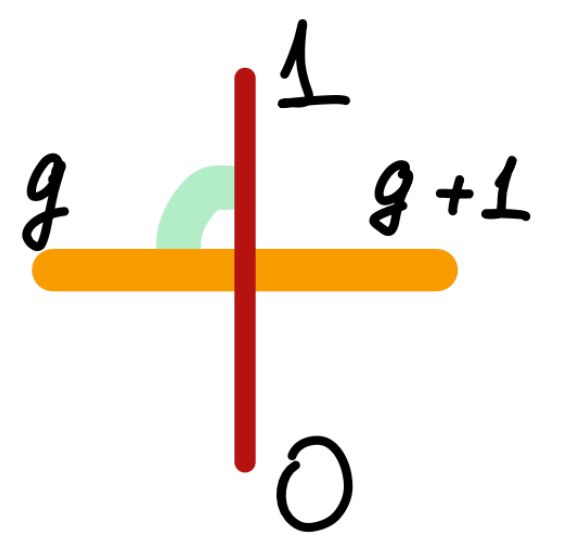
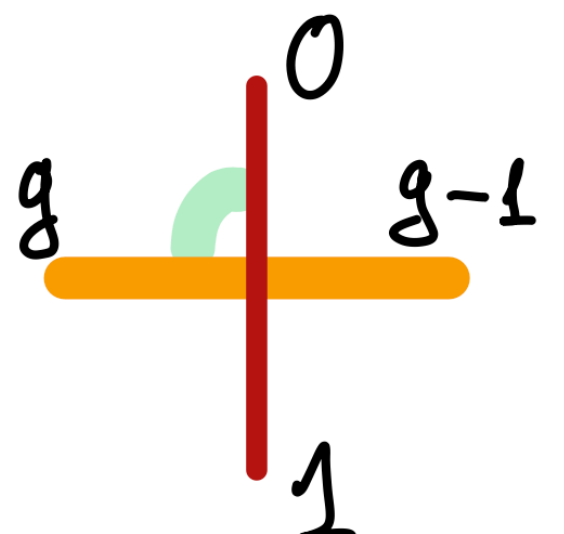
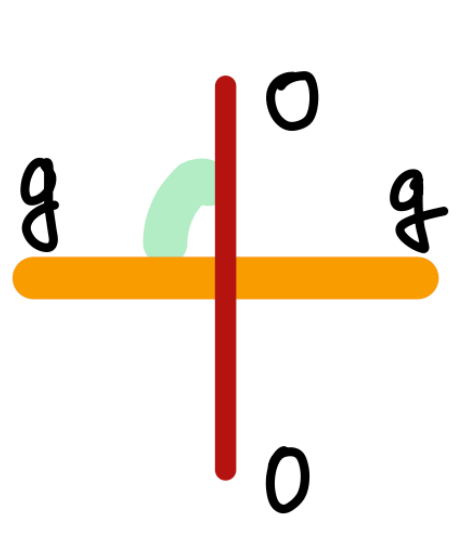
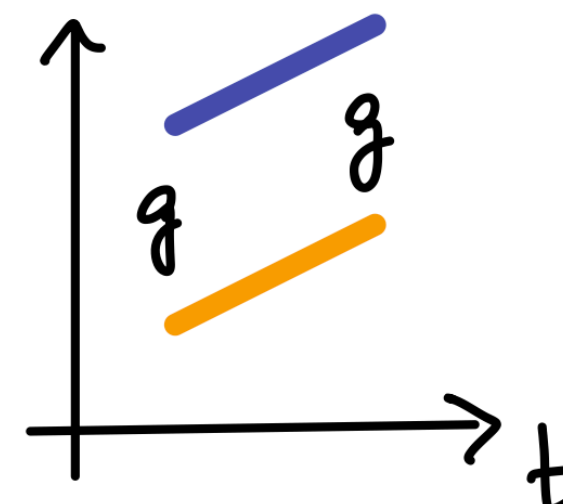
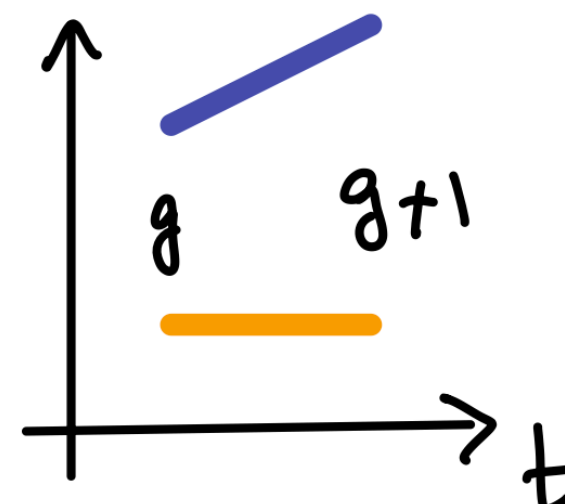
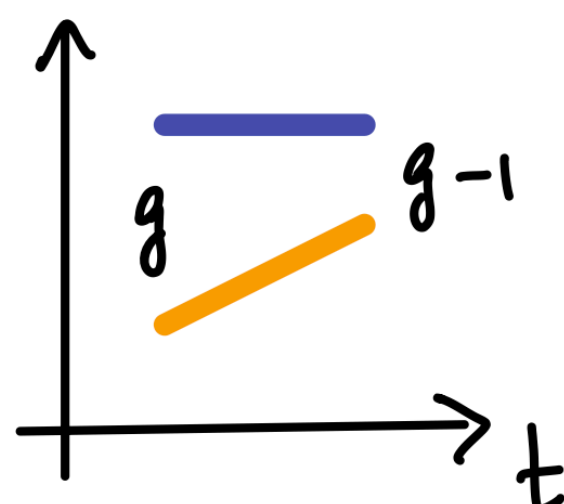
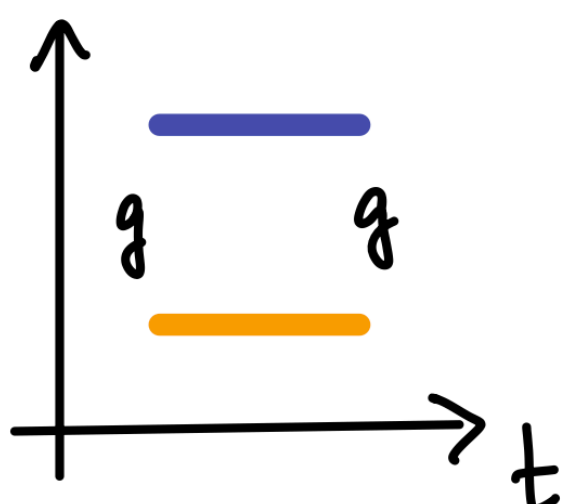
This **fails** when cars are not initially neighbors, $x_1(0) - x_2(0) - 1 > 0$



Theorem 1 [P.-Saenz 2022]. “Be wise - randomize”. Recall $a_1 > a_2 > 0$, $b_i = a_i / (a_i + 1)$. Let $y_1(0) = x_2(0) + 1 + \min(G, x_1(0) - x_2(0) - 1)$, where $G \in \mathbb{Z}_{\geq 0}$ is an independent geometric random variable with $P(G = k) = (a_2/a_1)^k (1 - a_2/a_1)$. Start SF from $(y_1(0), x_2(0))$.

Then the trajectories of the second particle become **the same in distribution**.

Proof via Yang-Baxter equation



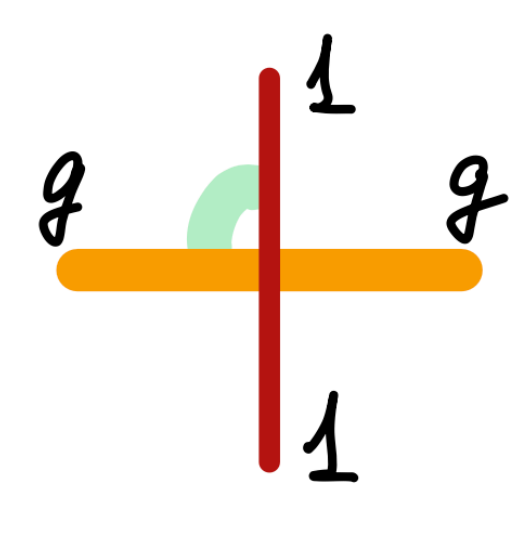
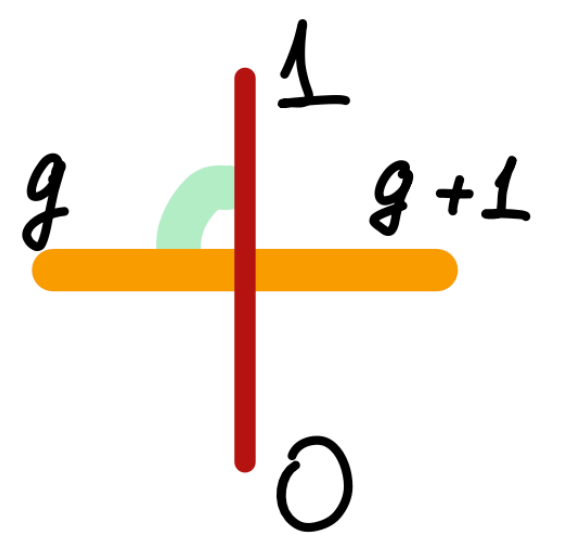
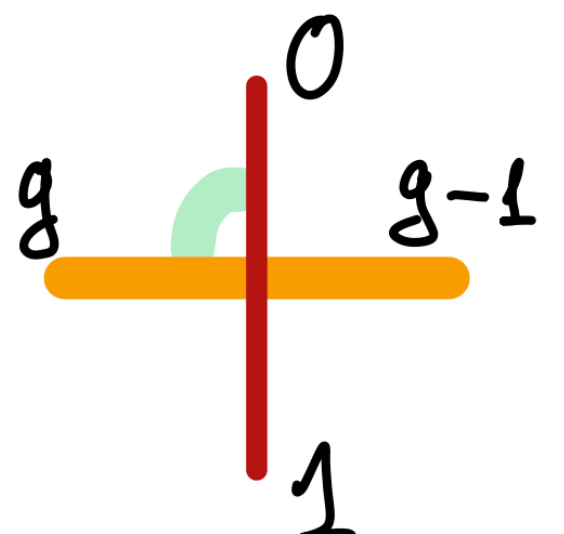
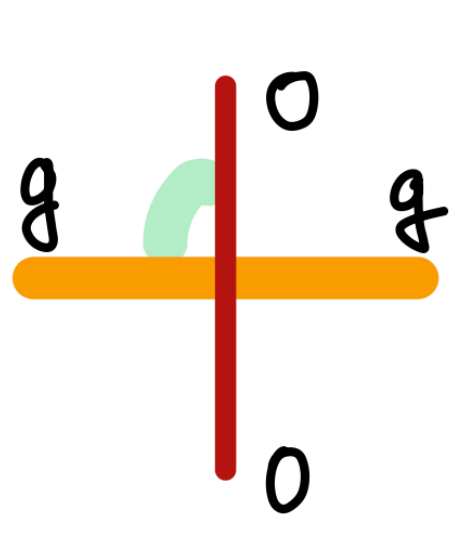
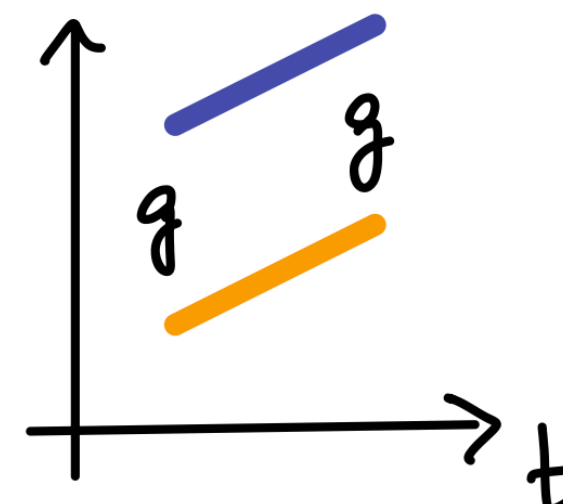
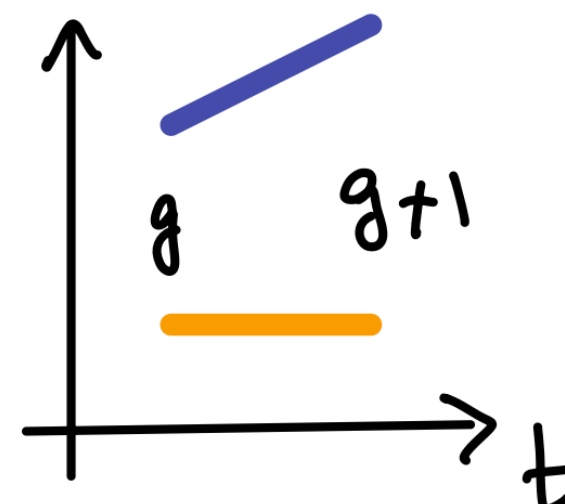
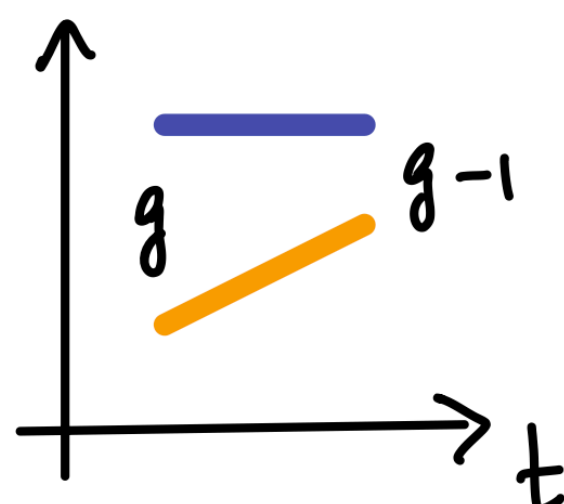
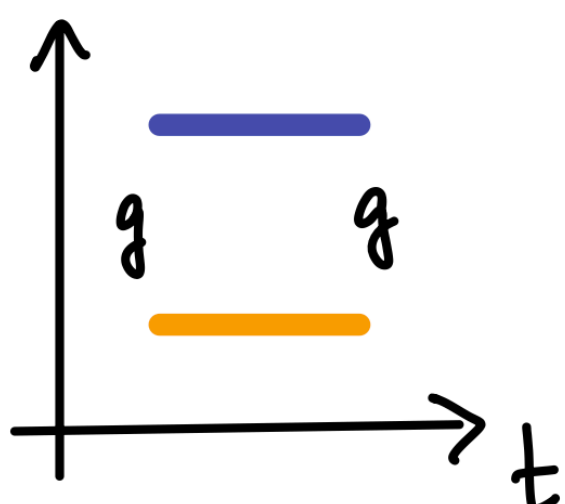
$$\frac{1 + a_2 \mathbf{1}_{g=0}}{1 + a_2}$$

$$\frac{a_2 \mathbf{1}_{g>0}}{1 + a_2}$$

$$\frac{1}{1 + a_2}$$

$$\frac{a_2}{1 + a_2}$$

Proof via Yang-Baxter equation

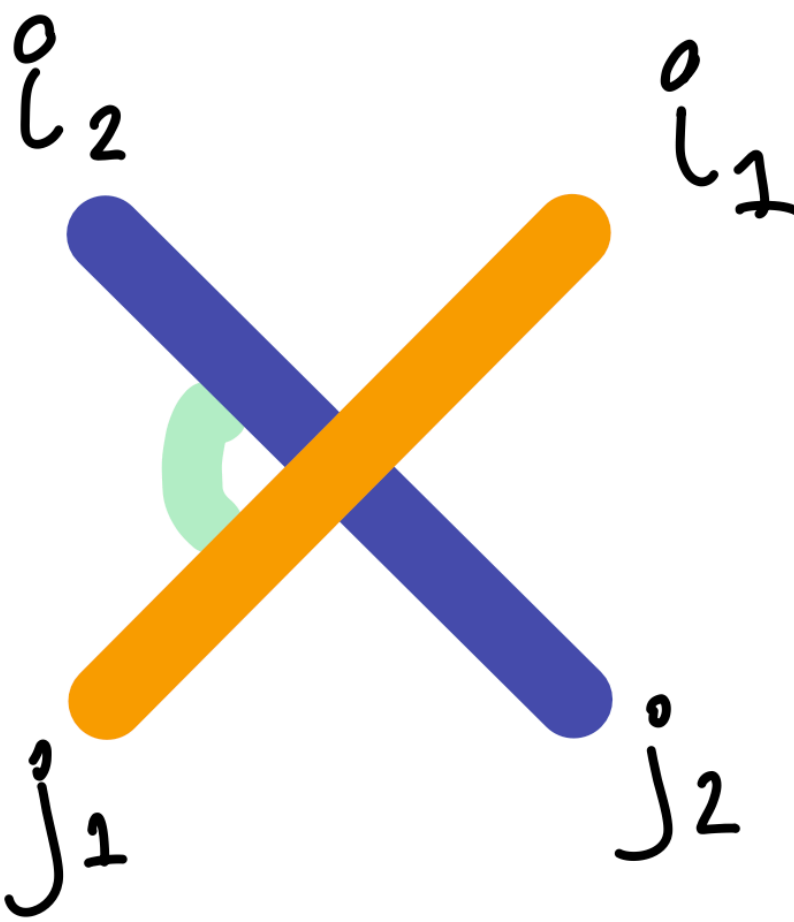


$$\frac{1 + a_2 \mathbf{1}_{g=0}}{1 + a_2}$$

$$\frac{a_2 \mathbf{1}_{g>0}}{1 + a_2}$$

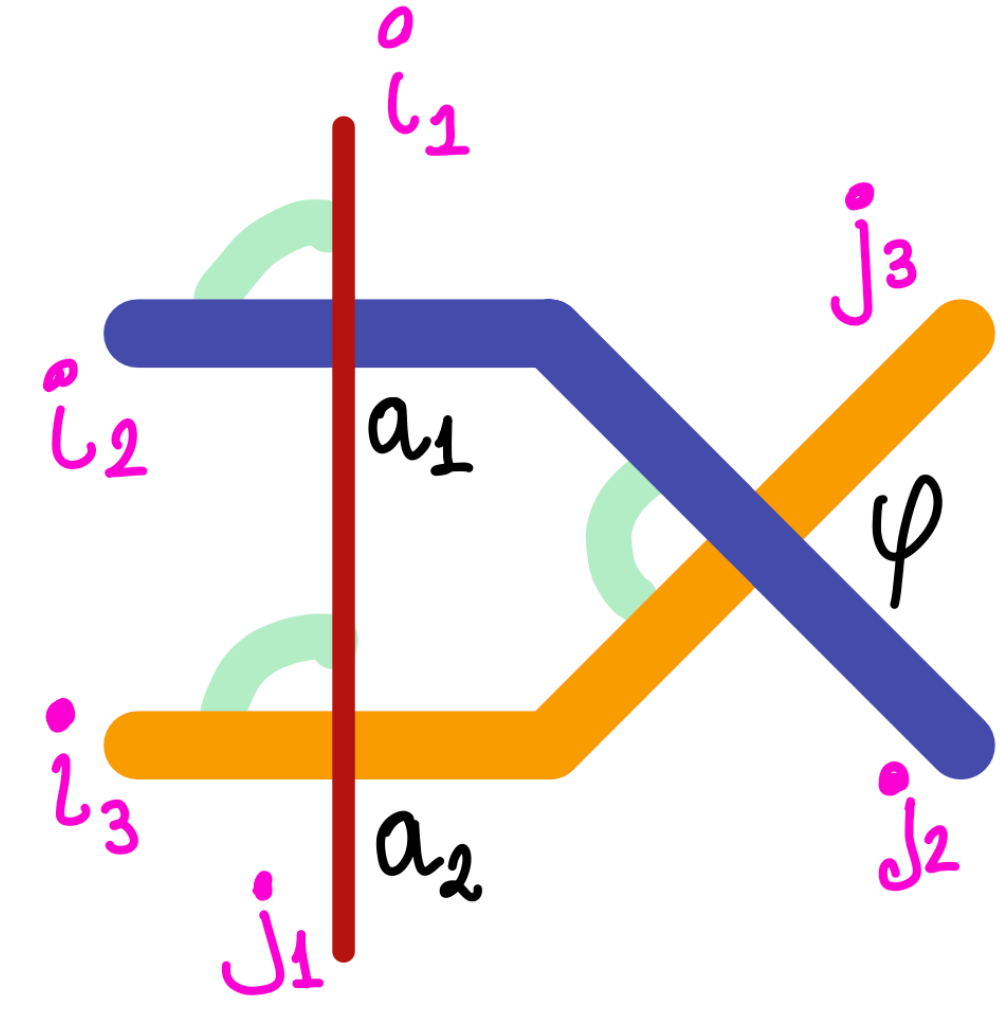
$$\frac{1}{1 + a_2}$$

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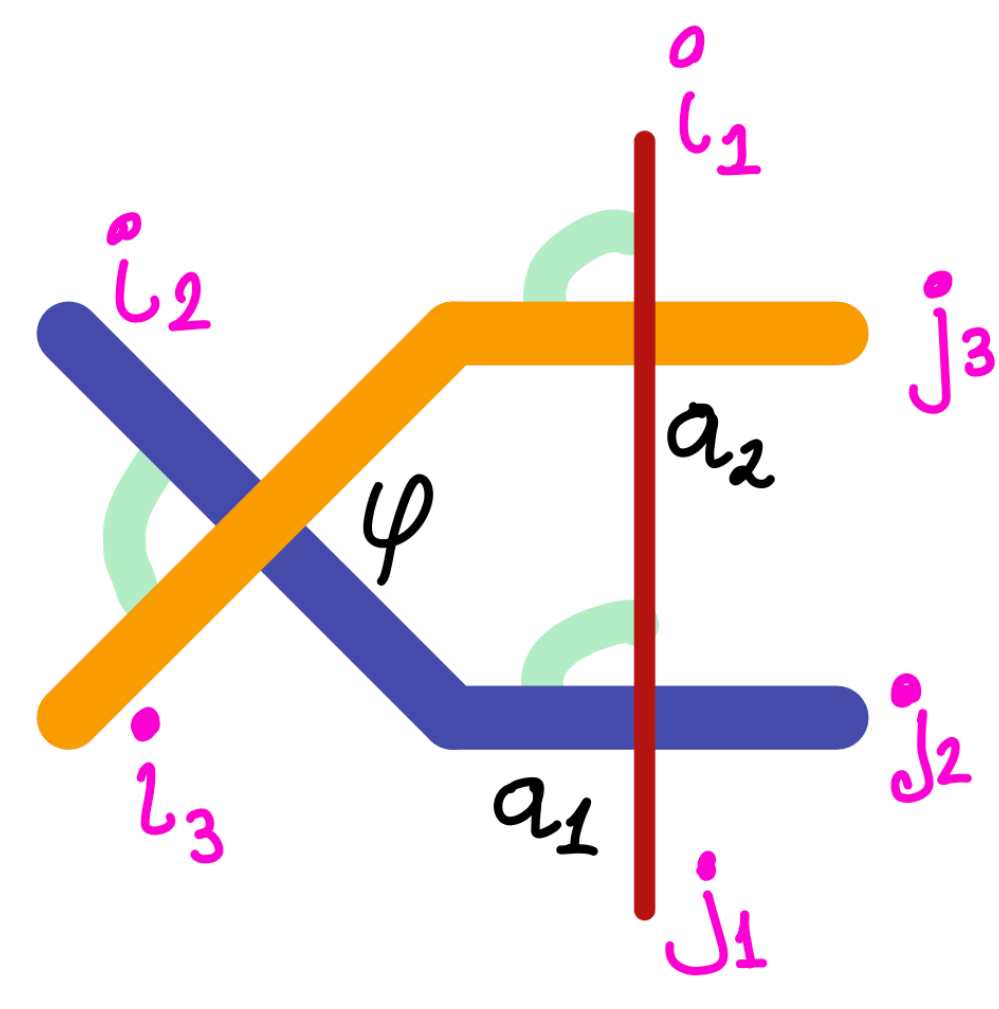


φ_{a_2/a_1} - geometric jumps

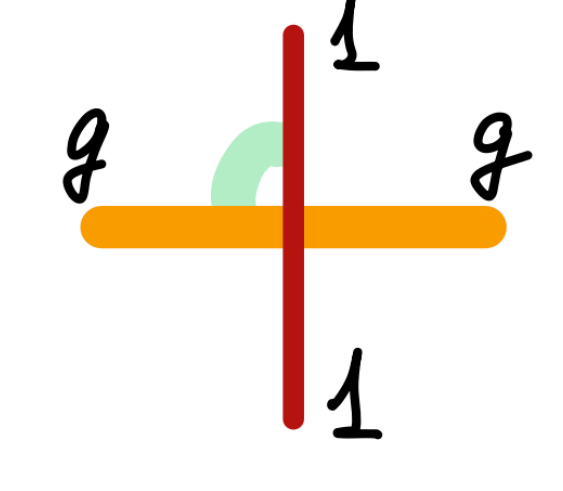
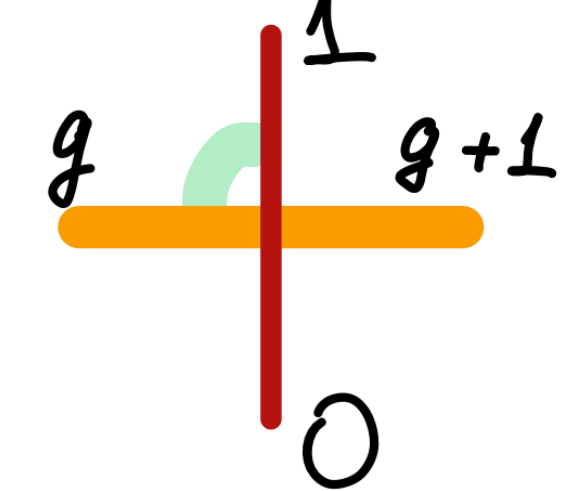
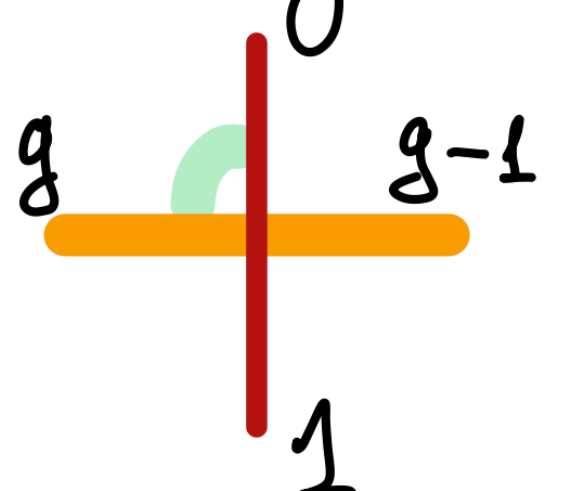
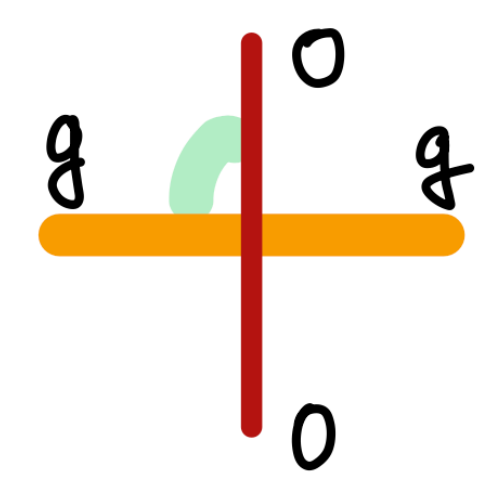
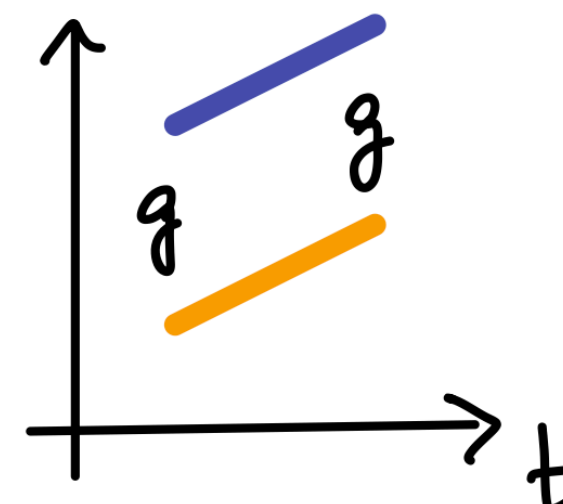
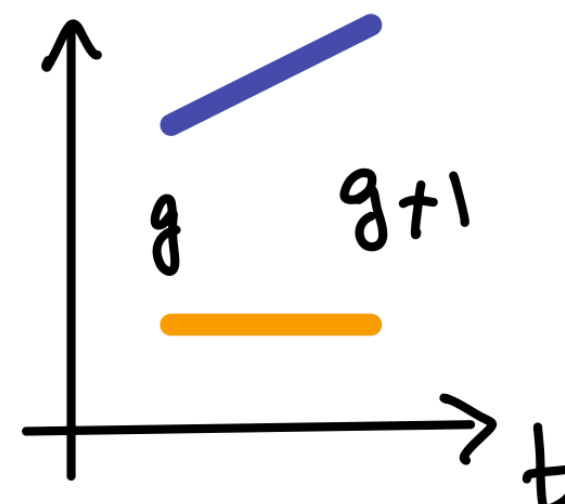
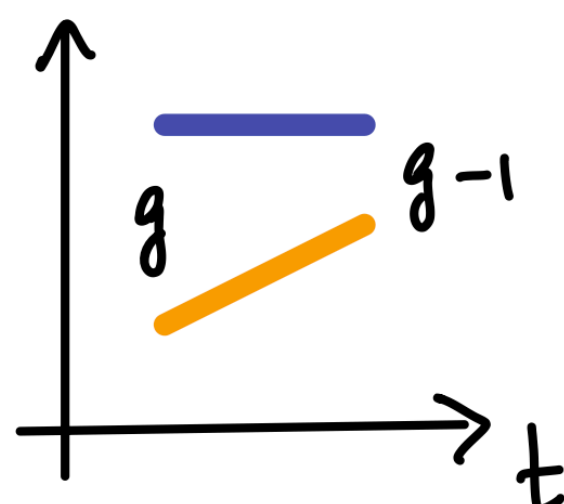
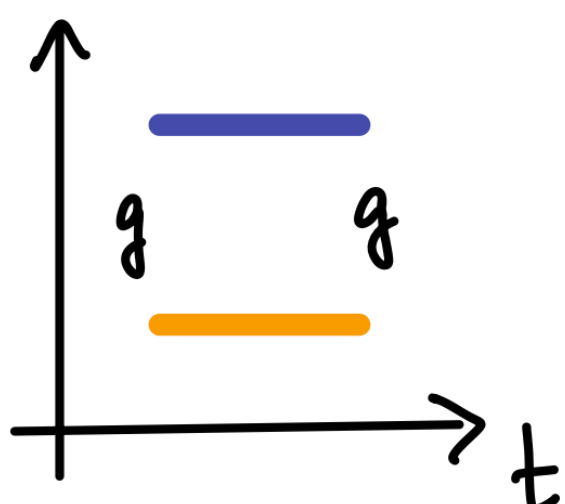
$$(a_2/a_1)^{j_2} (1 - \mathbf{1}_{j_2 < j_1} a_2/a_1) \mathbf{1}_{j_2 \leq j_1}$$



\equiv
YBE



Proof via Yang-Baxter equation



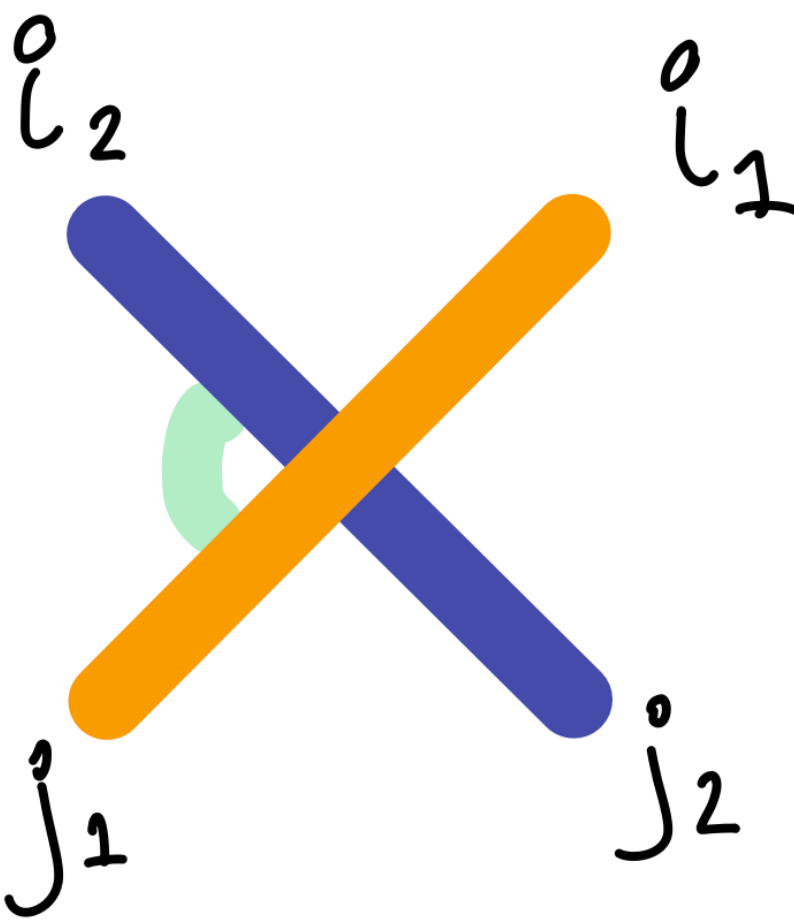
$$\frac{1 + a_2 \mathbf{1}_{g=0}}{1 + a_2}$$

$$\frac{a_2 \mathbf{1}_{g>0}}{1 + a_2}$$

$$\frac{1}{1 + a_2}$$

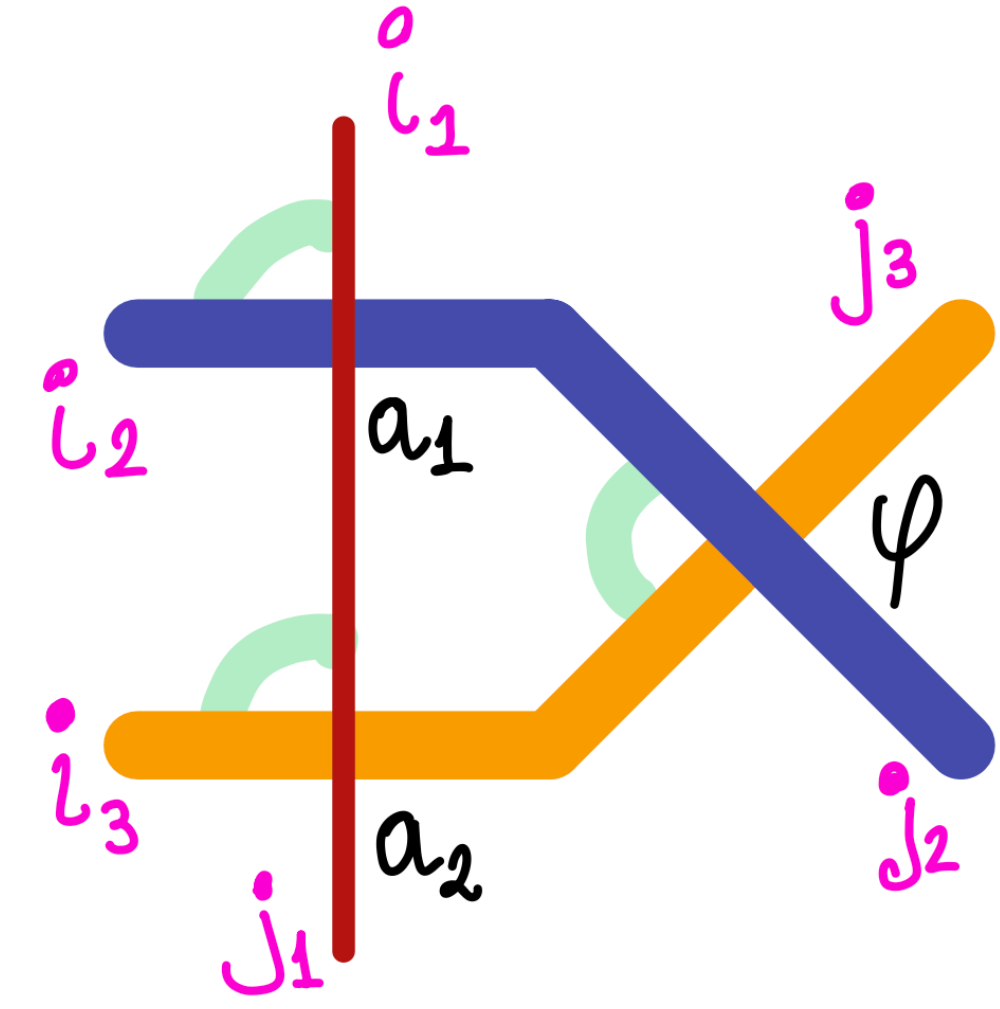
$$\frac{a_2}{1 + a_2}$$

- B_{a_2/a_1} - geometric jump operator on configurations of two particles
- $T_{a_1, a_2}, T_{a_2, a_1}$ - FS and SF transition operators

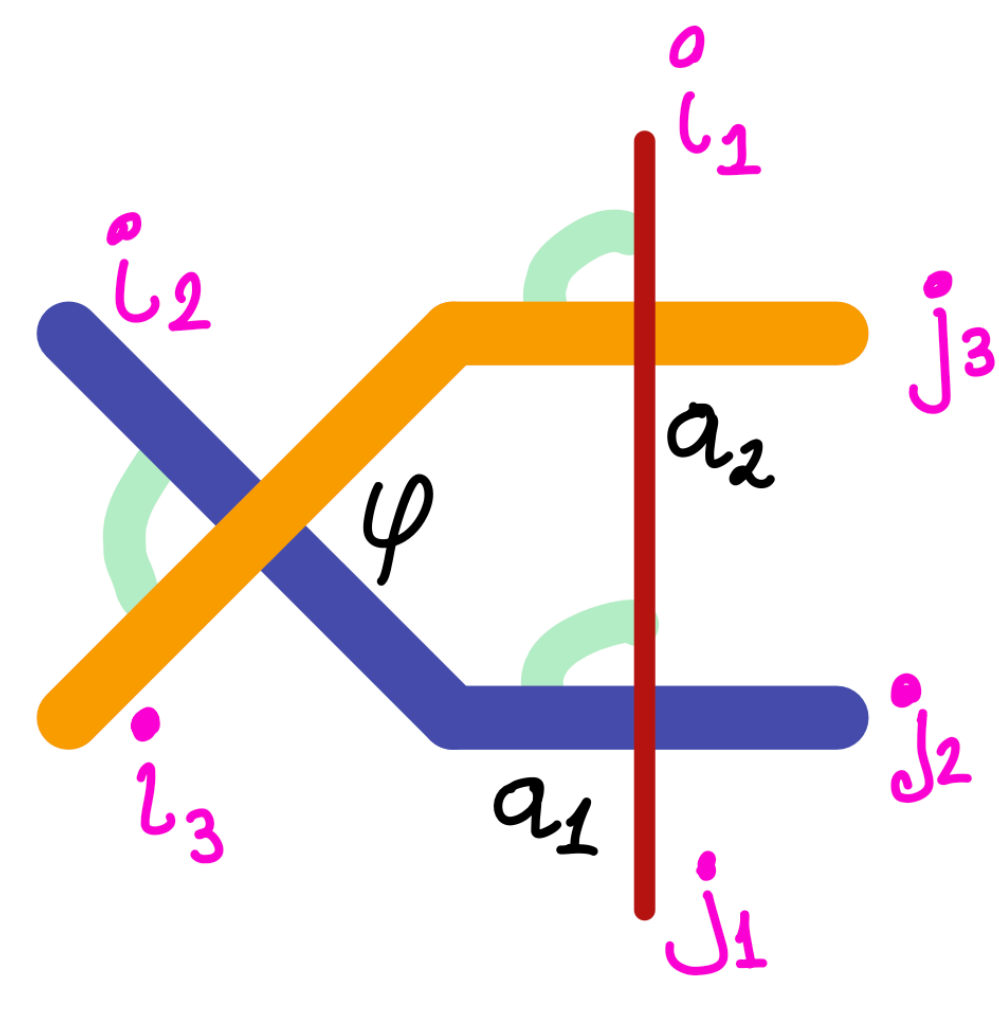


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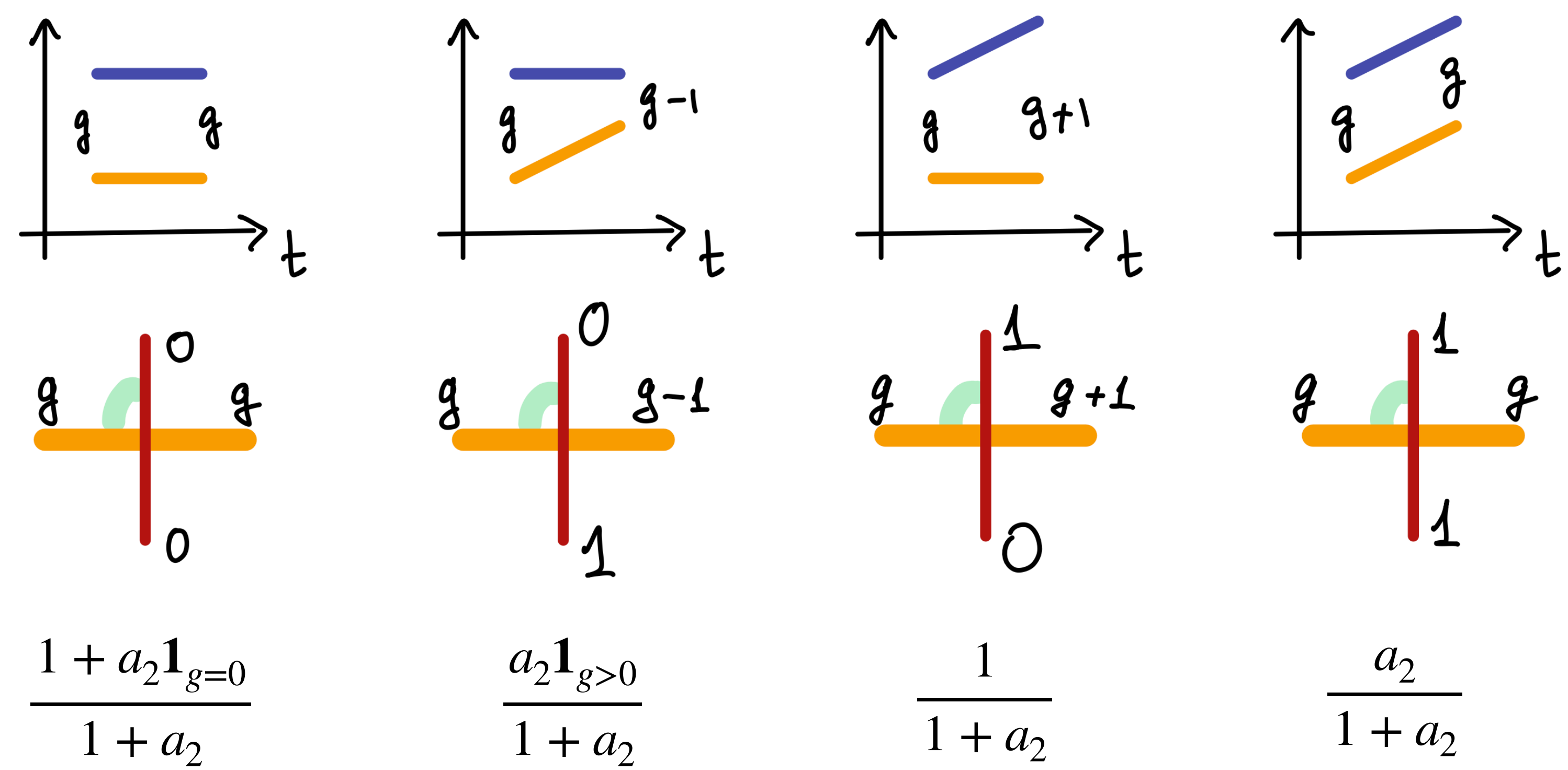
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\equiv
YBE

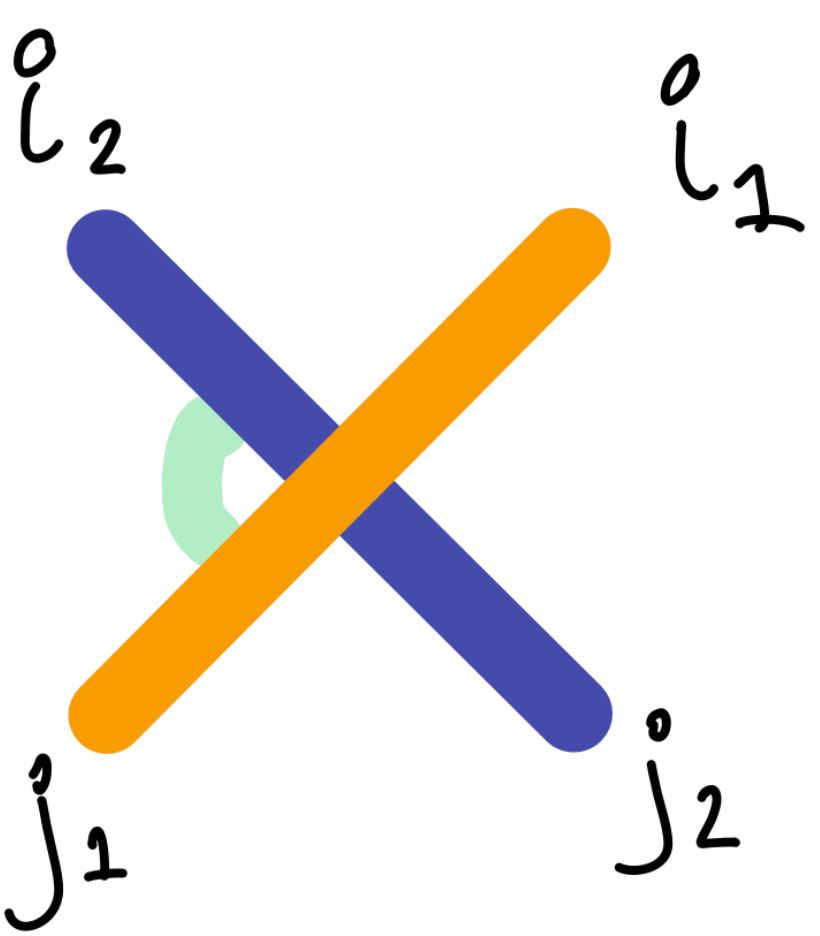


Proof via Yang-Baxter equation



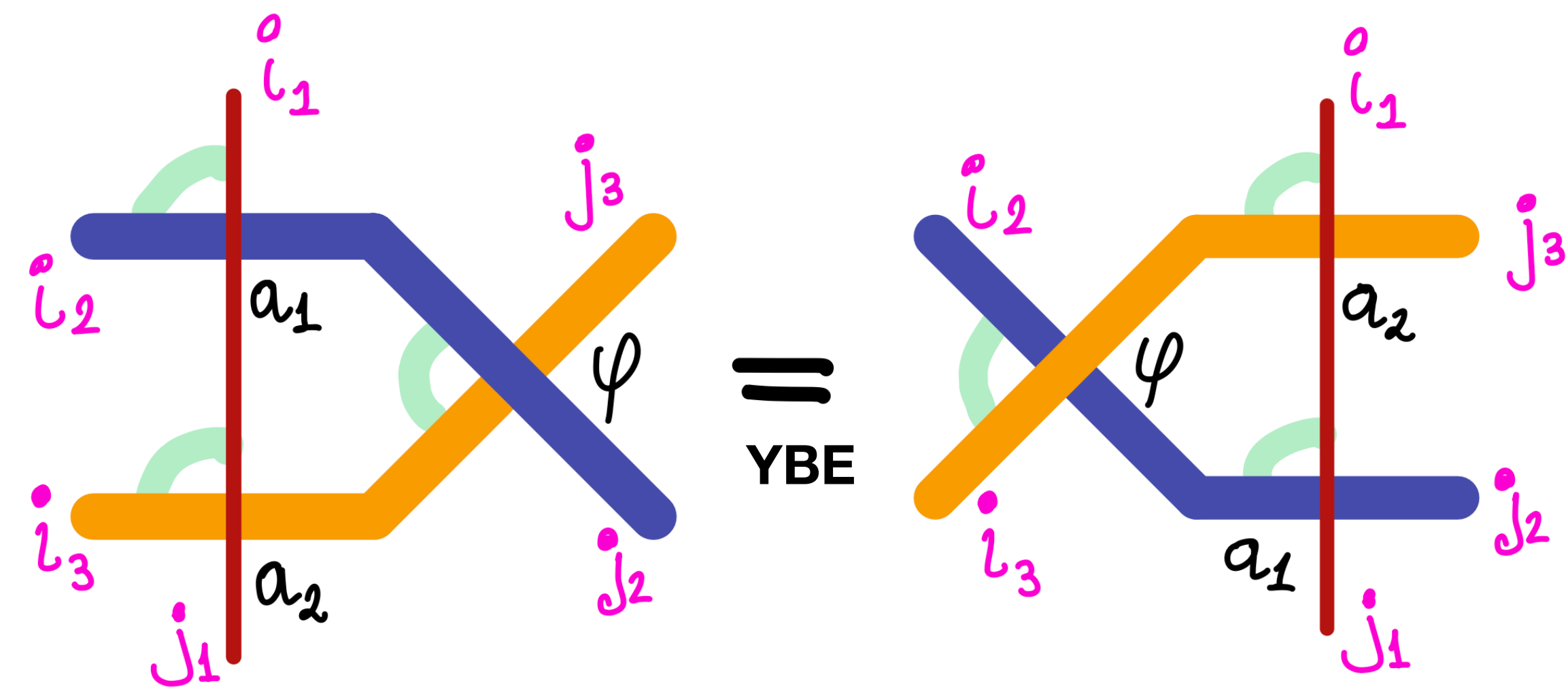
- B_{a_2/a_1} - geometric jump operator on configurations of two particles
- $T_{a_1, a_2}, T_{a_2, a_1}$ - FS and SF transition operators

Theorem 2 (P.-Saenz 2022).
Intertwining $T_{a_1, a_2} B_{a_2/a_1} = B_{a_2/a_1} T_{a_2, a_1}$



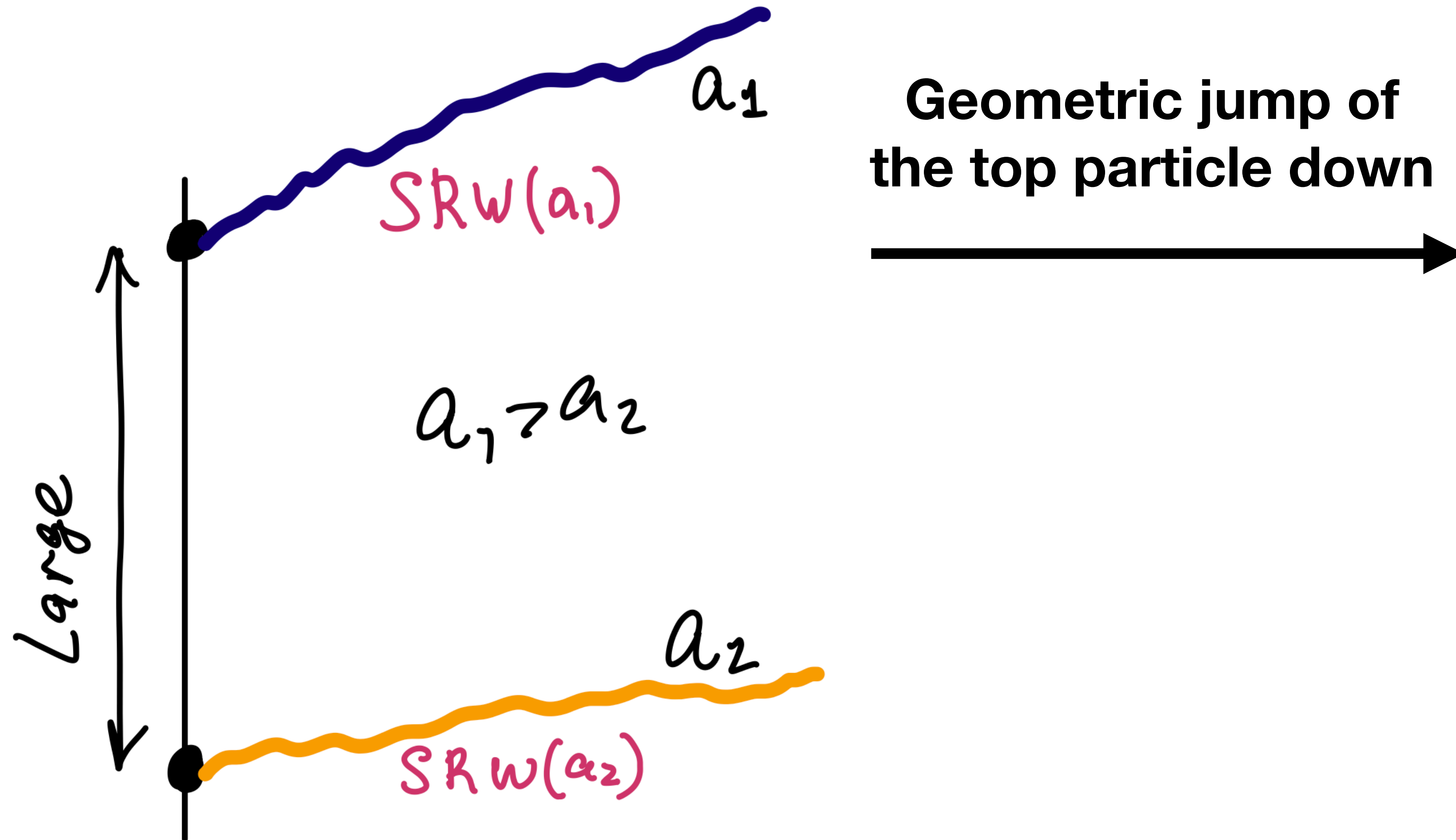
φ_{a_2/a_1} - geometric jumps

$$(a_2/a_1)^{j_2} (1 - \mathbf{1}_{j_2 < j_1} a_2/a_1) \mathbf{1}_{j_2 \leq j_1}$$

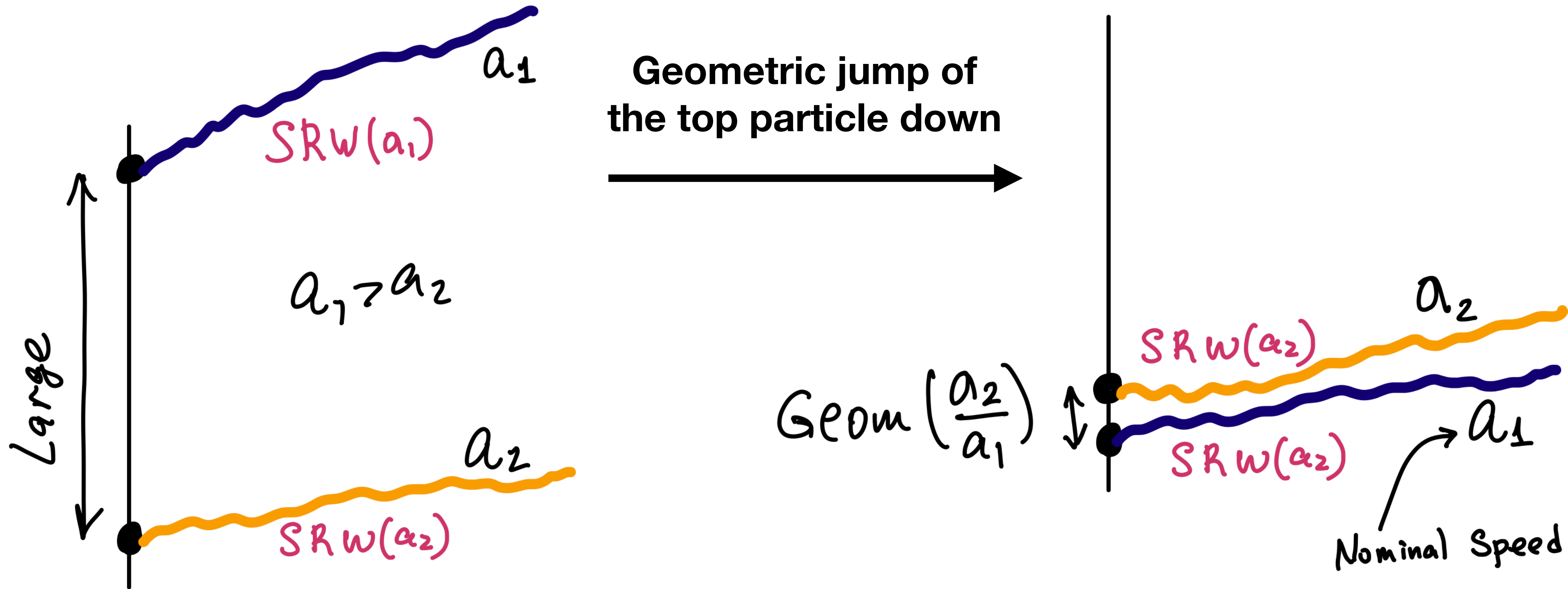


II. Three applications

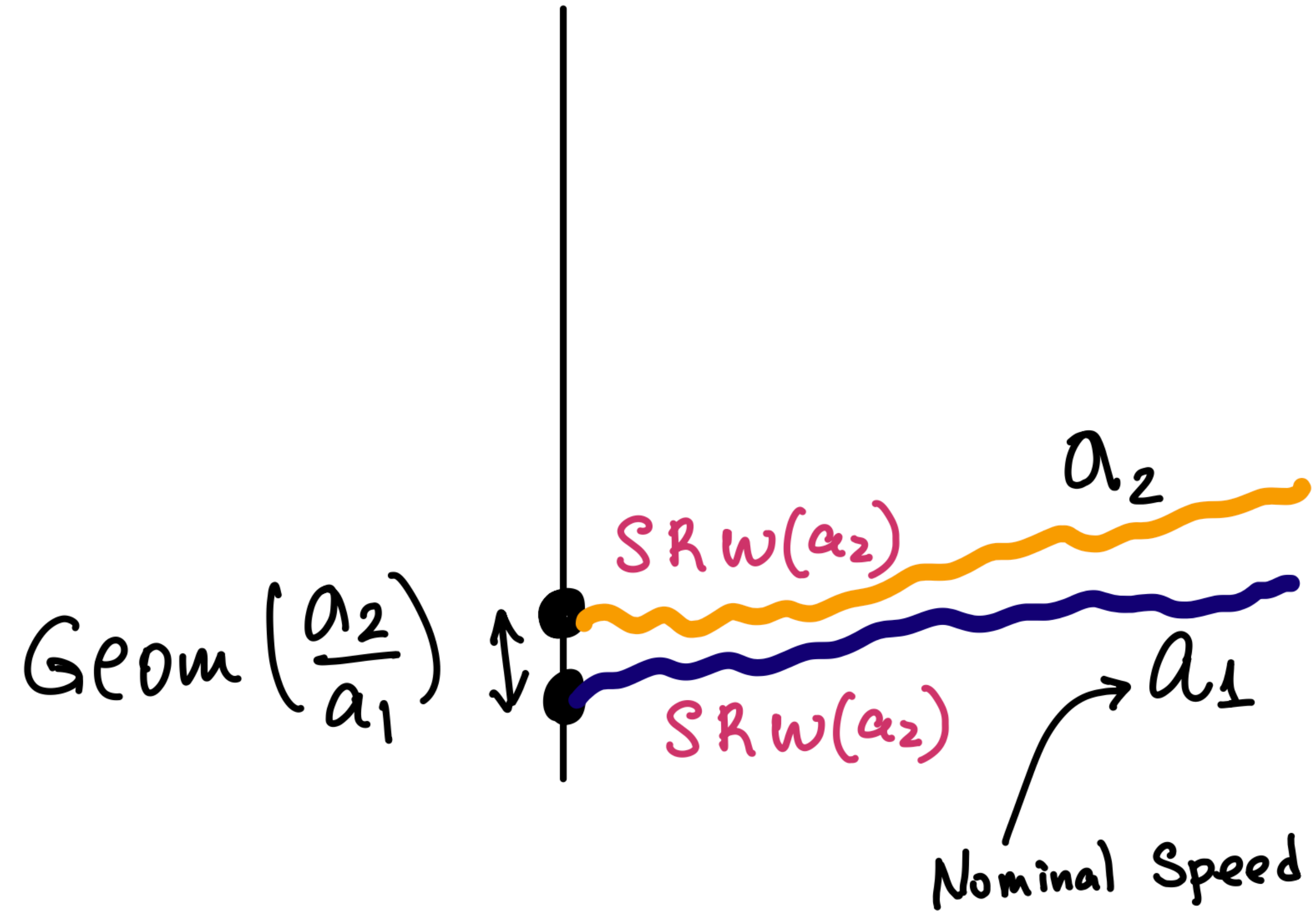
Application 1: Stationarity in TASEP



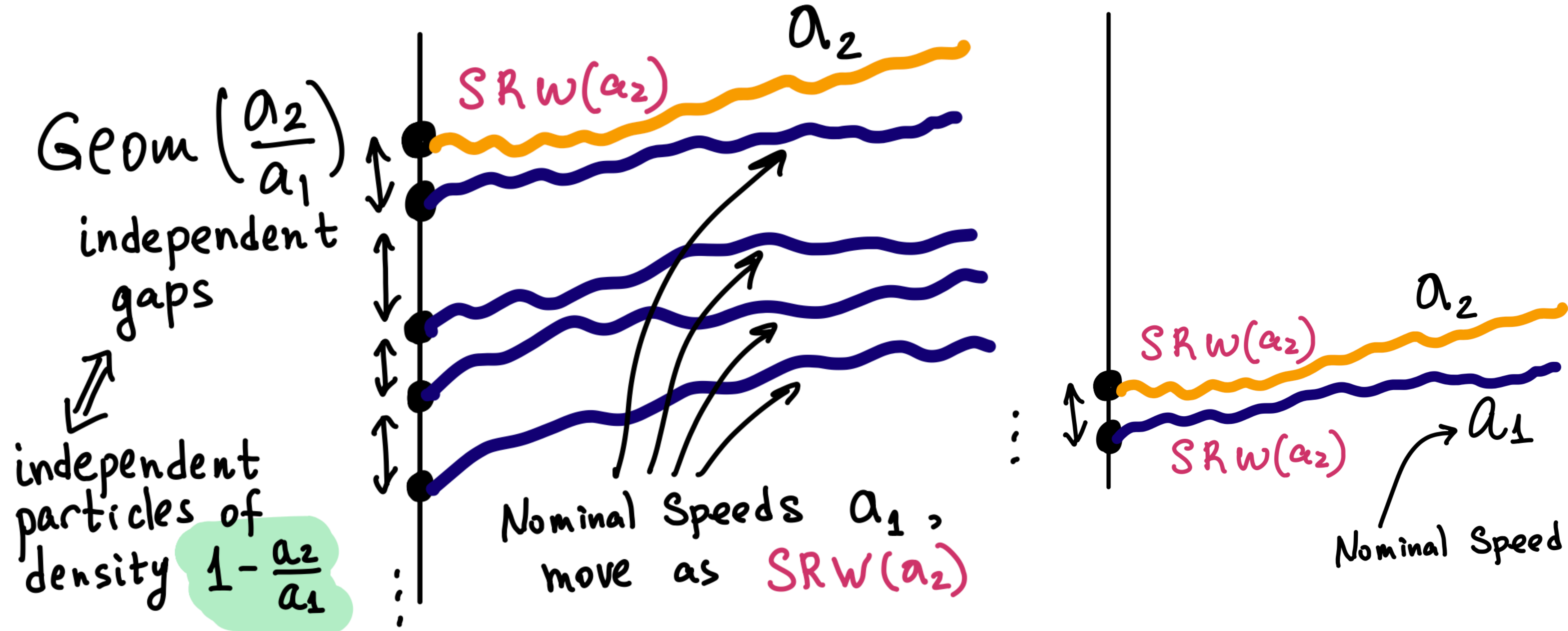
Application 1: Stationarity in TASEP



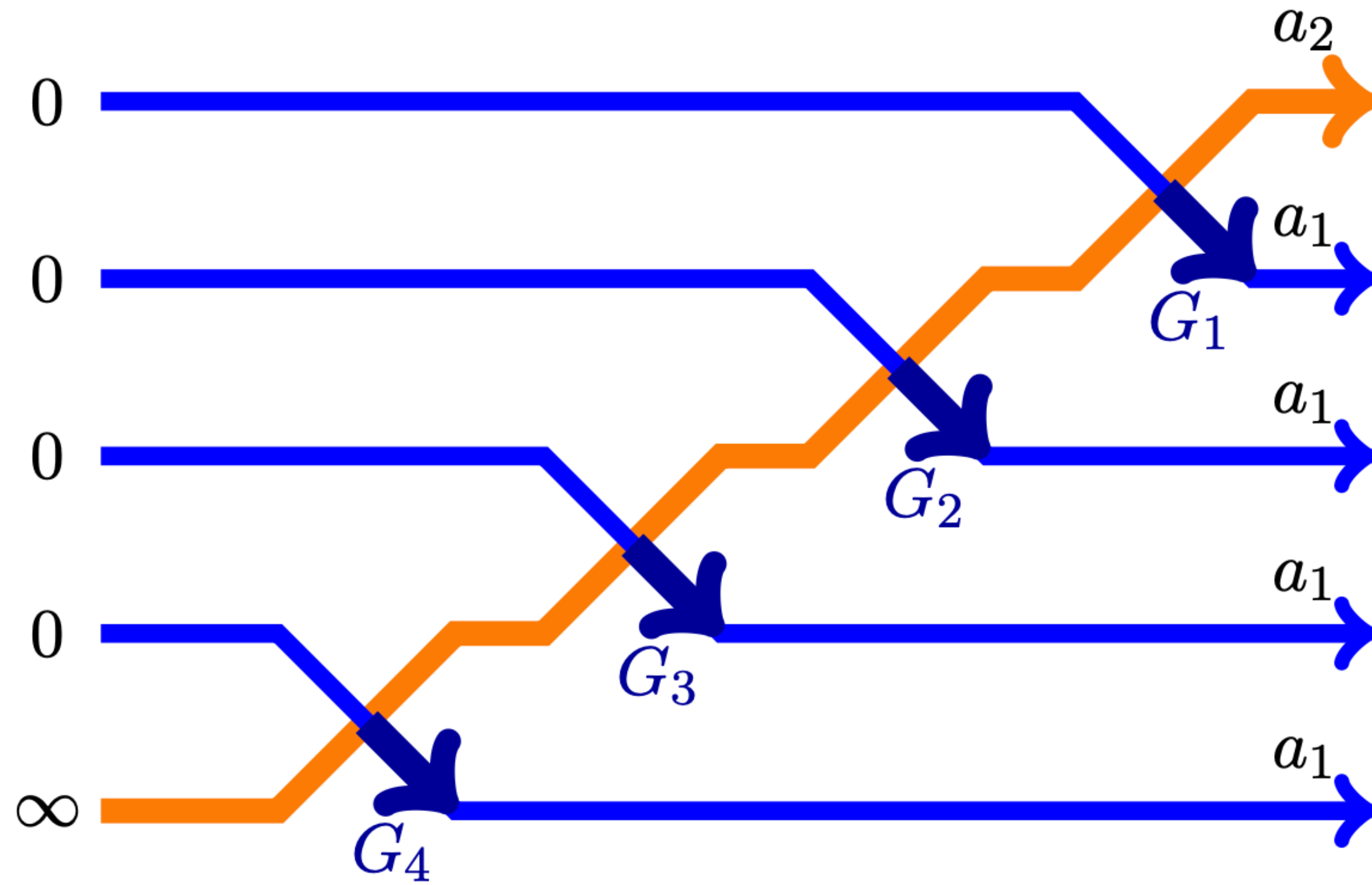
Application 1: Stationarity in TASEP



Application 1: Stationarity in TASEP

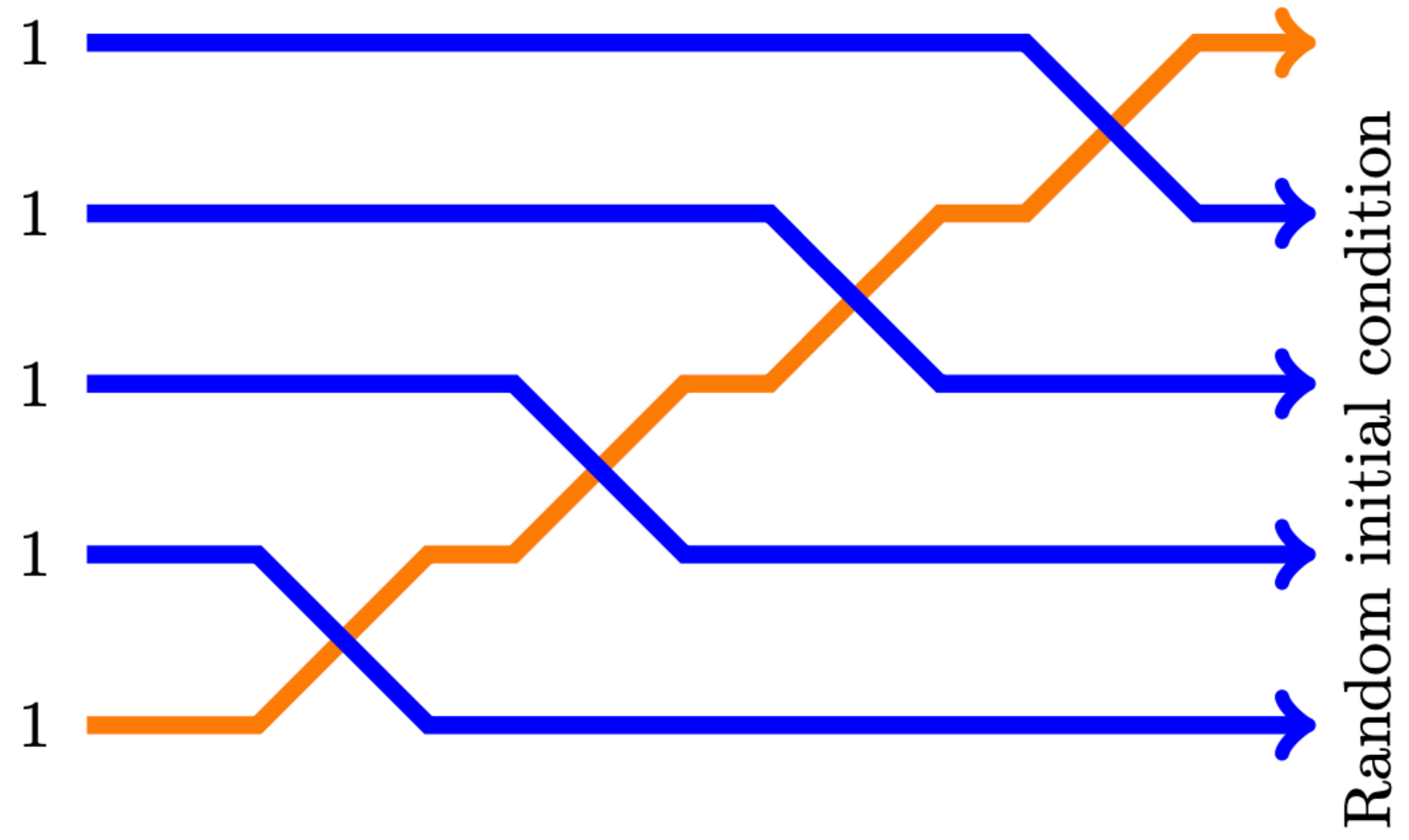


Same, but in terms of Yang-Baxter crosses ($a_1 > a_2$)

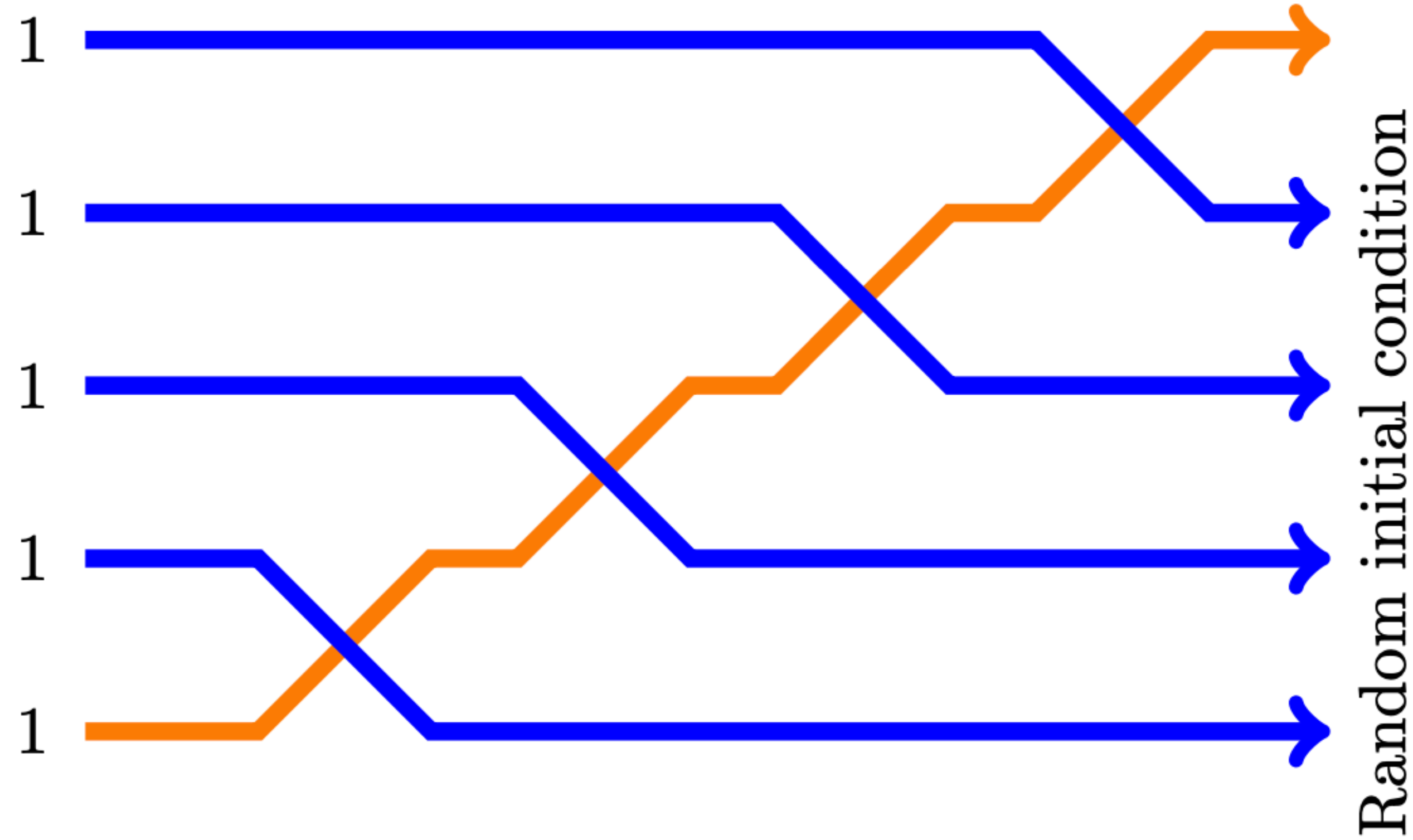


The TASEP stationary distribution ($G_i \sim \text{iid Geometric}(a_2/a_1)$) is *deposited* by a stochastic vertex with infinitely many arrows along one direction.

Application 2: Flat initial condition ($a_1 = 1$)

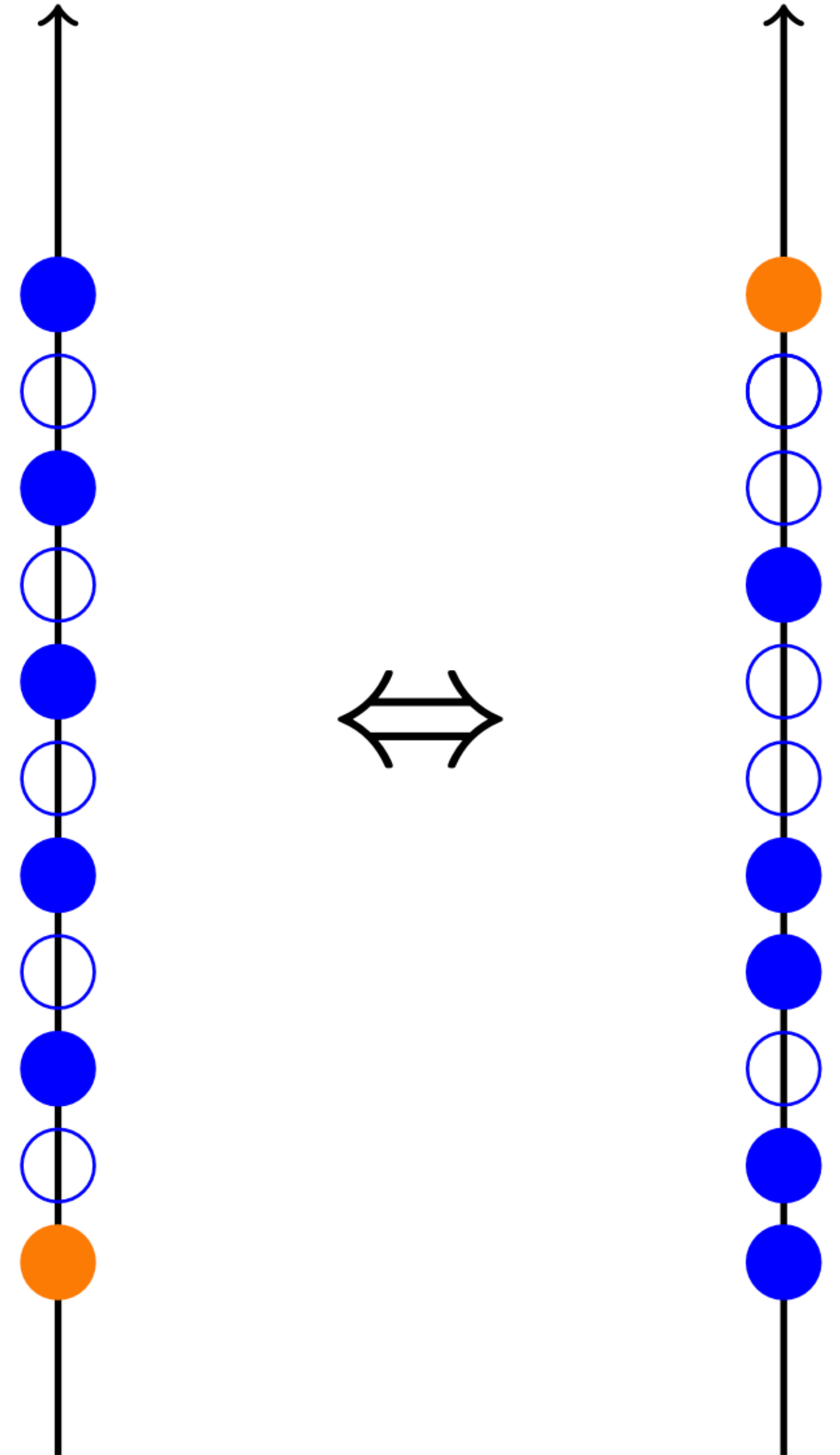


Application 2: Flat initial condition ($a_1 = 1$)

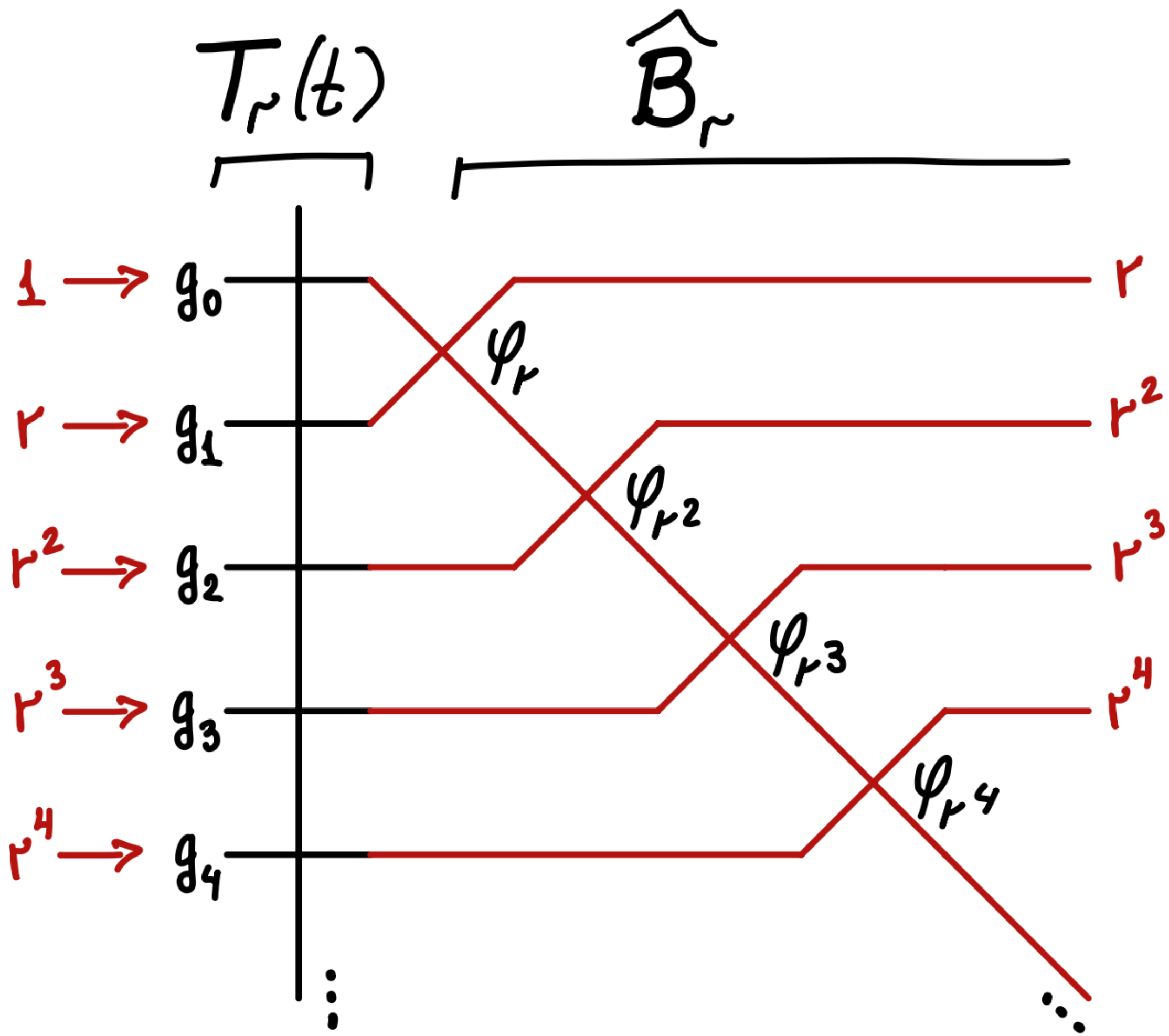


The trajectories of the back particle are the same in both situations

$$a_2 < 1$$

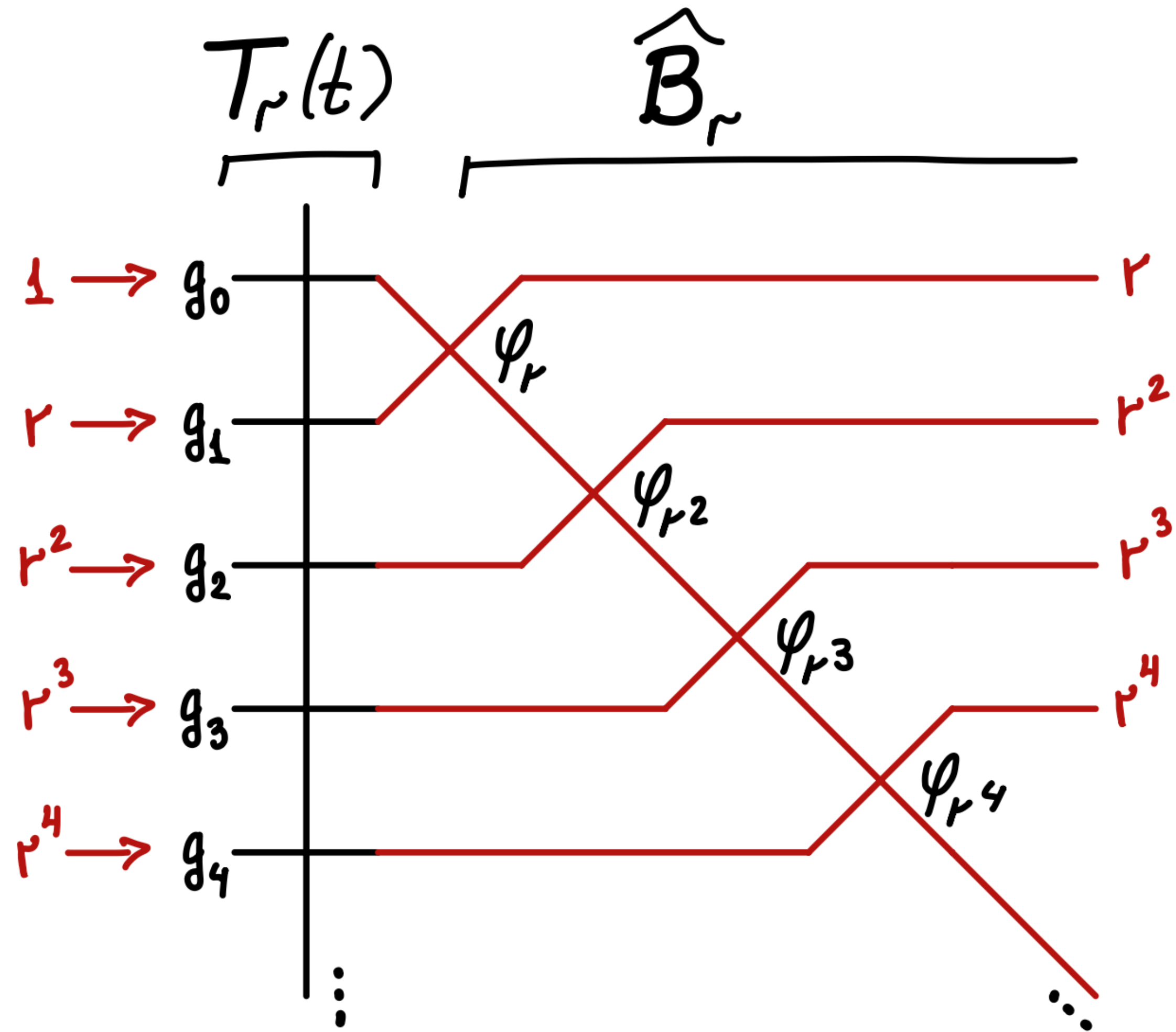


Application 3: Lax equation for TASEP semigroup



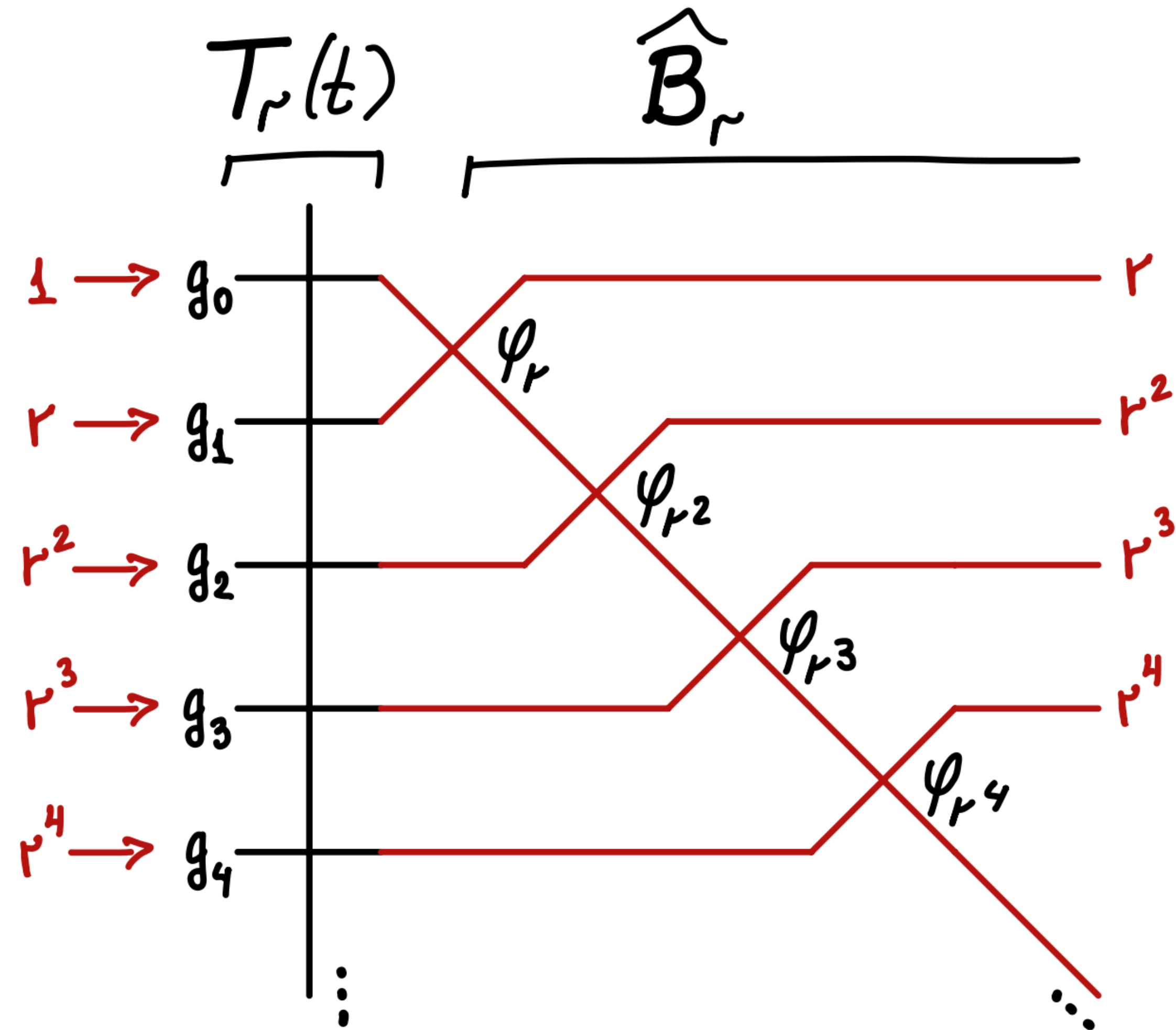
Application 3: Lax equation for TASEP semigroup

Take continuous time TASEP with $a_n = r^n$. Then $T_r(t)\hat{B}_r = \hat{B}_r T_r(rt)$, which is a **time change**.



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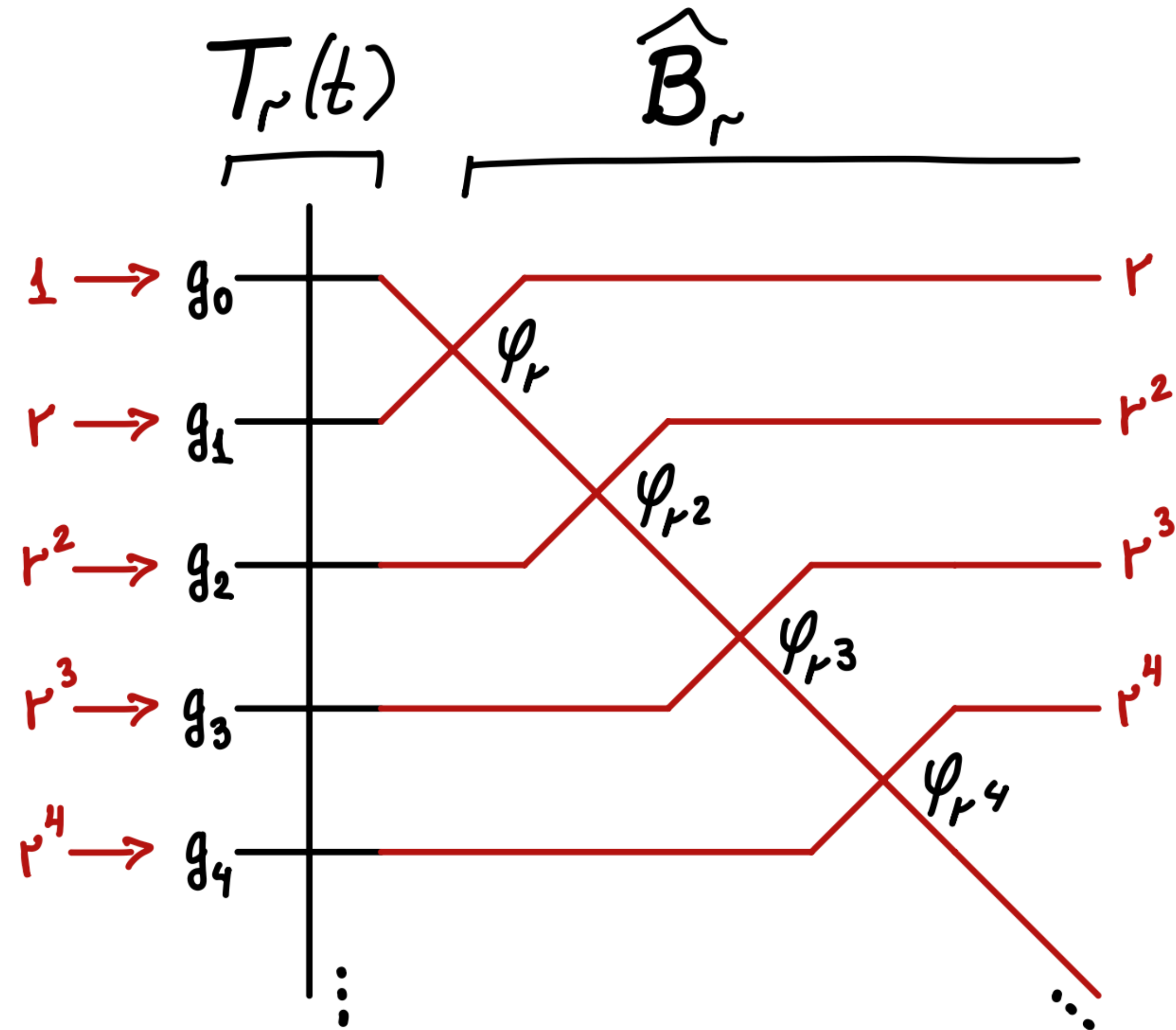


Send $r \rightarrow 1$, to **homogeneous TASEP**

In continuous time Poisson limit of $(\hat{B}_r)^{\tau/(1-r)}$, we get a Markov semigroup $B(\tau)$ - **backwards Hammersley process**.

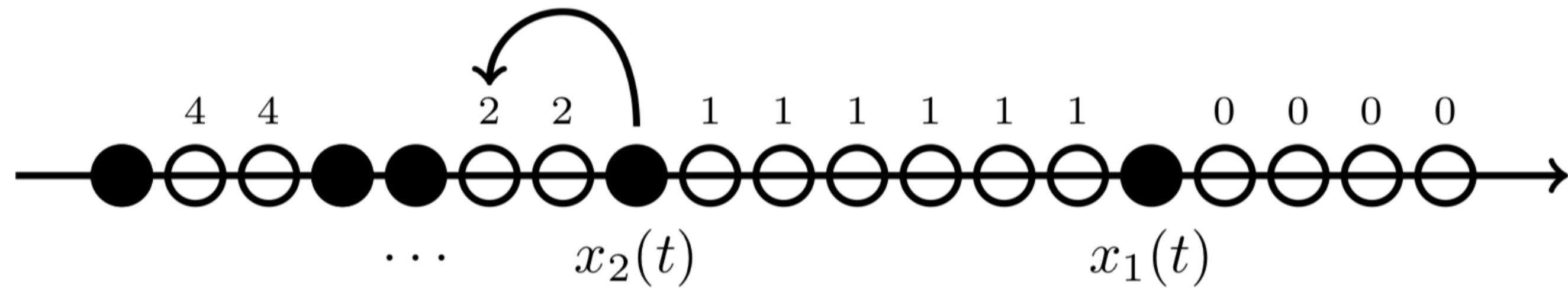
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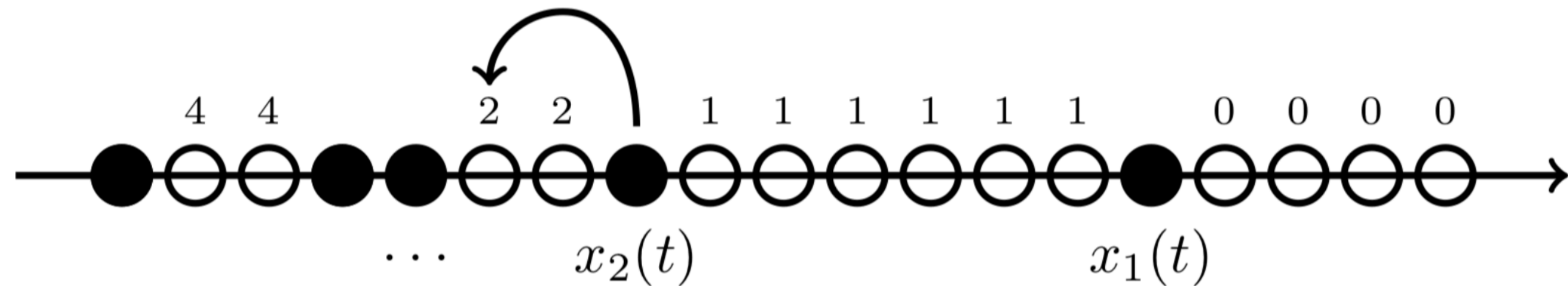
When the clock rings, the nearest particle to the right instantaneously jumps into this hole.

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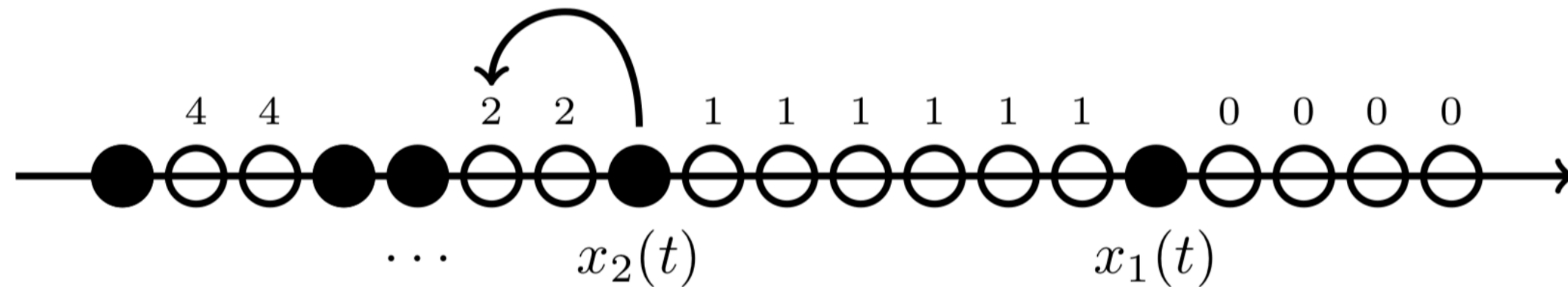
Send $r \rightarrow 1$, to **homogeneous TASEP**

Intertwining $T(t)B(\tau) = B(\tau)T(e^{-\tau}t)$

In continuous time Poisson limit of $(\hat{B}_r)^{\tau/(1-r)}$, we get a Markov semigroup $B(\tau)$ - **backwards Hammersley process**.

Lax equation (differential form)

$$\frac{d}{dt}T(t) = \left[\frac{1}{t} \mathbf{B}, T(t) \right]$$



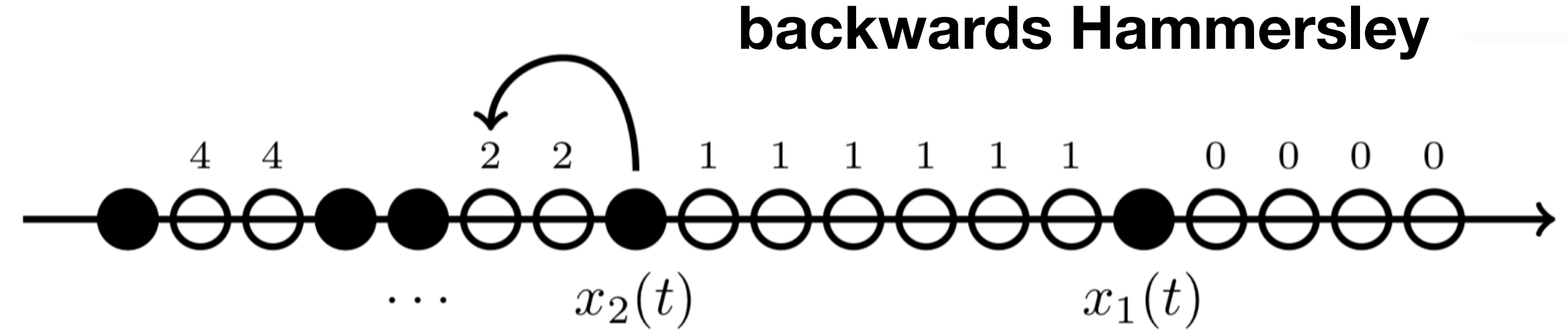
Lax equation (for expectations)

$$t \frac{\partial}{\partial t} \mathbb{E}_{\vec{y}} [F(\vec{x}(t))] = \mathbf{B} \mathbb{E}_{\vec{y}} [F(\vec{x}(t))] - \mathbb{E}_{\vec{y}} [(\mathbf{B}F)(\vec{x}(t))]$$

When the clock rings, the nearest particle to the right instantaneously jumps into this hole.

Application 3: Lax equation for TASEP semigroup

- Let $T(t)$ be the TASEP semigroup, and $B(\tau)$ be another process which we call **backwards Hammersley**



($q = 0$) Each hole has exponential clock of rate $h(t, x)$

When the clock rings, the nearest particle to the right instantaneously jumps into this hole.

- Theorem [P-Saenz '22].** Lax equation

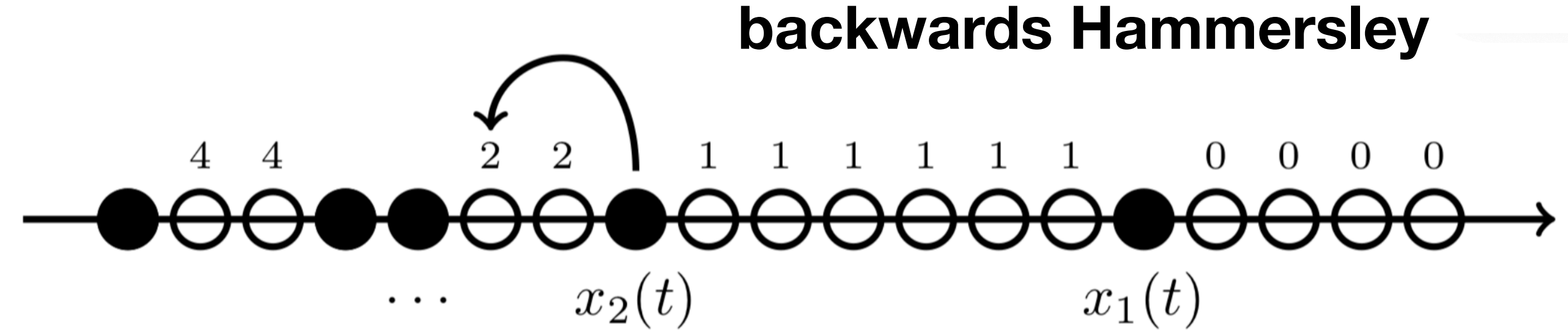
$$\frac{d}{dt} T(t) = \left[\frac{1}{t} \mathbf{B}, T(t) \right]$$

- \Rightarrow Lax equation for expectations

$$\begin{aligned} t \frac{\partial}{\partial t} \mathbb{E}_{\vec{y}} \left[F(\vec{x}(t)) \right] \\ = \mathbf{B} \mathbb{E}_{\vec{y}} \left[F(\vec{x}(t)) \right] - \mathbb{E}_{\vec{y}} \left[(\mathbf{B}F)(\vec{x}(t)) \right] \end{aligned}$$

Application 3: Lax equation for TASEP semigroup

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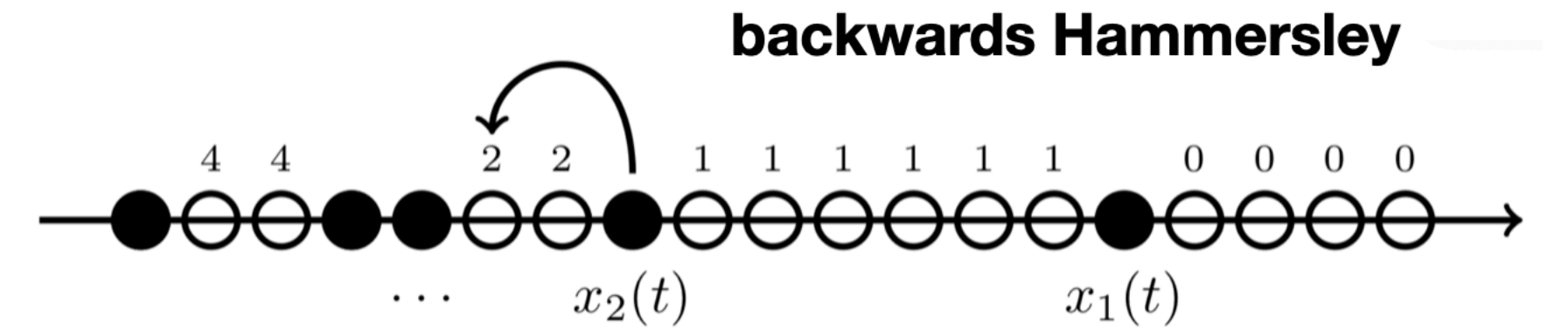
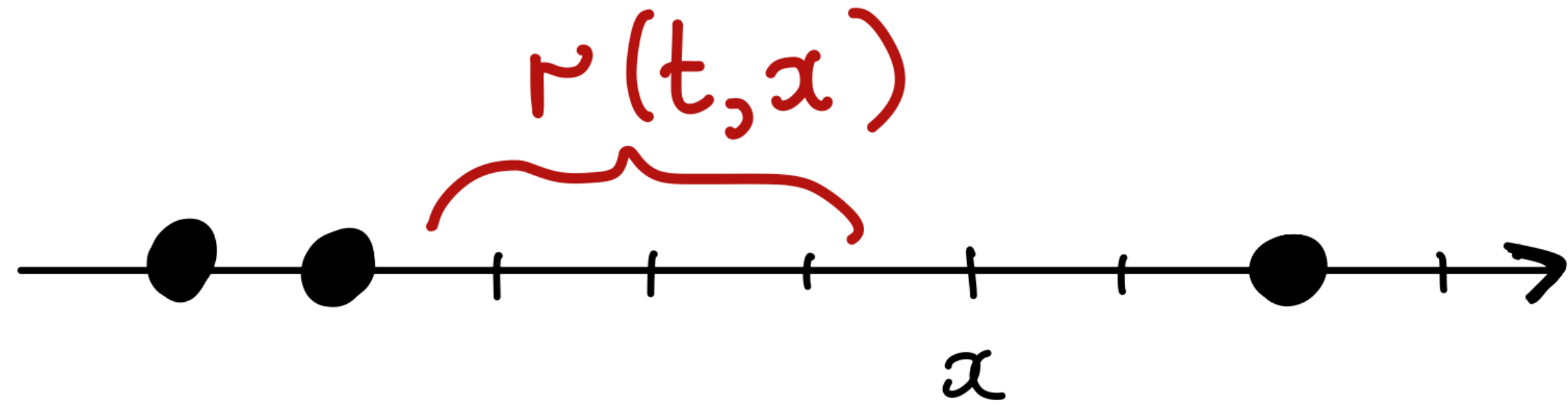
$$\begin{aligned}
 t \frac{\partial}{\partial t} \mathbb{E}_{\vec{y}} [F(\vec{x}(t))] &= \mathbf{B} \mathbb{E}_{\vec{y}} [F(\vec{x}(t))] - \mathbb{E}_{\vec{y}} [(\mathbf{B}F)(\vec{x}(t))]
 \end{aligned}$$

\oplus for **any** function F , so characterizes the dynamics

\oplus same form for TASEP and q -TASEP (differ in \mathbf{B})

\ominus hard to extract asymptotic information from

Example



($q = 0$) Each hole has exponential clock of rate $h(t, x)$

When the clock rings, the nearest particle to the right instantaneously jumps into this hole.

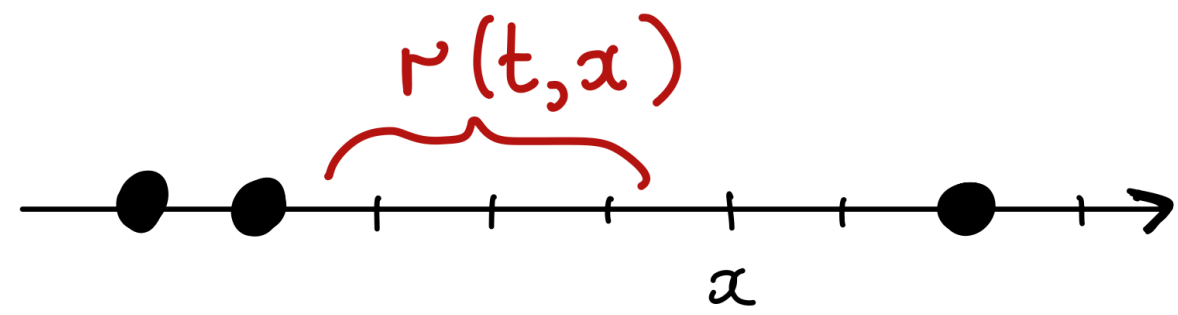
$$t \frac{\partial}{\partial t} \mathbb{E}_{\vec{y}} [F(\vec{x}(t))] = \mathbf{B} \mathbb{E}_{\vec{y}} [F(\vec{x}(t))] - \mathbb{E}_{\vec{y}} [(\mathbf{B}F)(\vec{x}(t))]$$

If $y = \text{step}$ and $F(x(t)) = g(h(t, x))$, then

$$\frac{\partial}{\partial t} \mathbb{E}_{\text{step}} [g(h)] = -\frac{1}{t} \mathbb{E}_{\text{step}} \left[h \cdot \underbrace{(g(h-1) - g(h))}_{=-1 \text{ for } g(h)=h} \cdot r(x, t) \right]$$

where $r(t, x)$ is the number of holes to the left of x at time t for $q = 0$

Example



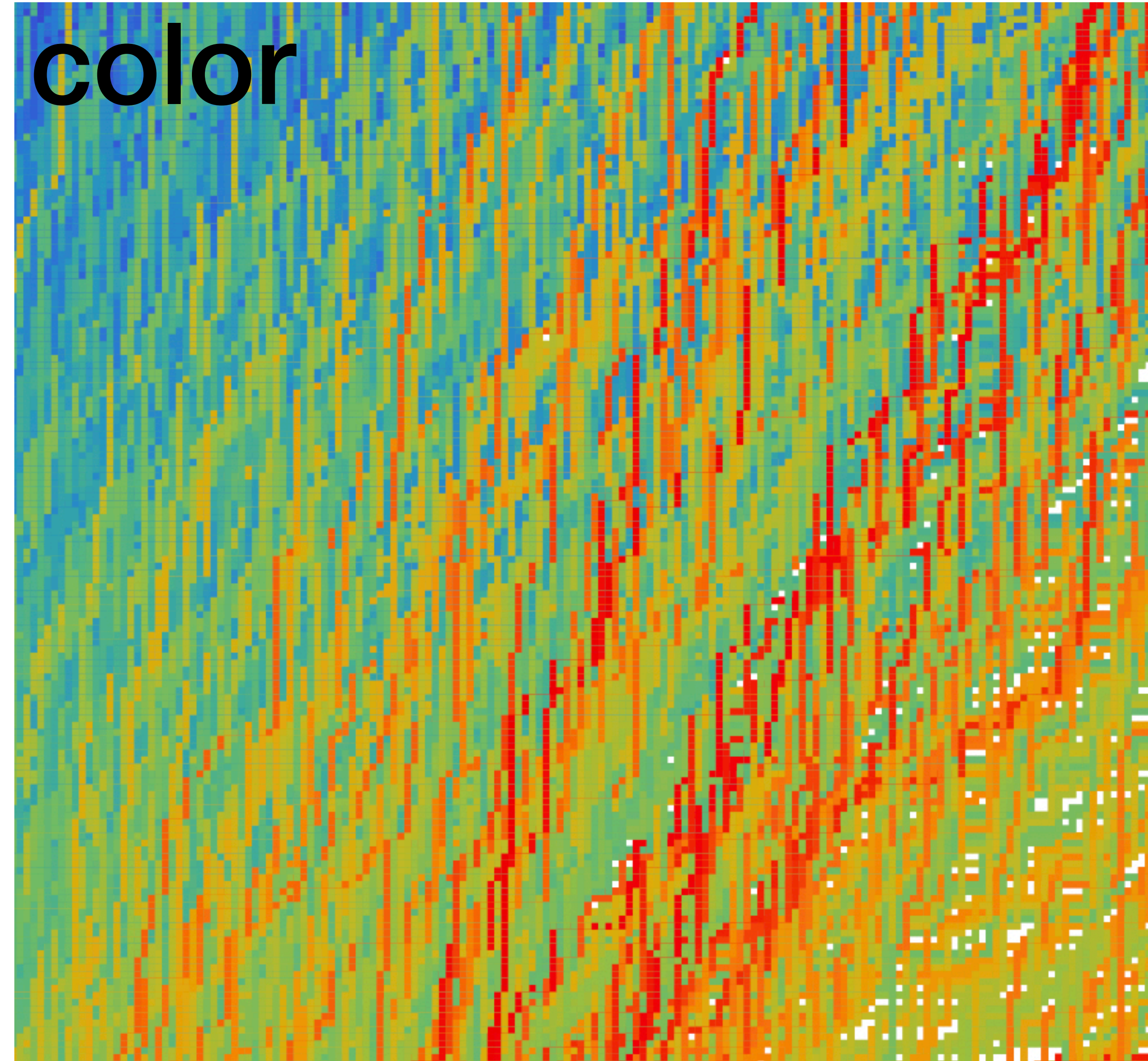
Let $g(h) = h(h - 1)\dots(h - k + 1)$, then
(under local equilibrium assumptions)

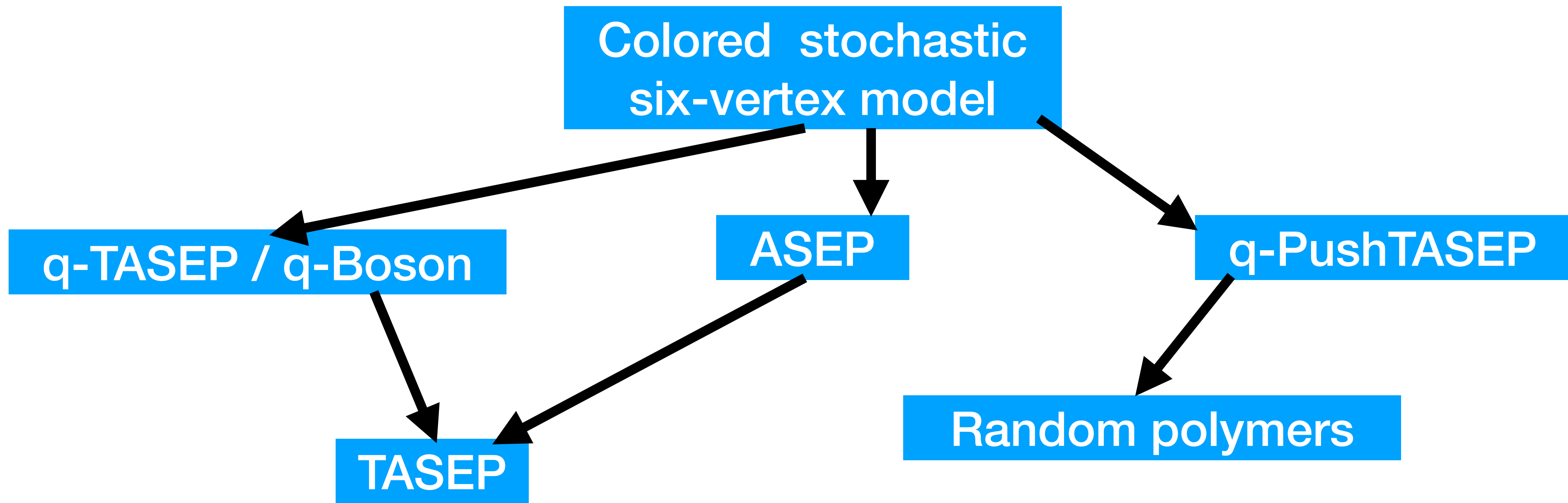
$$\frac{\partial}{\partial t} \mathbb{E}_{\text{step}} [g(h)] \sim \frac{k}{t} \mathbb{E}_{\text{step}} [g(h)] \cdot \mathbb{E}_{\text{step}} [r(t, x)]$$

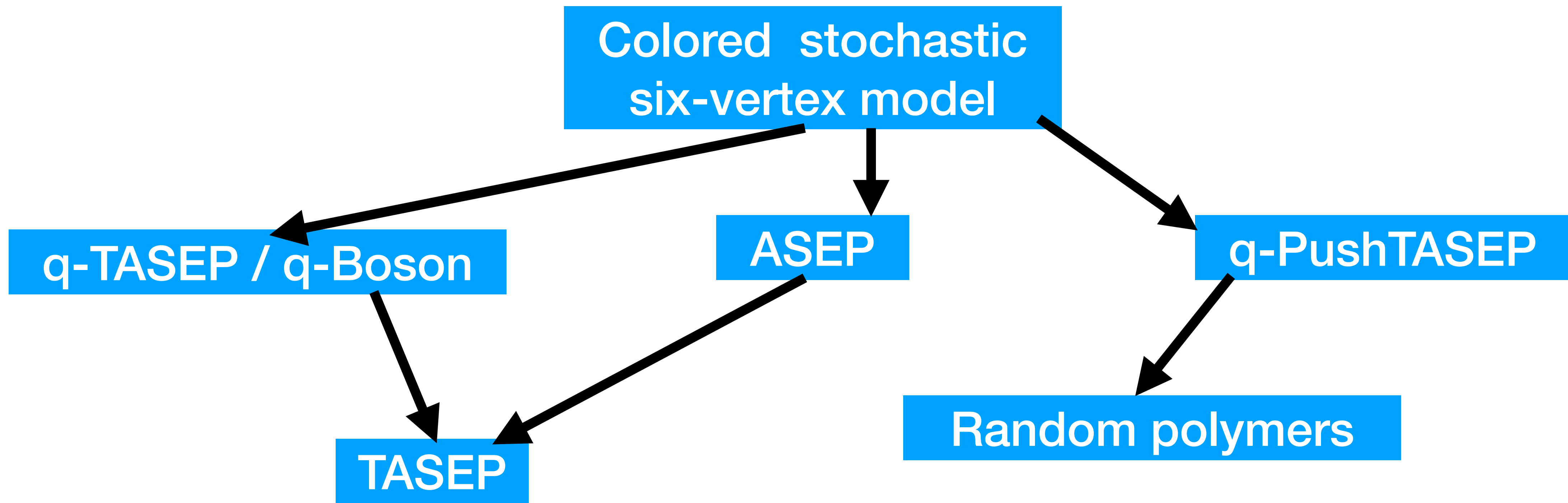
We have $\mathbb{E}_{\text{step}} [r(t, x)] = \frac{1 - \rho(t, x)}{\rho(t, x)}$, where $\rho(t, x)$ is the local density of particles

Same computations can be done for $q > 0$, where $\mathbb{E}_{\text{step}} [r(t, x)]$ is a certain explicit q -sum, and it gives a different coefficient of growth.

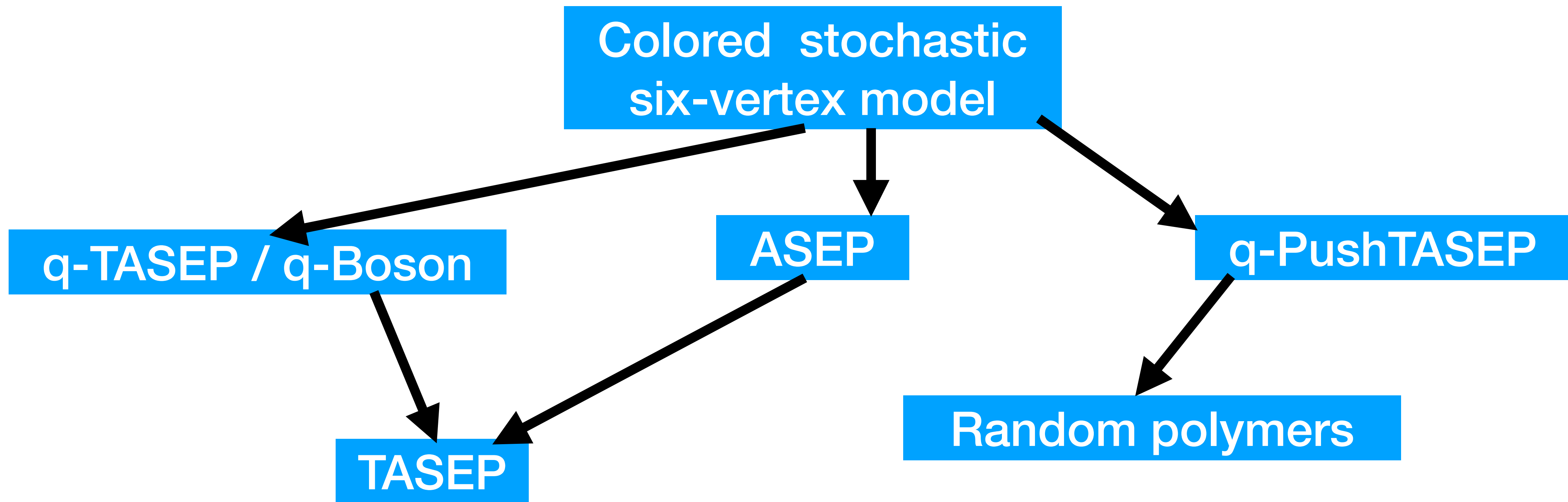
III. Stationarity in color and on the circle



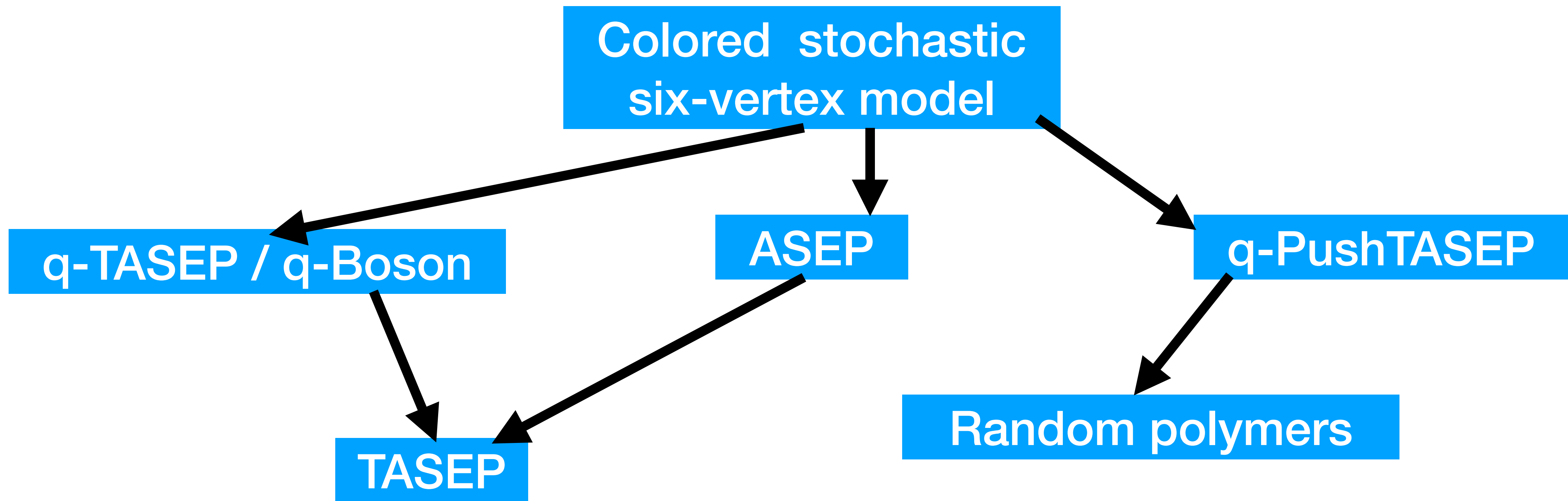




- All previous symmetry results work for TASEP and q-TASEP



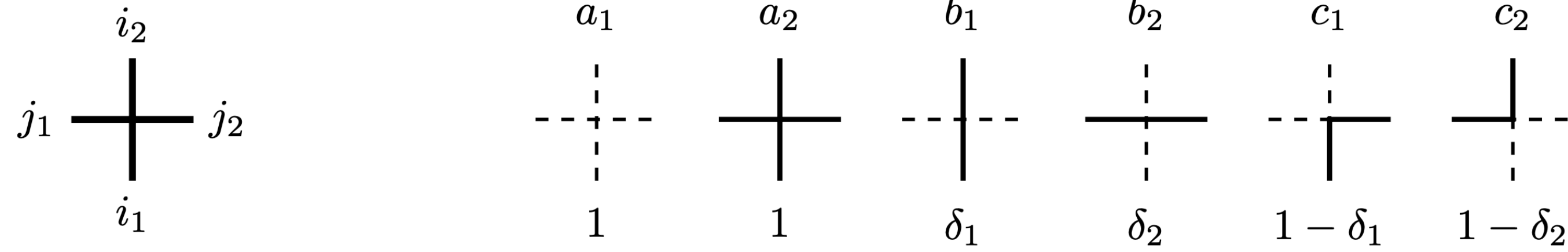
- All previous symmetry results work for TASEP and q-TASEP
- Not for ASEP



- All previous symmetry results work for TASEP and q-TASEP
- Not for ASEP
- Back to the drawing board, start at the level of stochastic six-vertex model

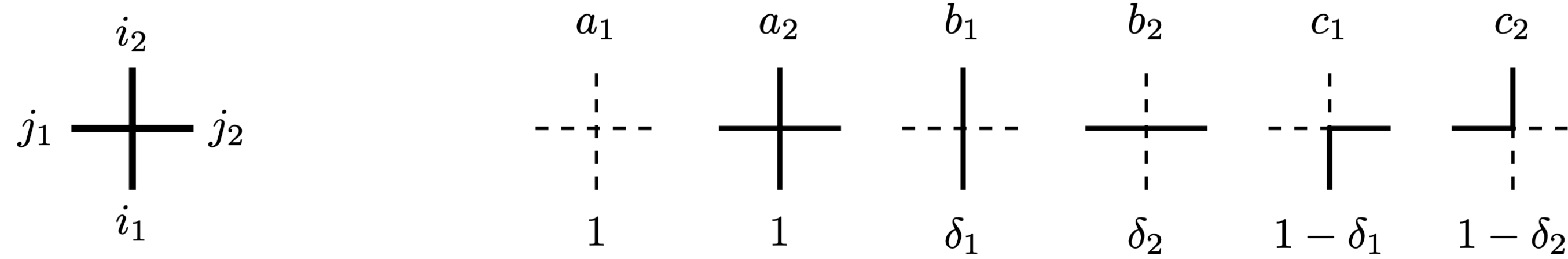
Stationarity for the single-color stochastic six-vertex model

[Gwa-Spohn 1992], [Borodin-Corwin-Gorin 2014],
[Aggarwal-Borodin 2016]



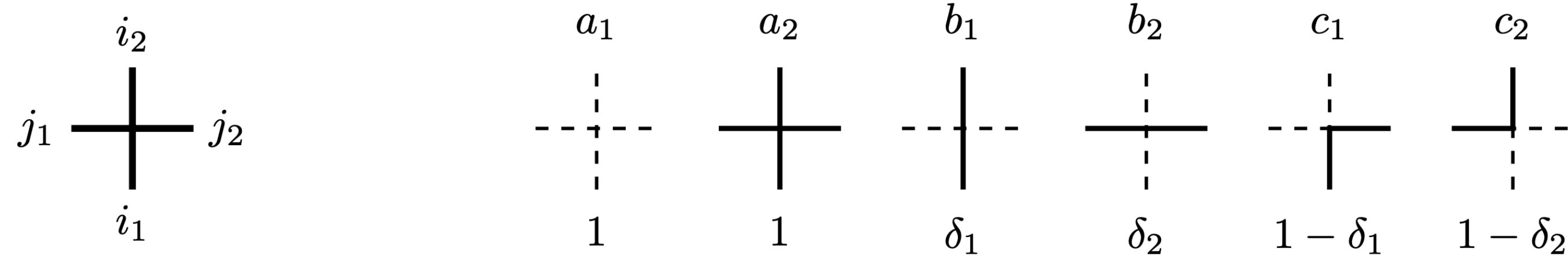
Stationarity for the single-color stochastic six-vertex model

[Gwa-Spohn 1992], [Borodin-Corwin-Gorin 2014],
[Aggarwal-Borodin 2016]



The weights with $a_1 = a_2 = 1$, $b_1 = \delta_1$, $c_1 = 1 - \delta_1$, $b_2 = \delta_2$, $c_2 = 1 - \delta_2$ are *stochastic*: $\sum_{i_2, j_2} w(i_1, j_1; i_2, j_2) = 1$.

Stationarity for the single-color stochastic six-vertex model

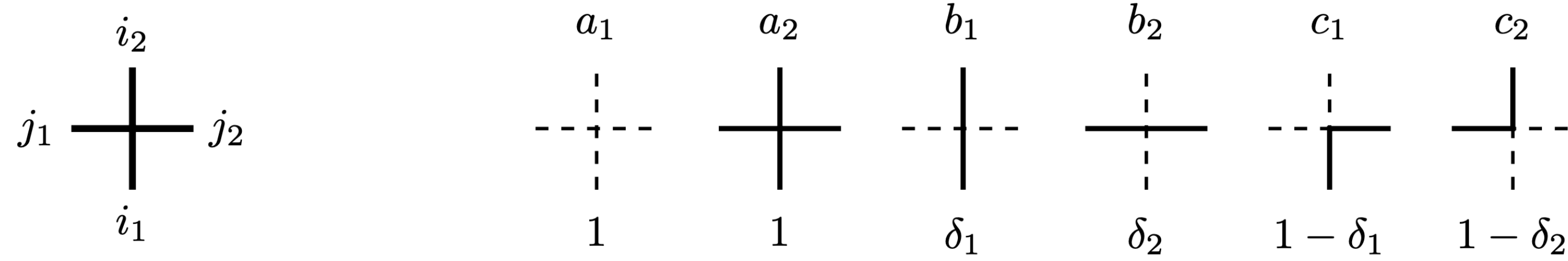


[Gwa-Spohn 1992], [Borodin-Corwin-Gorin 2014],
[Aggarwal-Borodin 2016]

$$u := \frac{1 - \delta_1}{1 - \delta_2}, \quad q := \delta_1 / \delta_2$$

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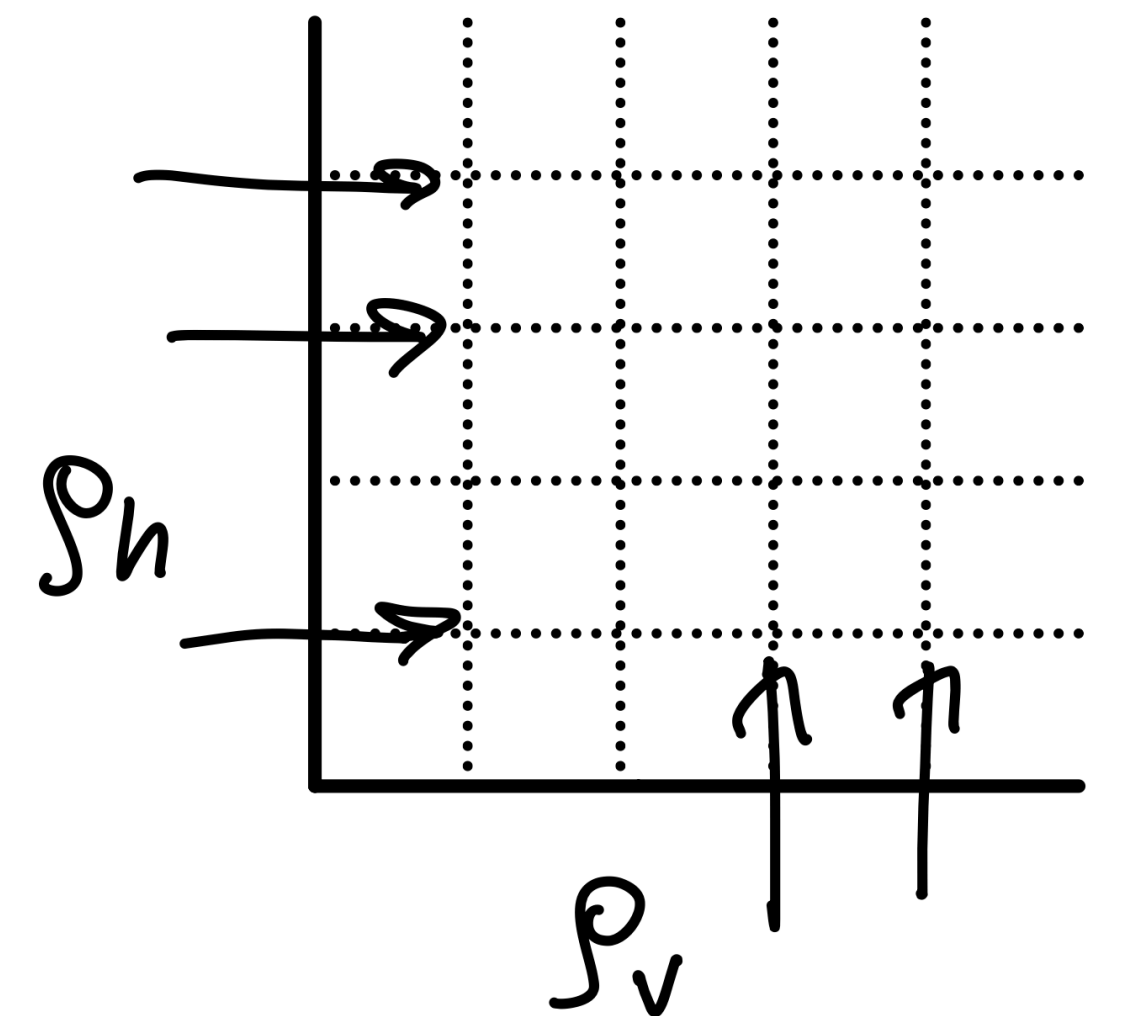
Stationarity for the single-color stochastic six-vertex model



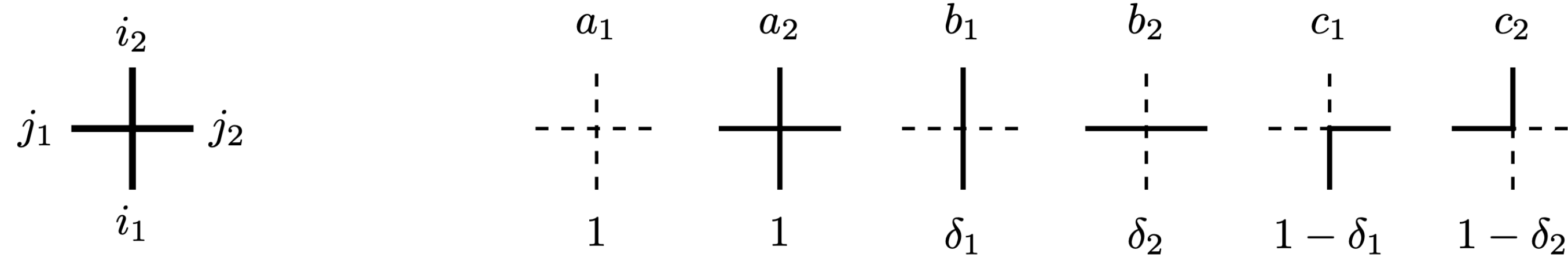
[Gwa-Spohn 1992], [Borodin-Corwin-Gorin 2014],
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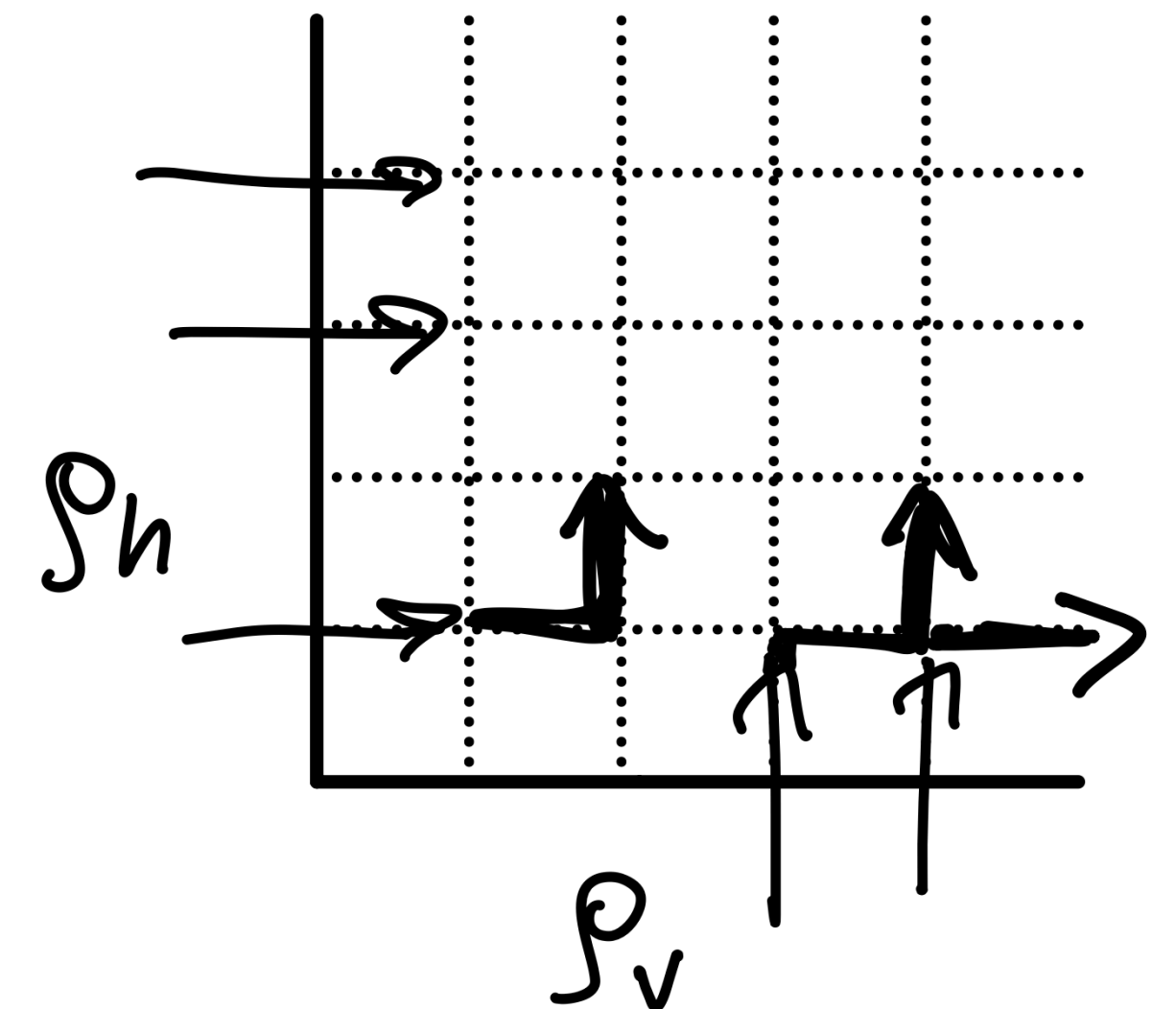
Stationarity for the single-color stochastic six-vertex model



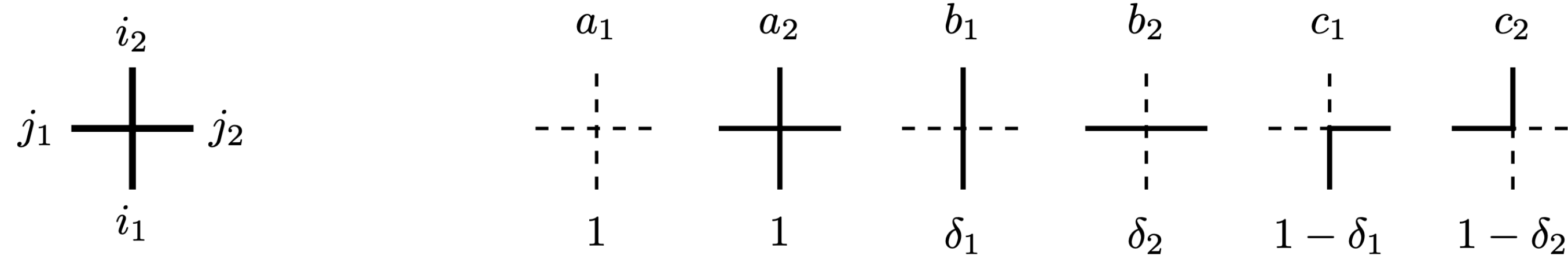
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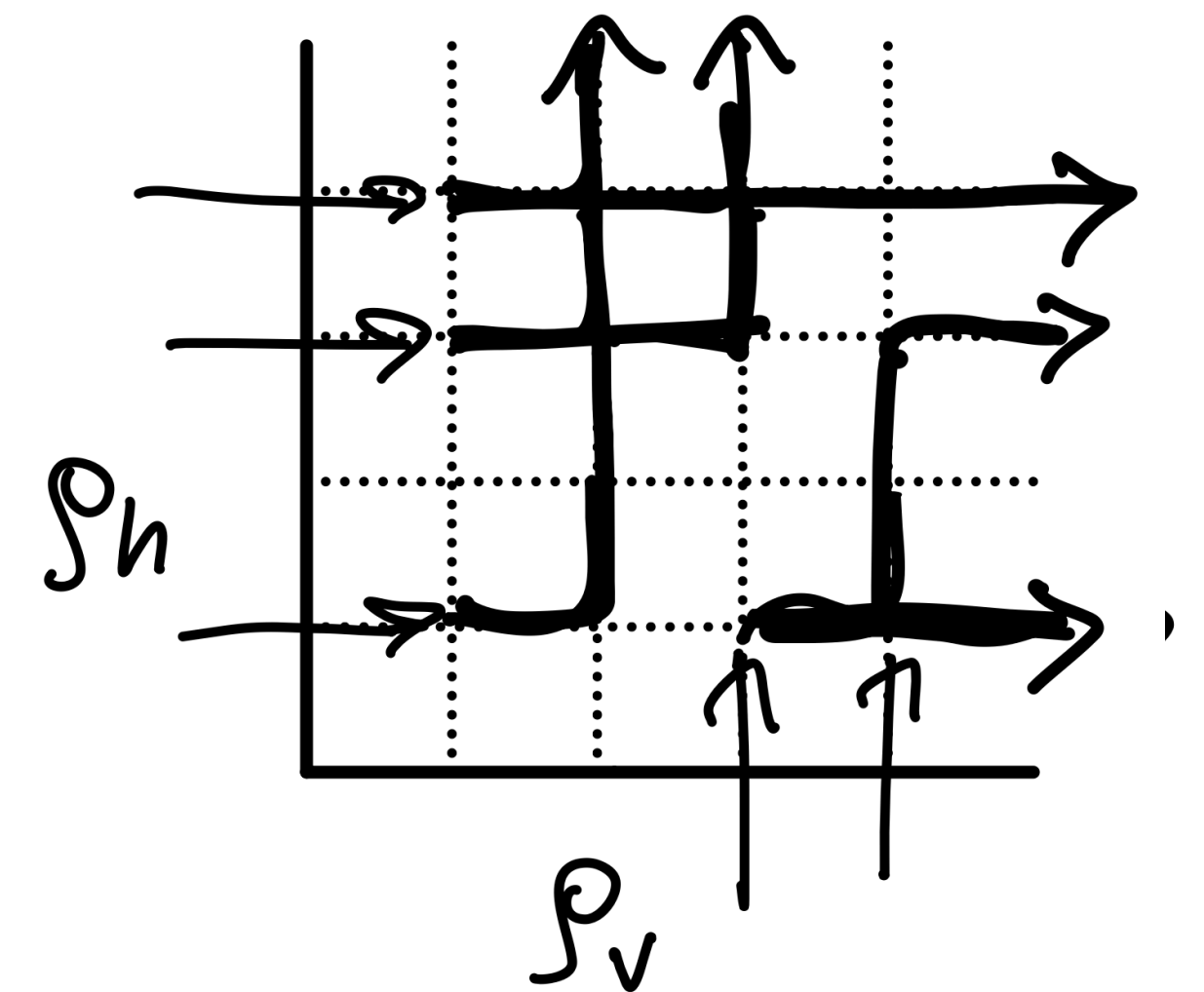
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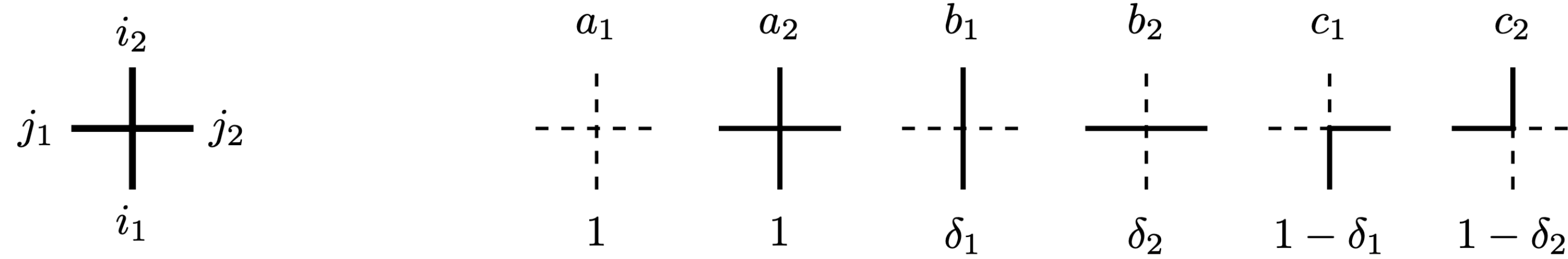
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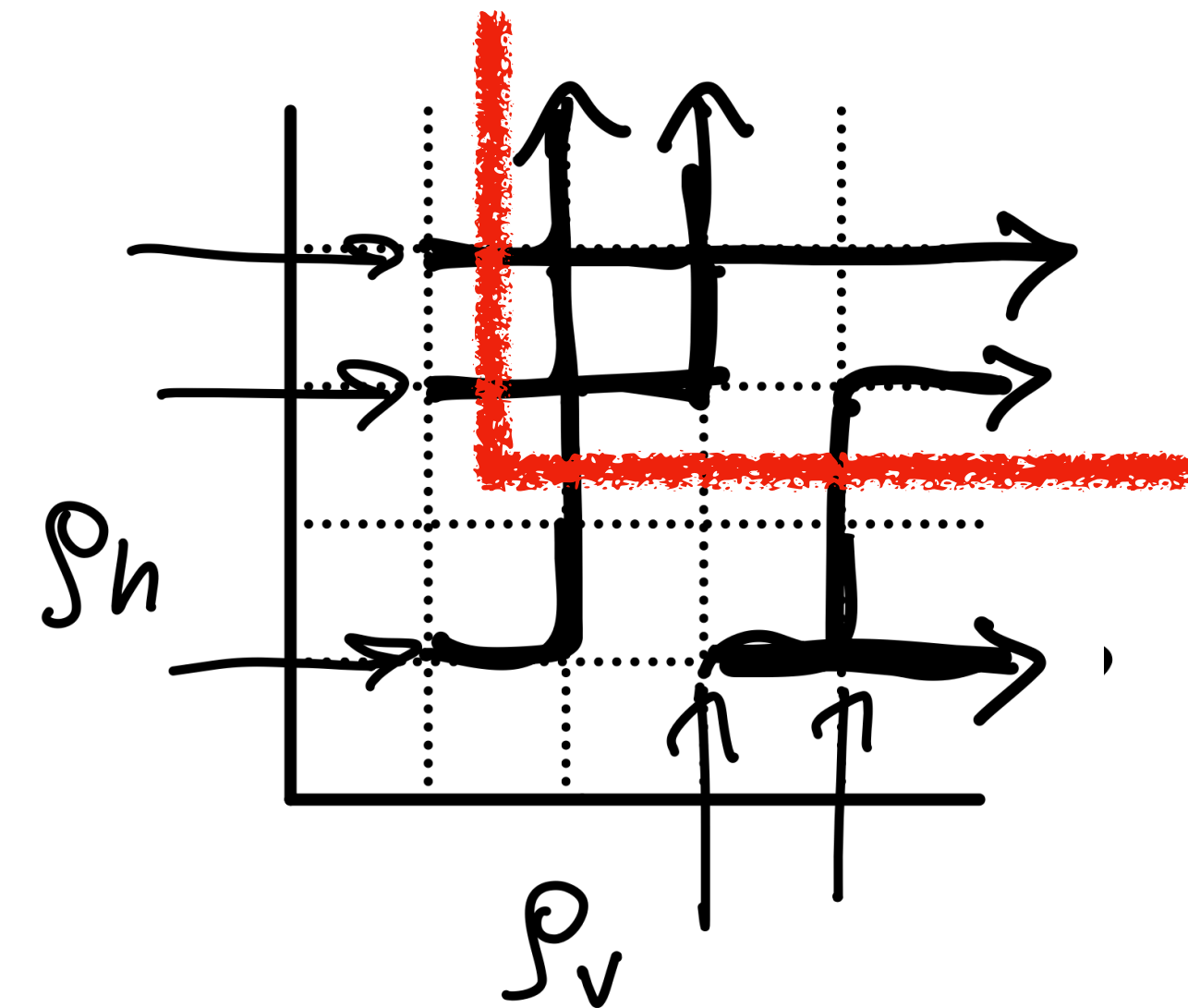
Stationarity for the single-color stochastic six-vertex model



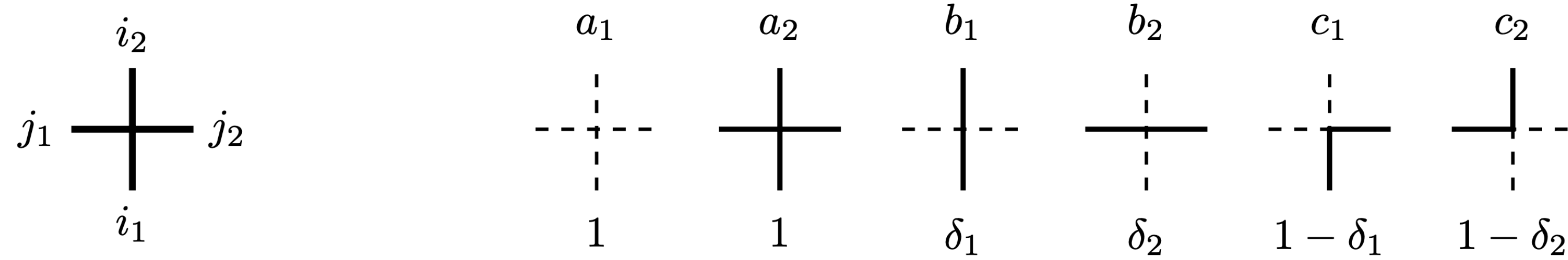
[Gwa-Spohn 1992], [Borodin-Corwin-Gorin 2014],
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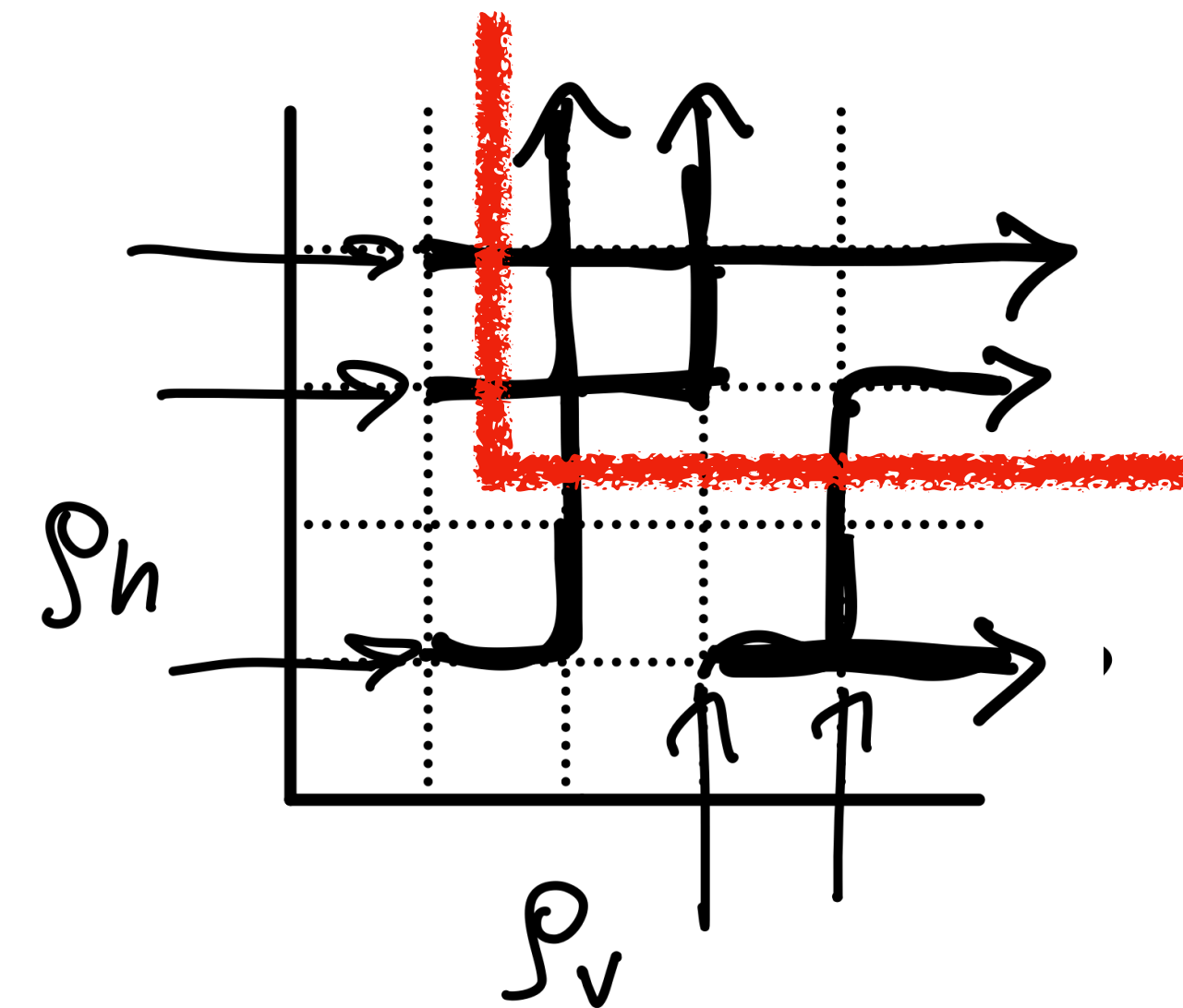
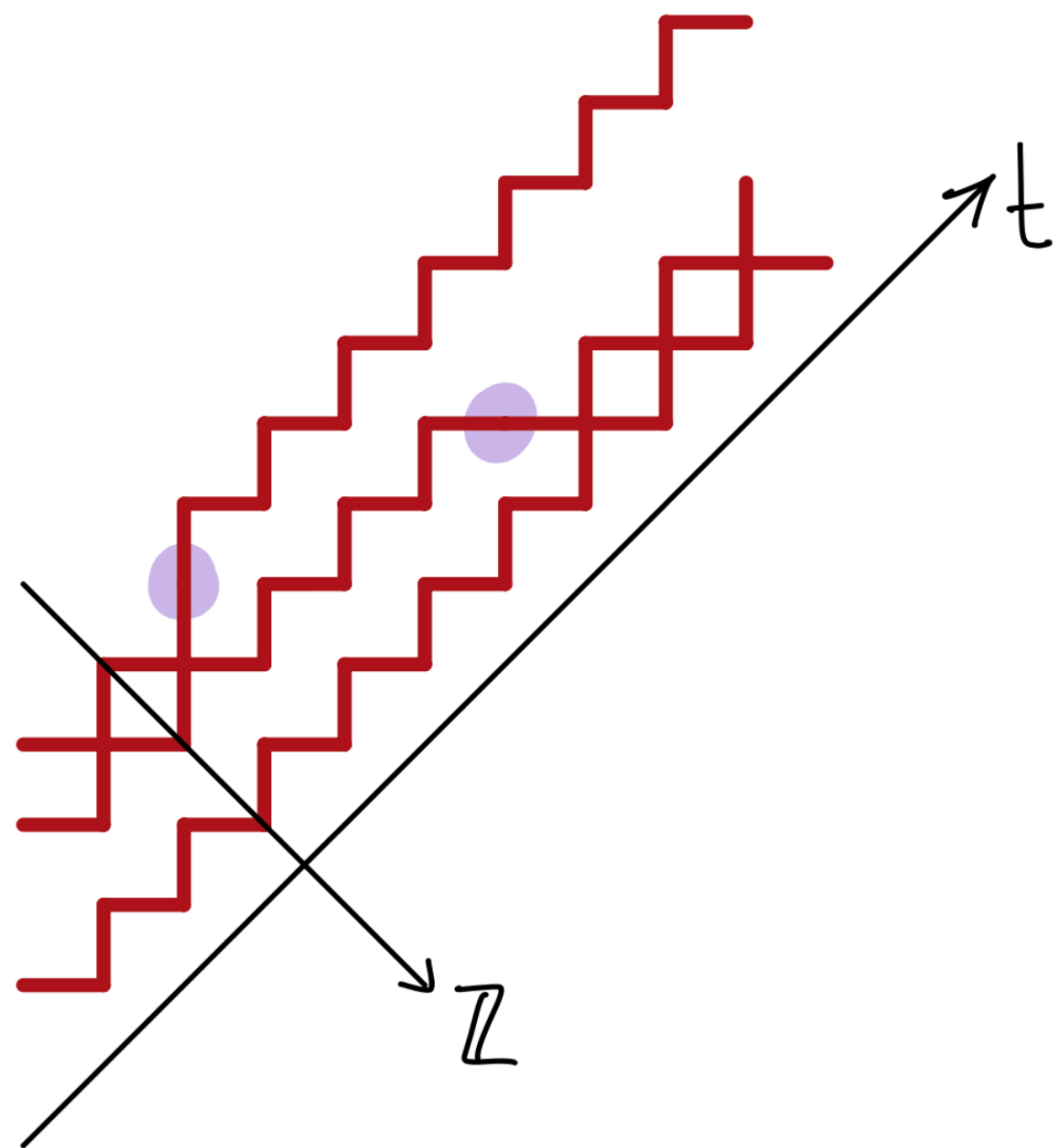
[Gwa-Spohn 1992], [Borodin-Corwin-Gorin 2014],
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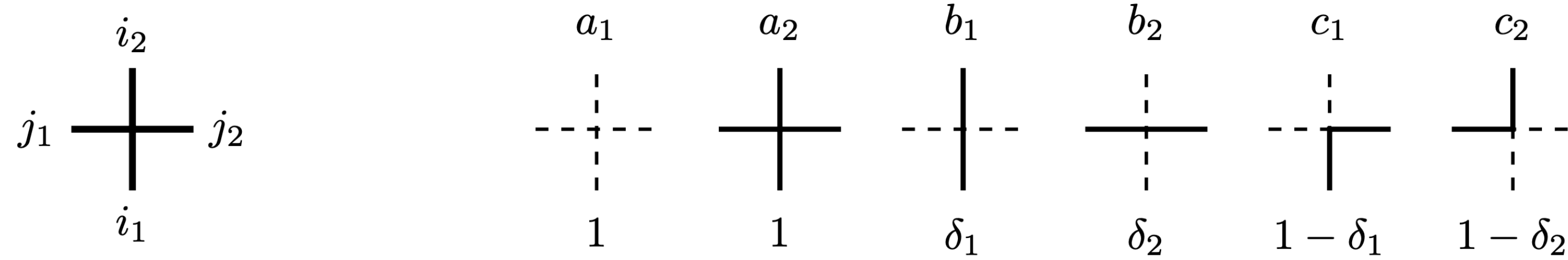
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Converges to ASEP along the diagonal as

$\delta_1, \delta_2 \rightarrow 0$ and q stays fixed (so, $u \rightarrow 1$)



Stationarity for the single-color stochastic six-vertex model



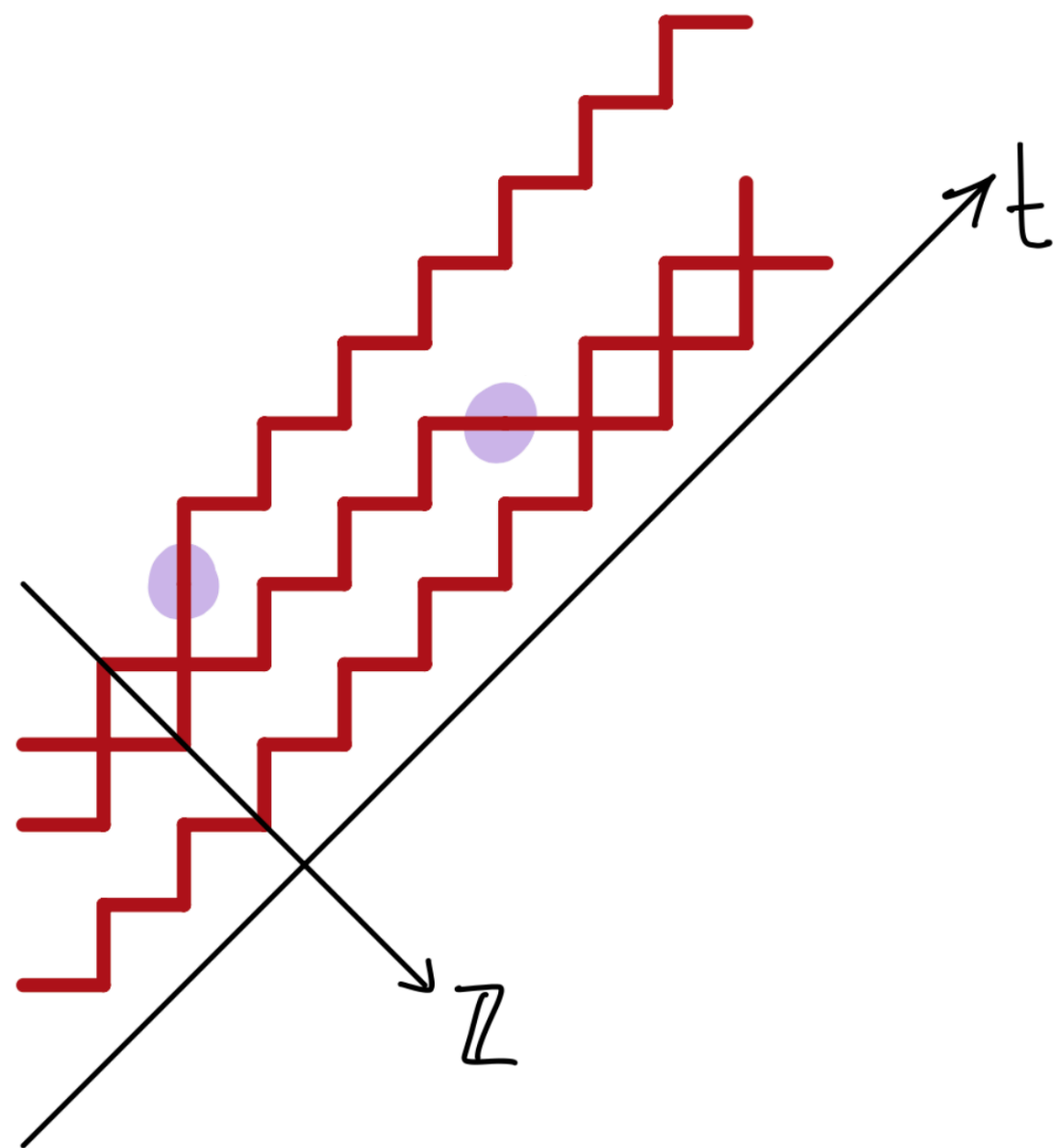
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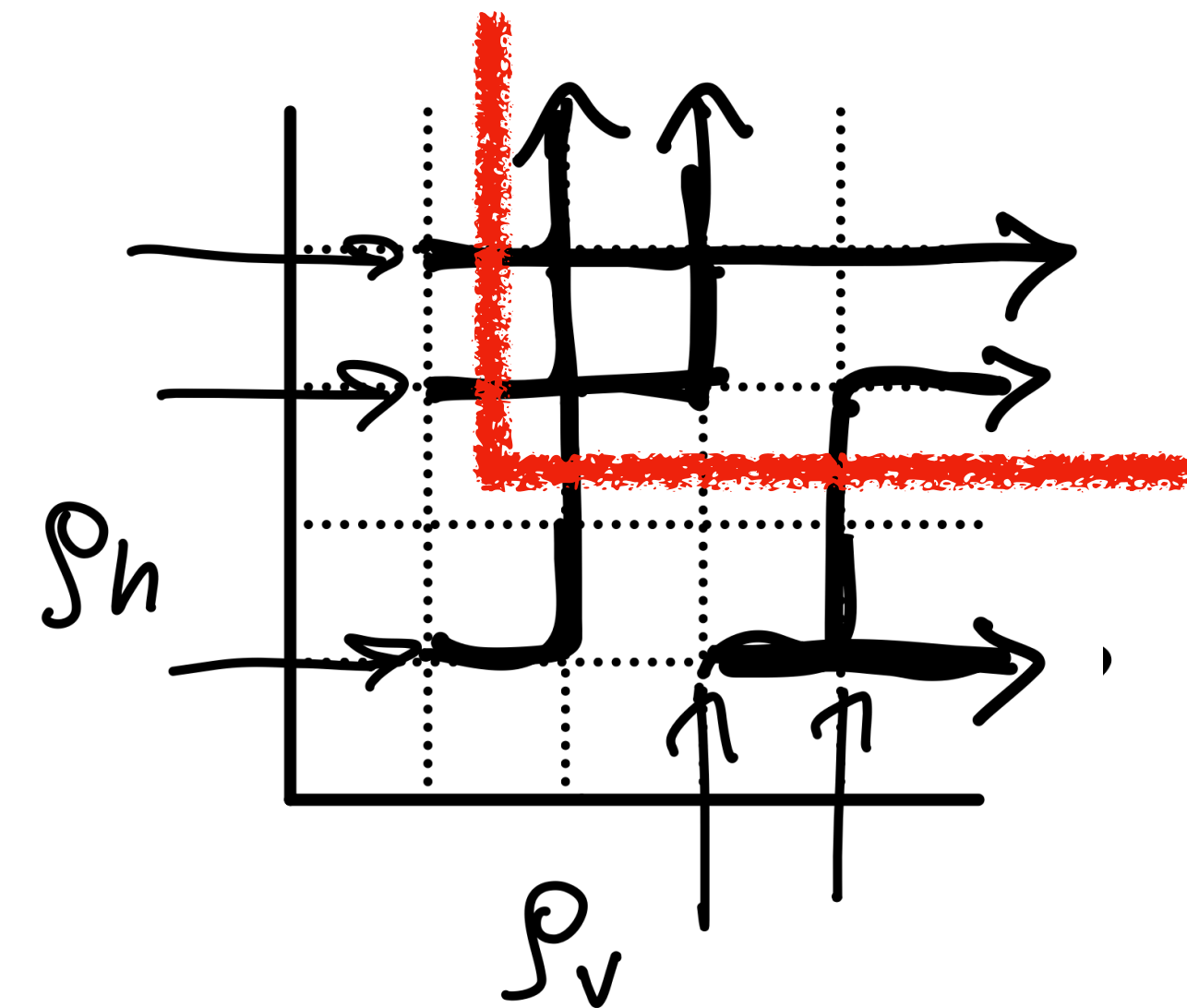
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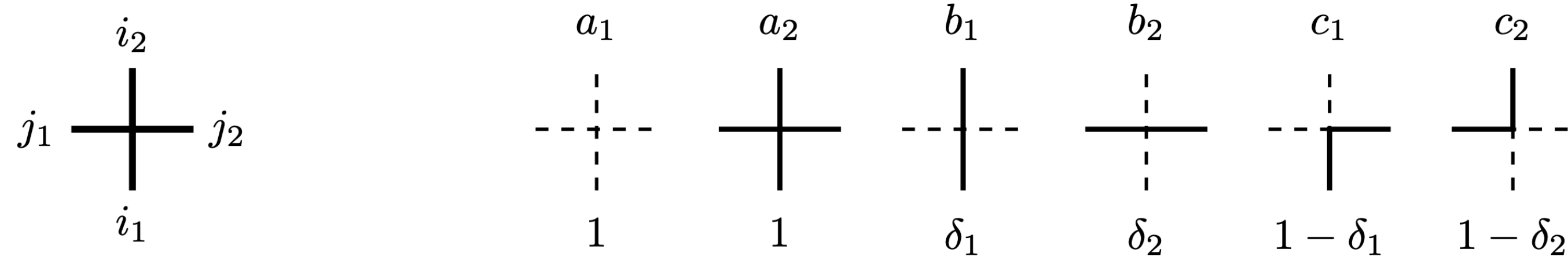
- **Stationarity.** Assume that the boundary conditions are Bernoulli with densities ρ_h, ρ_v .

Then for $\rho_h = \frac{u\rho_v}{1 - \rho_v + u\rho_v}$, the distribution is

stationary in the quadrant.



Stationarity for the single-color stochastic six-vertex model

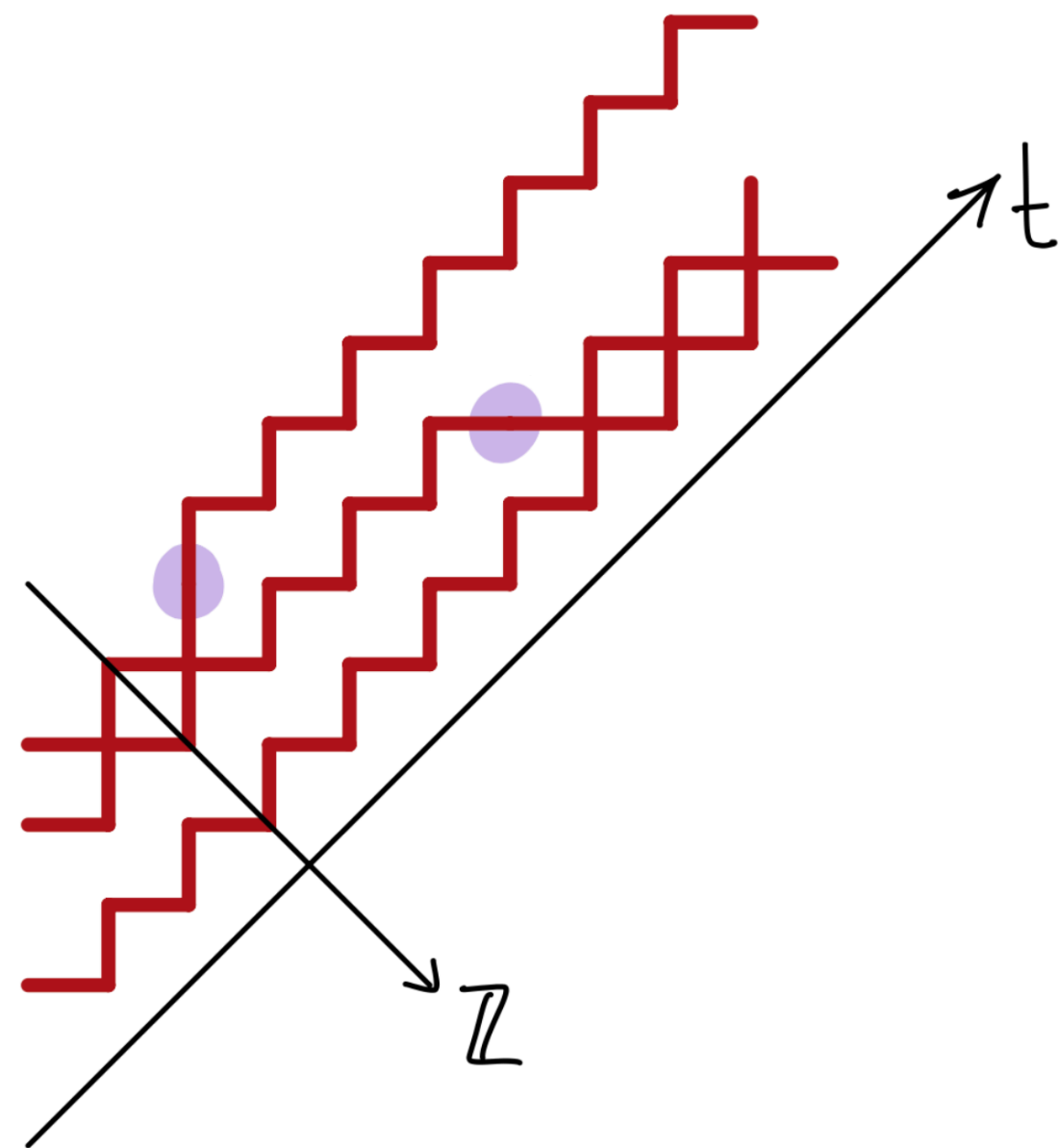


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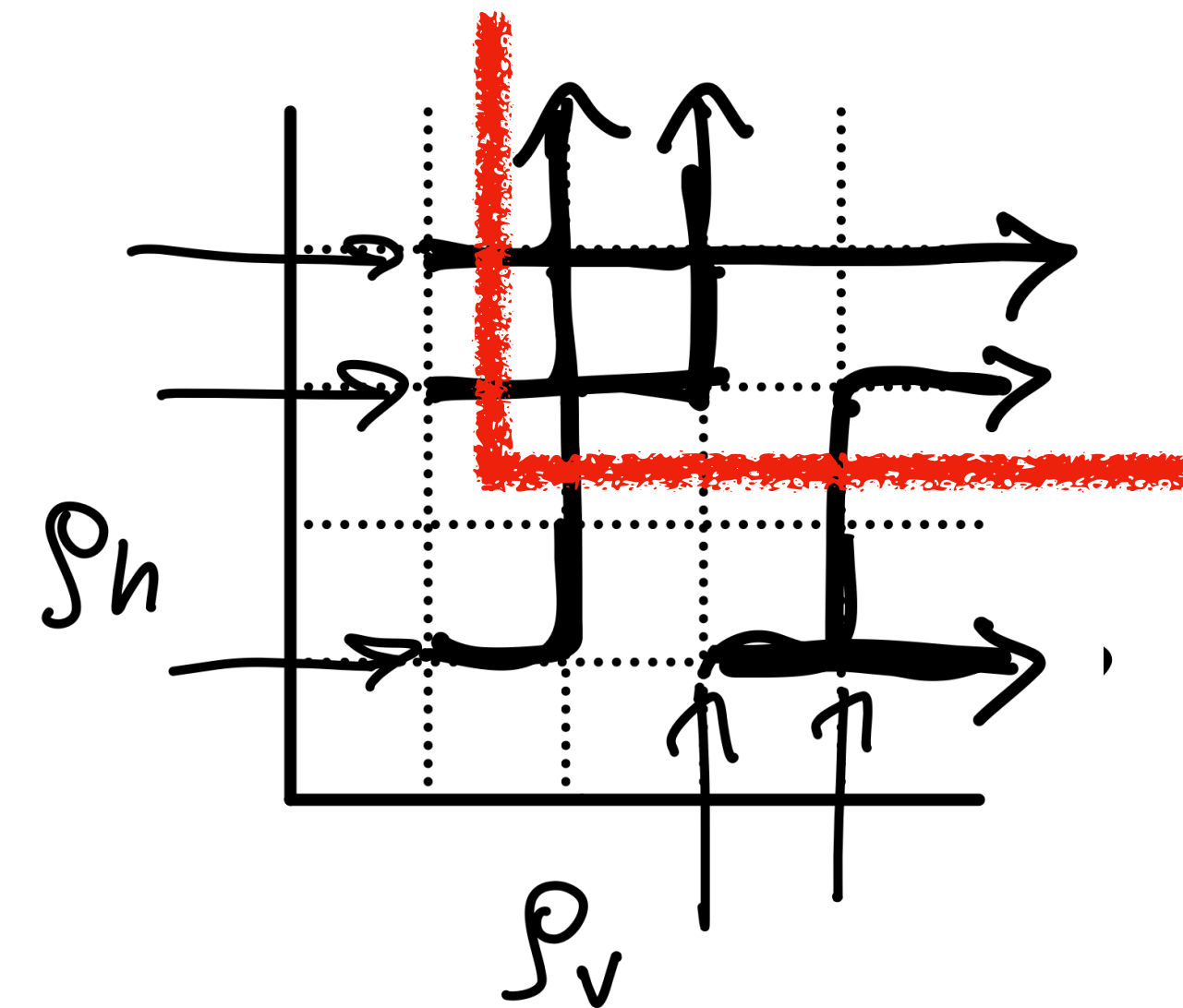
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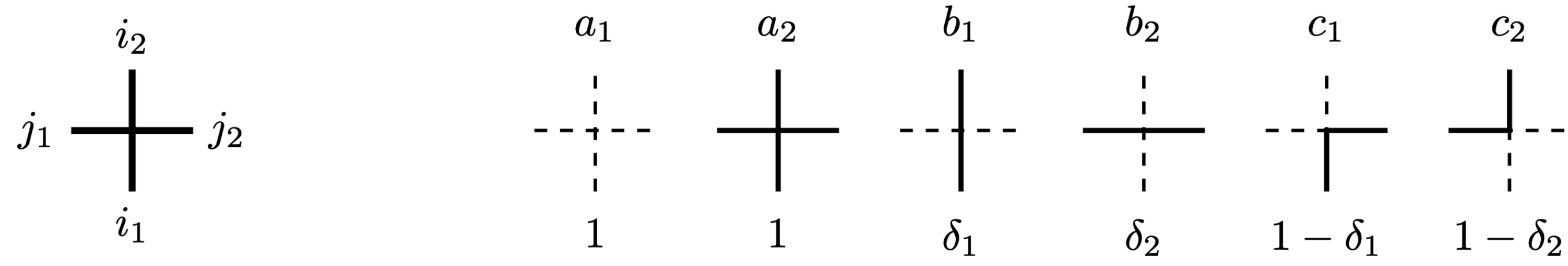
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$$\rho_v(1 - \rho_h) = \rho_h(1 - \rho_v)(1 - \delta_2) + \rho_v(1 - \rho_h)\delta_1$$



Stationarity for the single-color stochastic six-vertex model



[Gwa-Spohn 1992], [Borodin-Corwin-Gorin 2014], [Aggarwal-Borodin 2016]

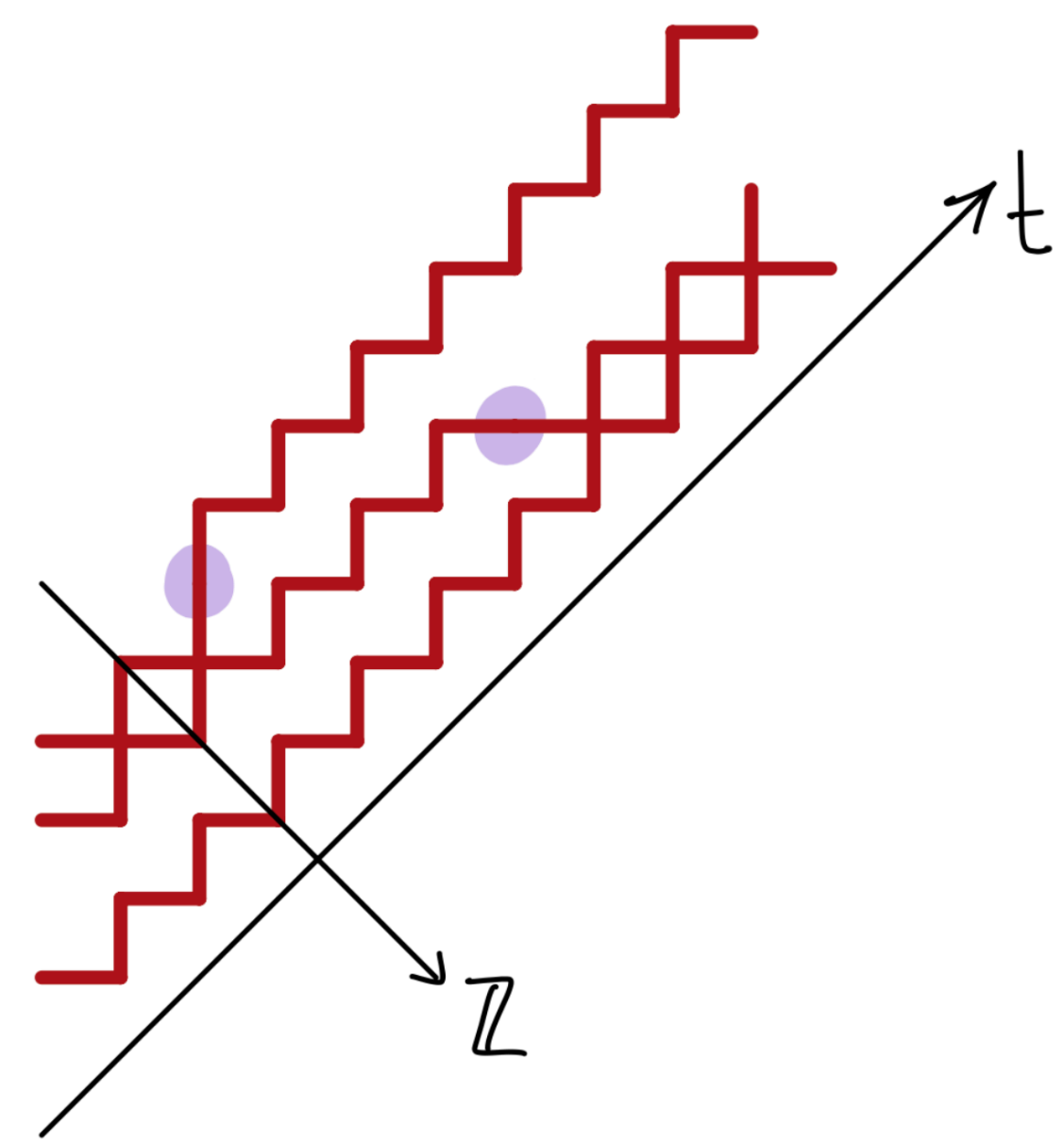
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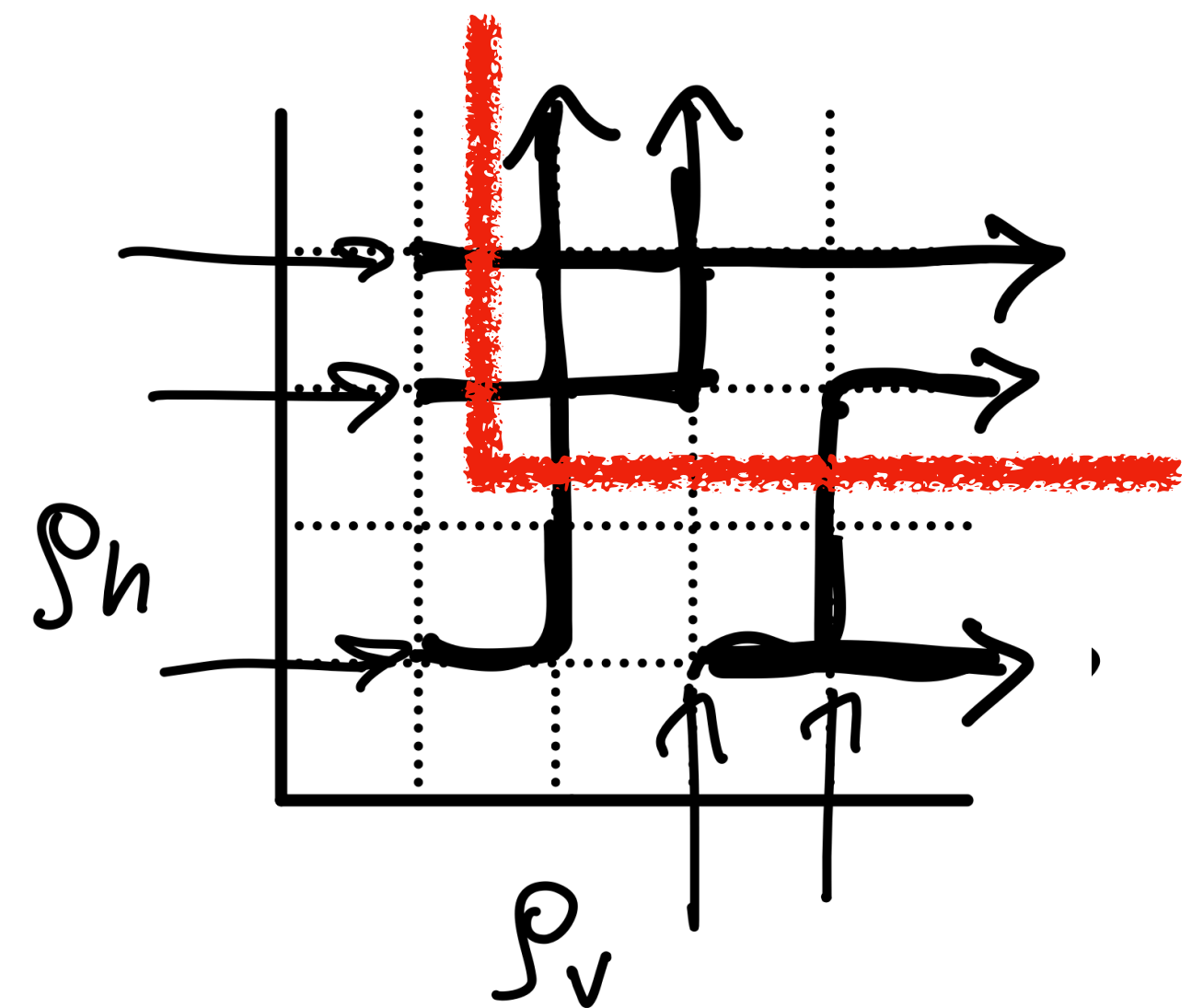
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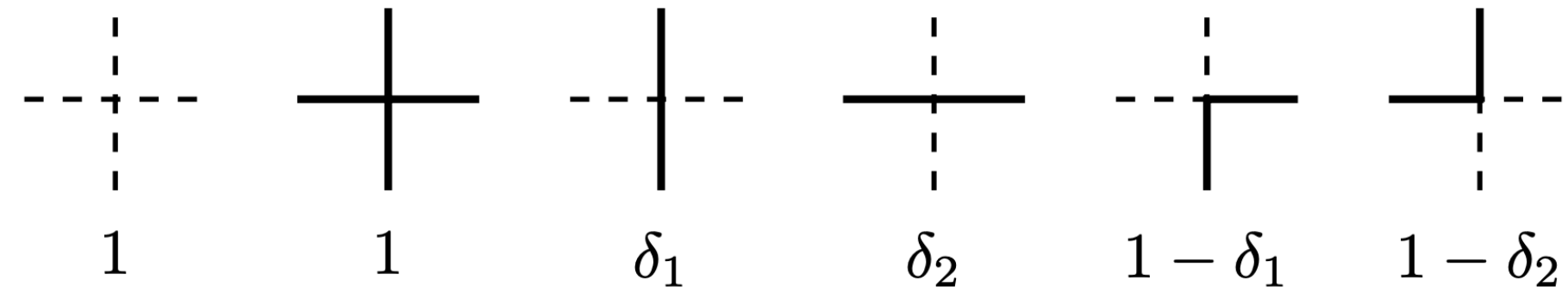
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“Burke property”



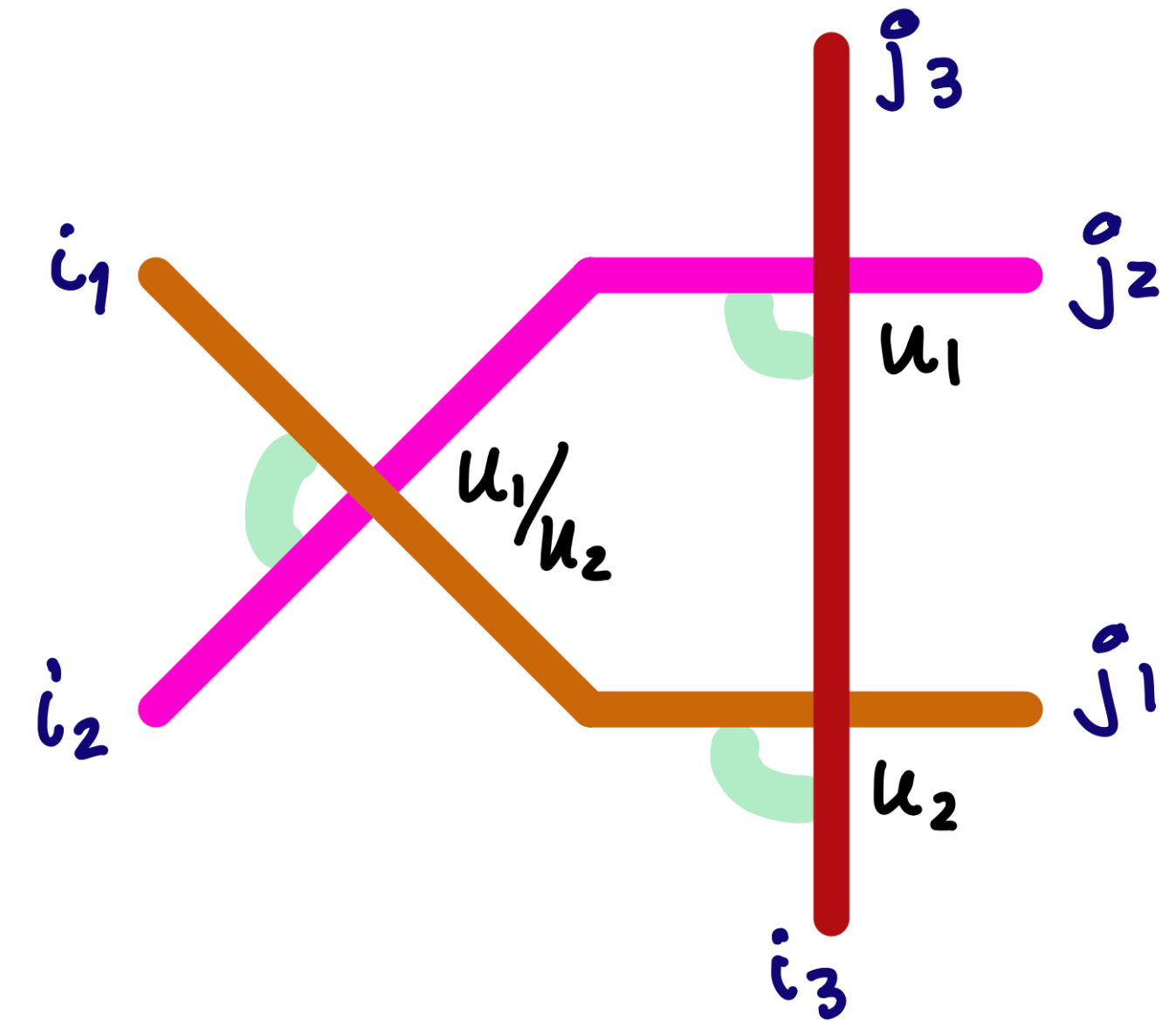
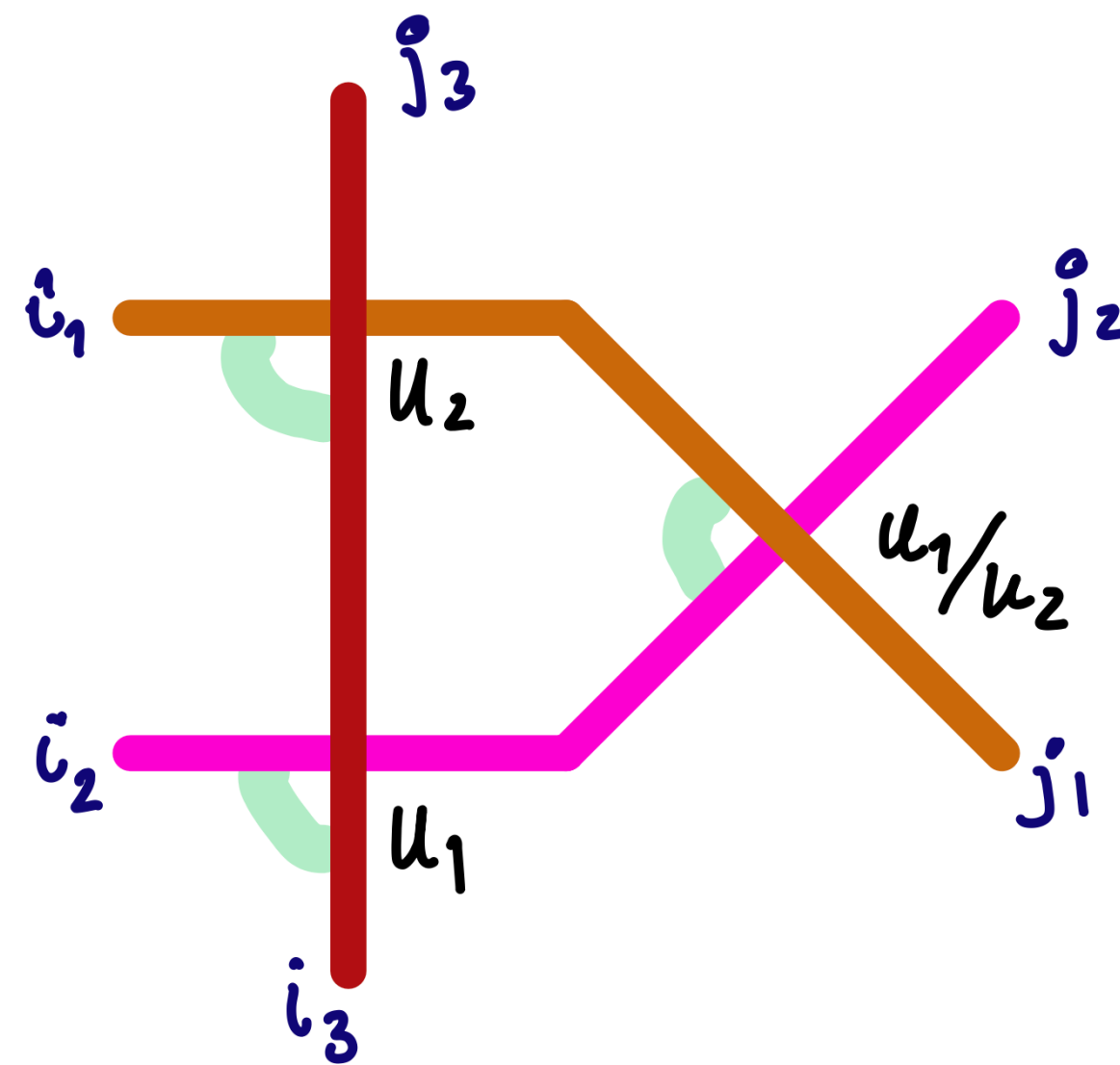
Stationarity for the single-color stochastic six-vertex model

[Gwa-Spohn 1992], [Borodin-Corwin-Gorin 2014],
[Aggarwal-Borodin 2016]



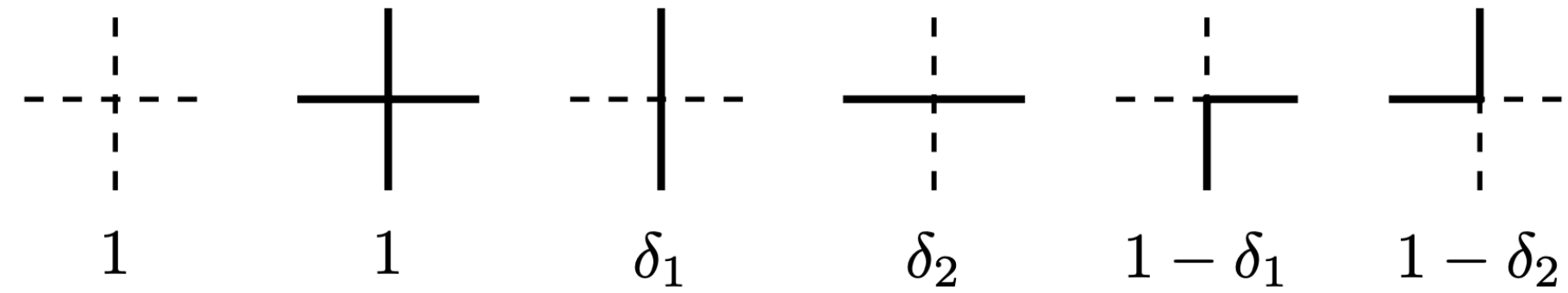
$$\rho_h = \frac{u\rho_v}{1 - \rho_v + u\rho_v} \quad u := \frac{1 - \delta_1}{1 - \delta_2}, \quad q := \delta_1/\delta_2$$

- **Yang-Baxter equation.** For fixed q , and fixed $i_1, i_2, i_3 \in \{0, 1\}$, the joint distribution of j_1, j_2, j_3 in two pictures is the same:



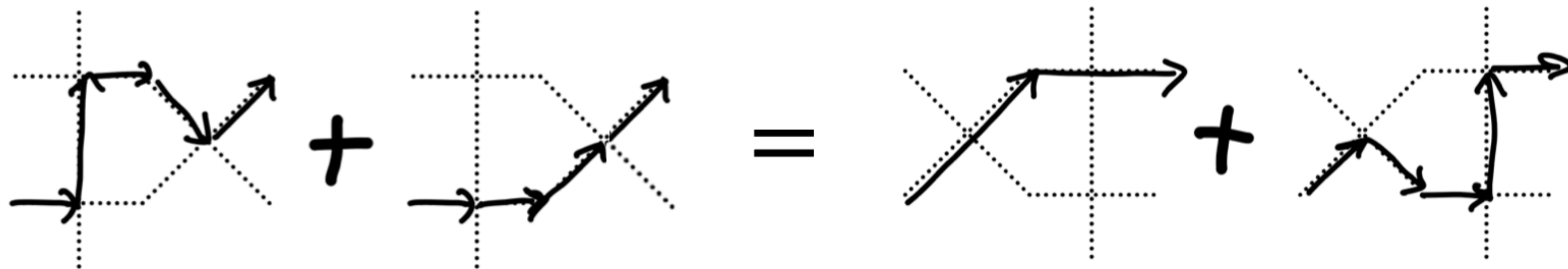
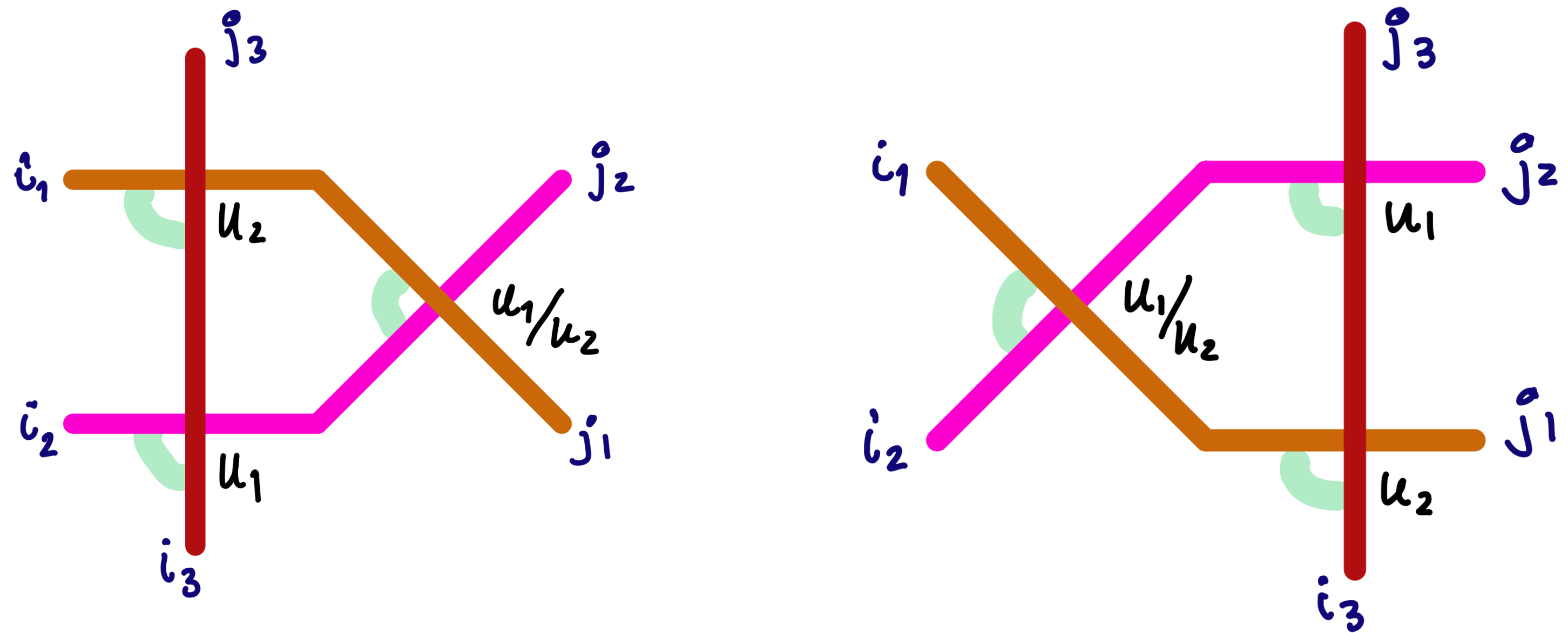
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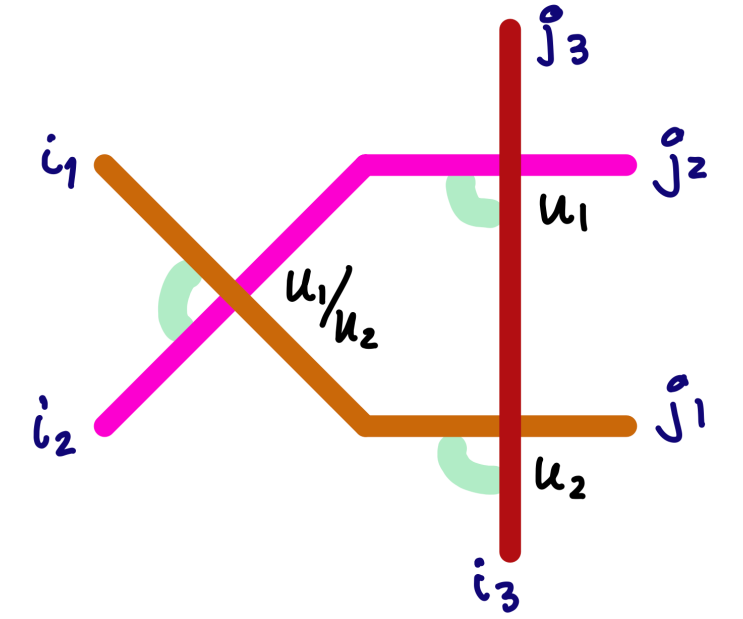
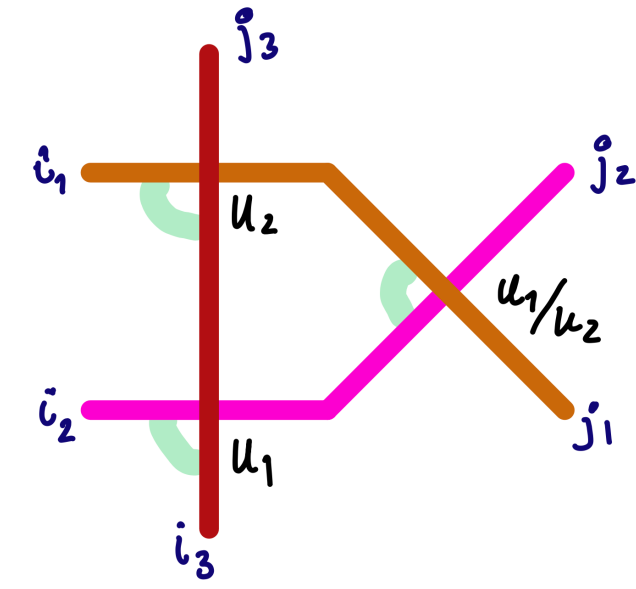
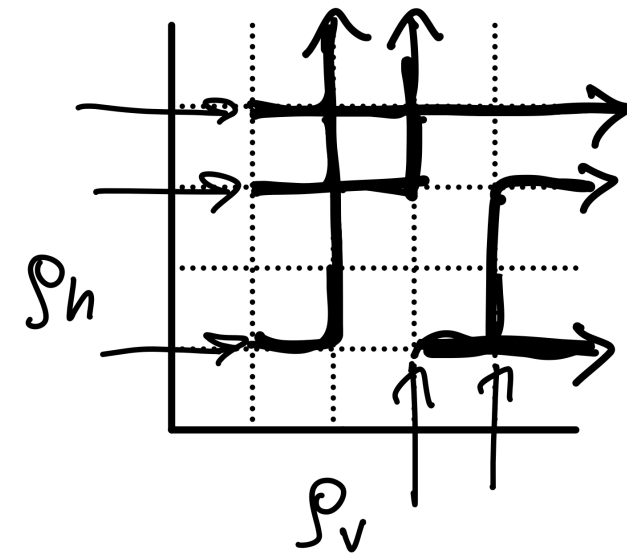
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Stationarity for the single-color stochastic six-vertex model

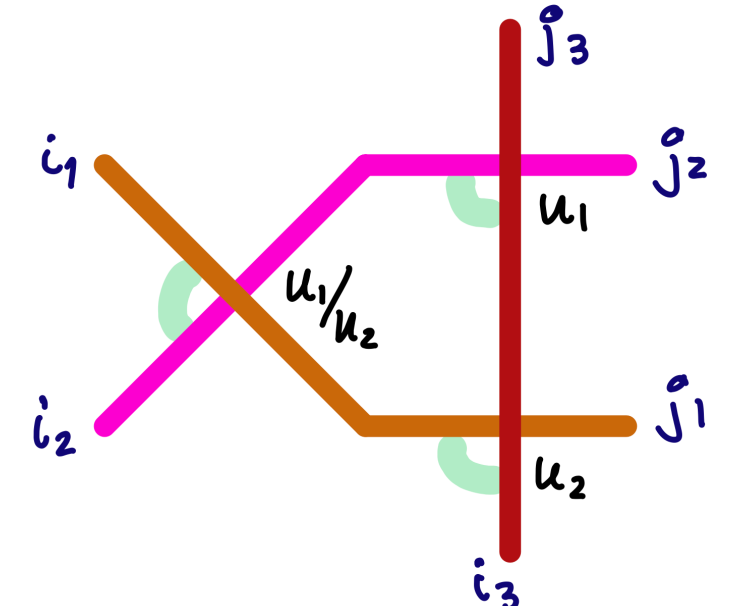
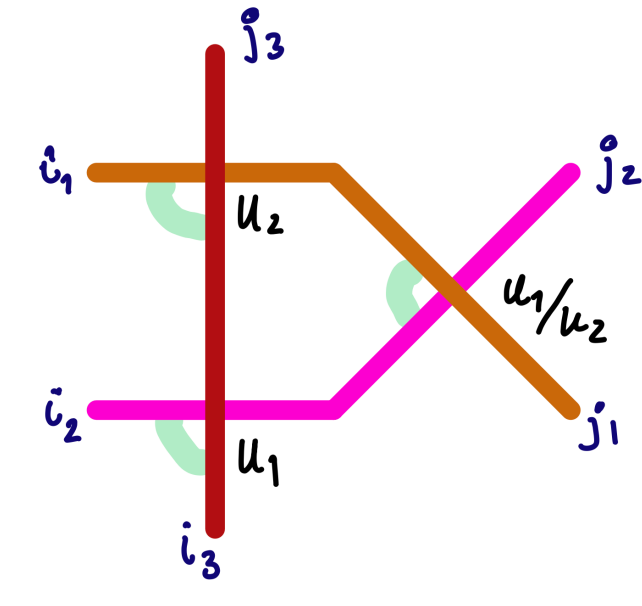
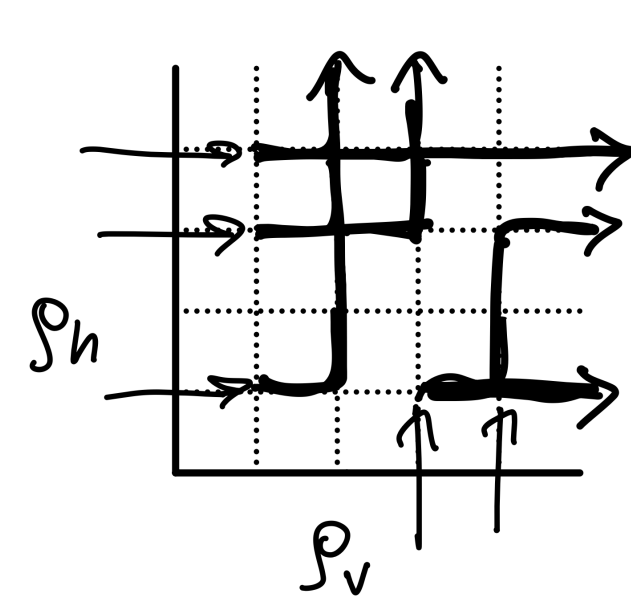
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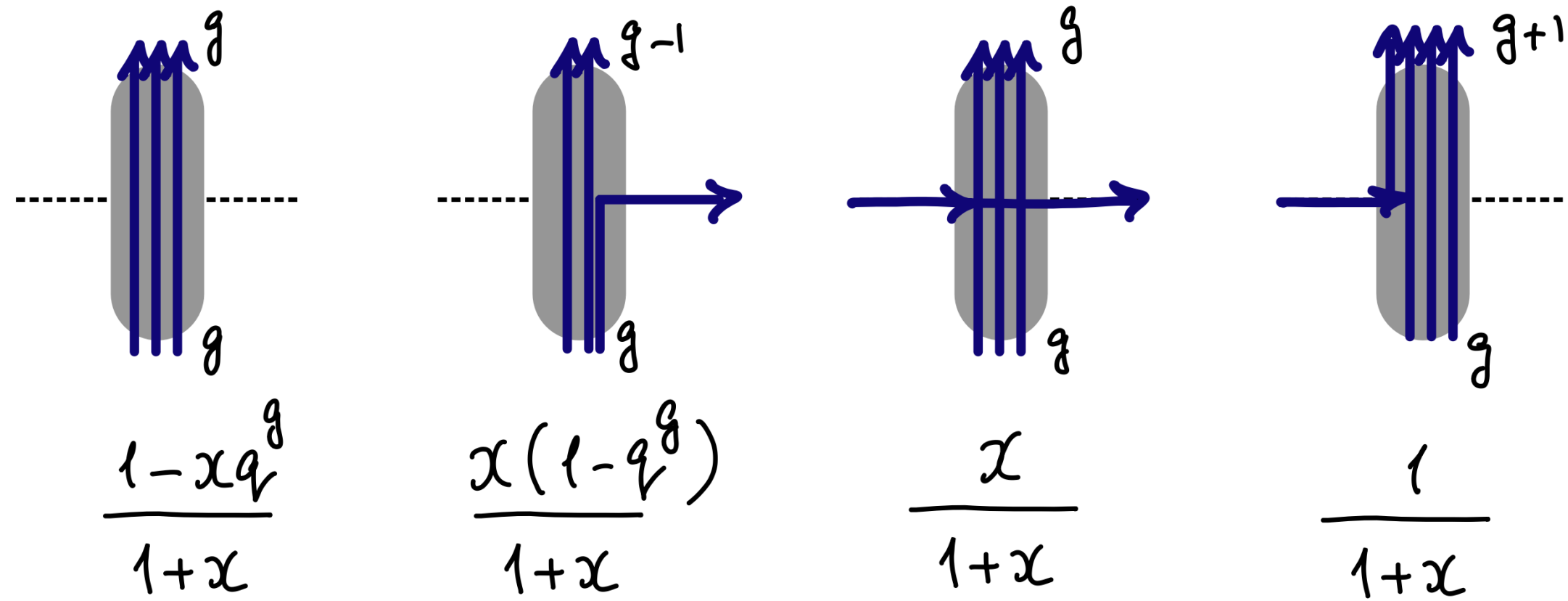
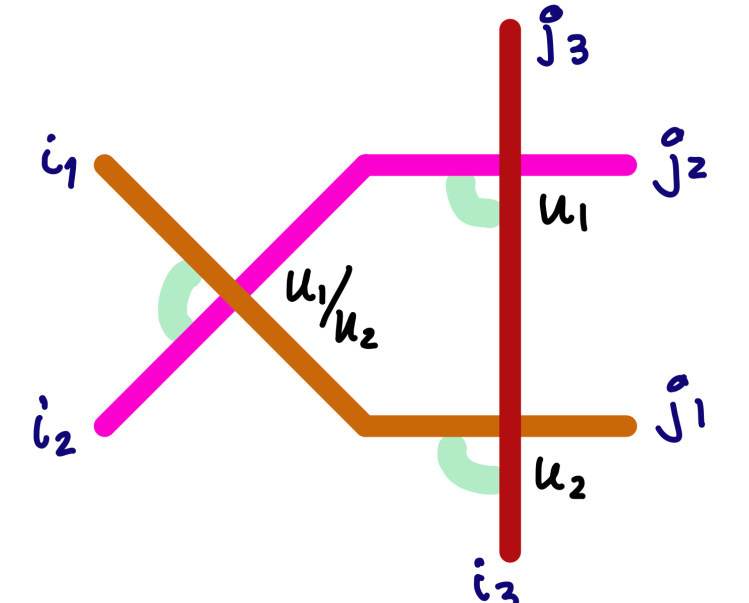
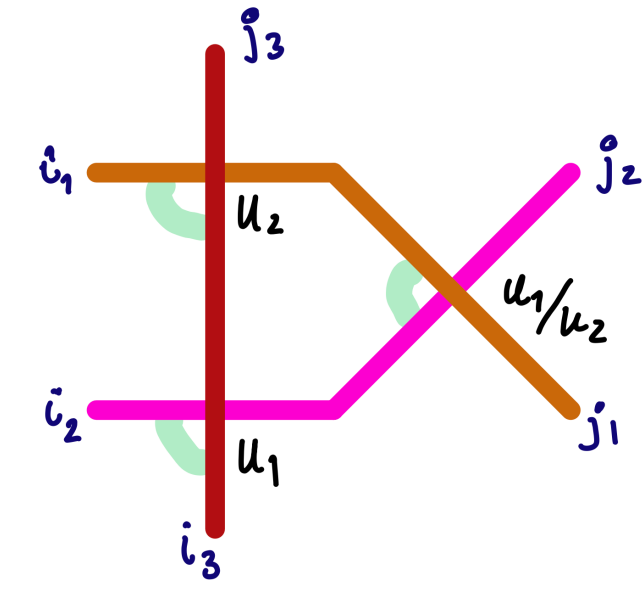
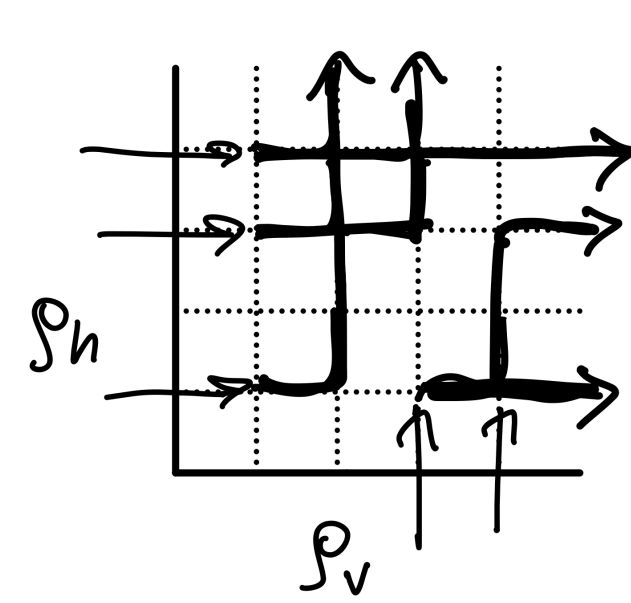
- **Fusion [Kulish-Reshetikhin-Sklyanin 1983], [Corwin-P. 2015]** - a way to construct new YBE solutions from existing ones. **Inserts ∞ arrows.**



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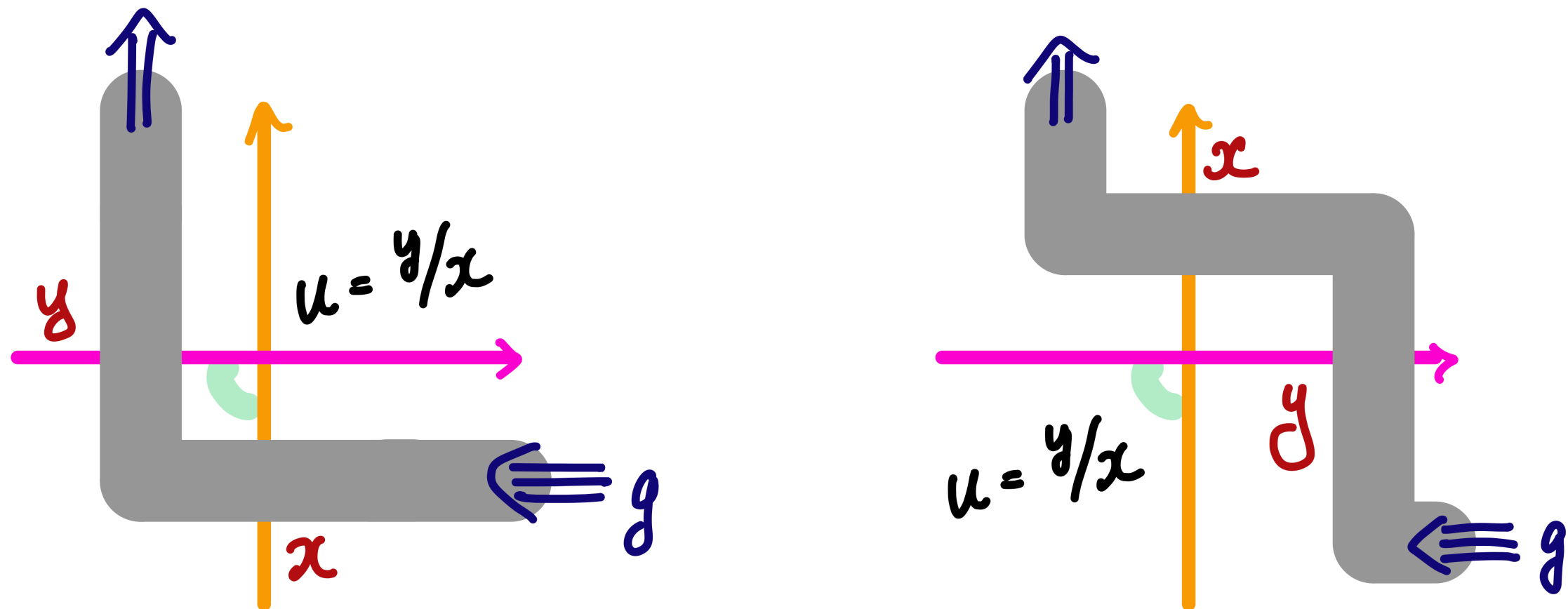
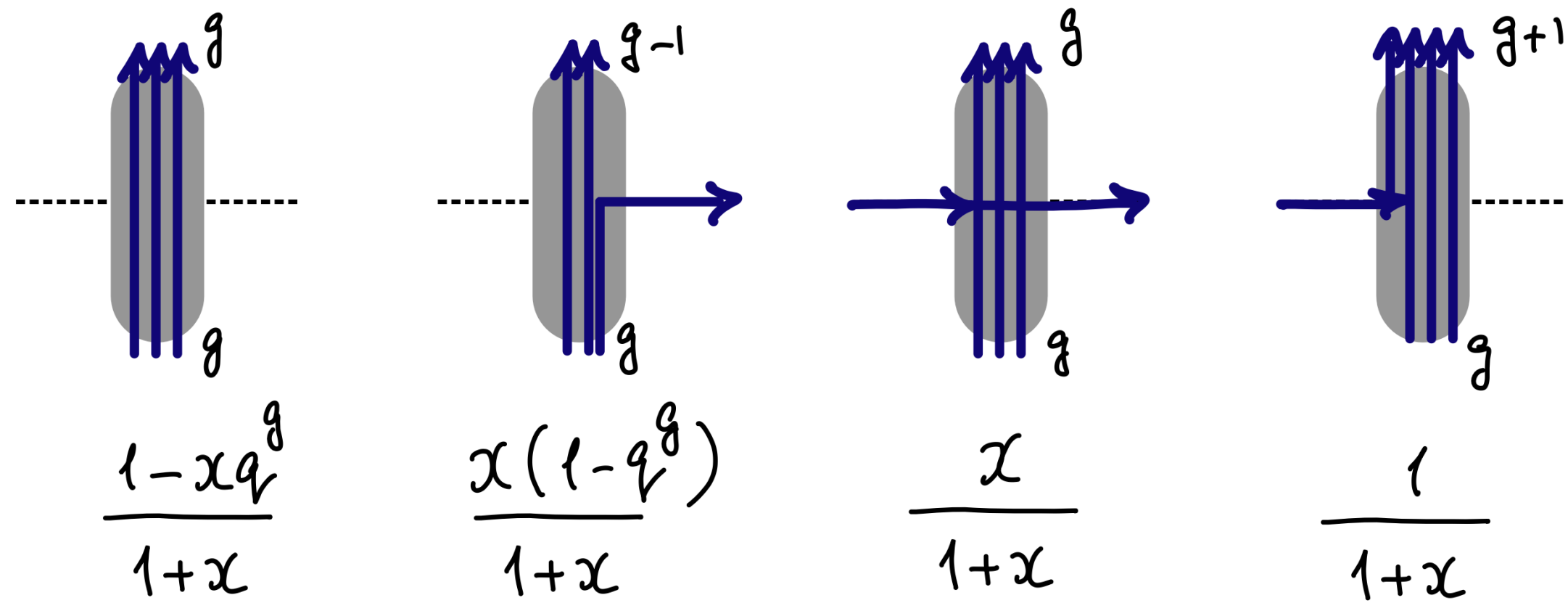
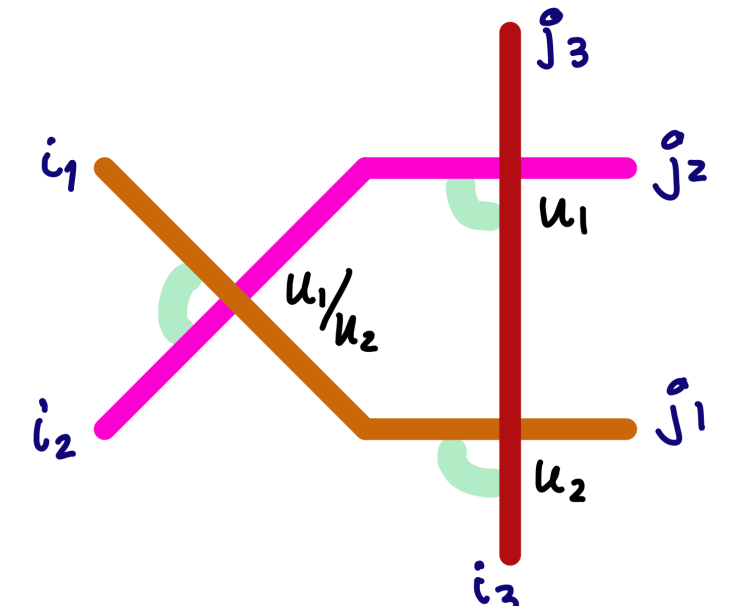
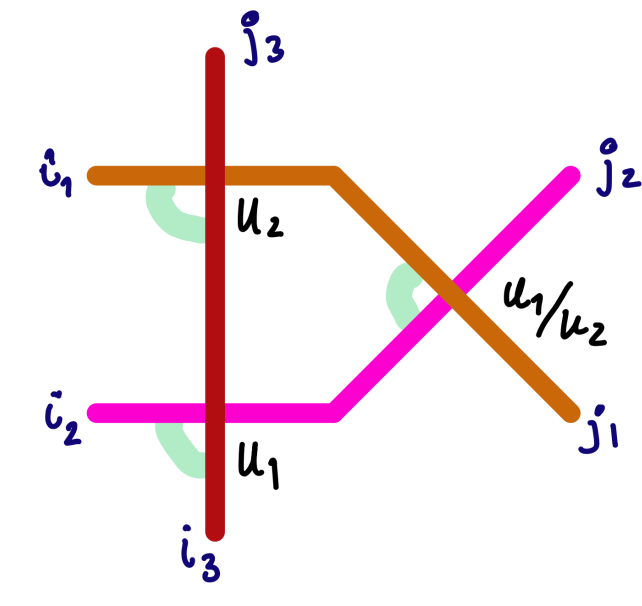
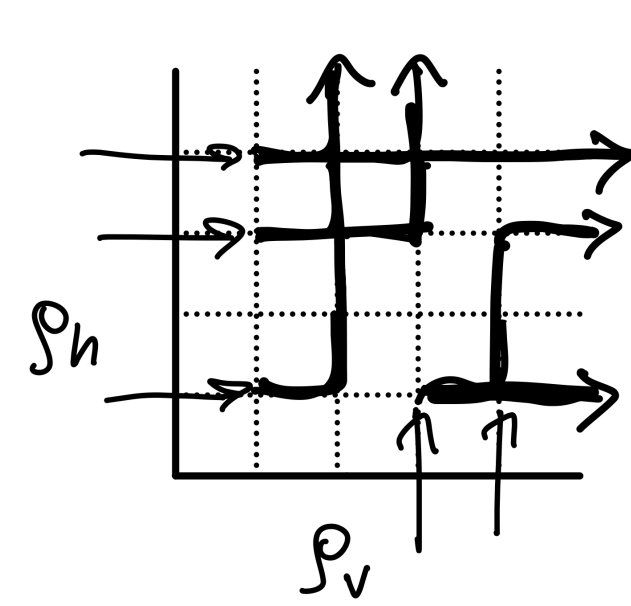
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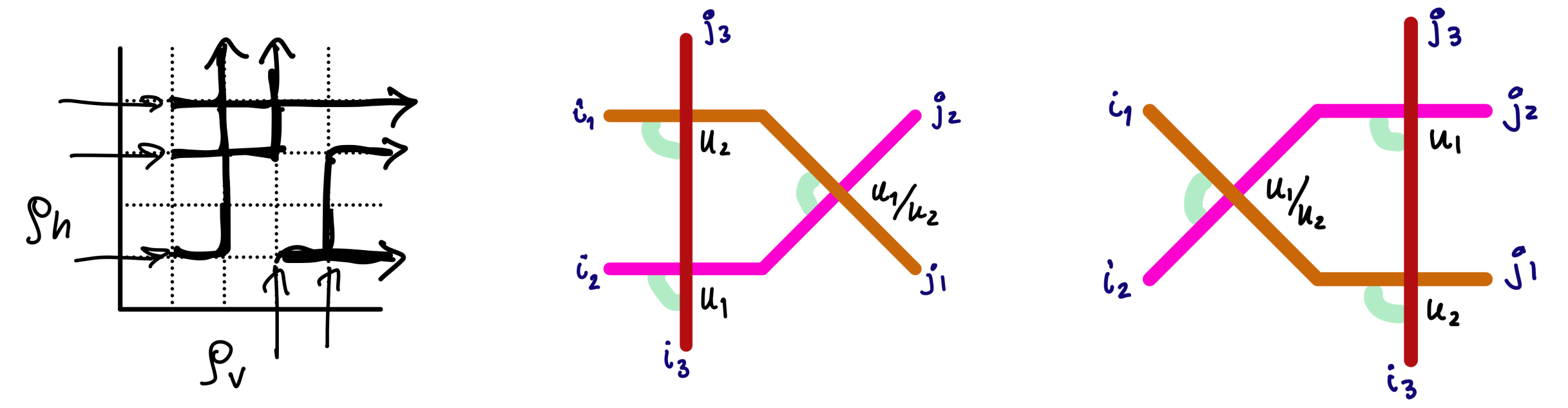
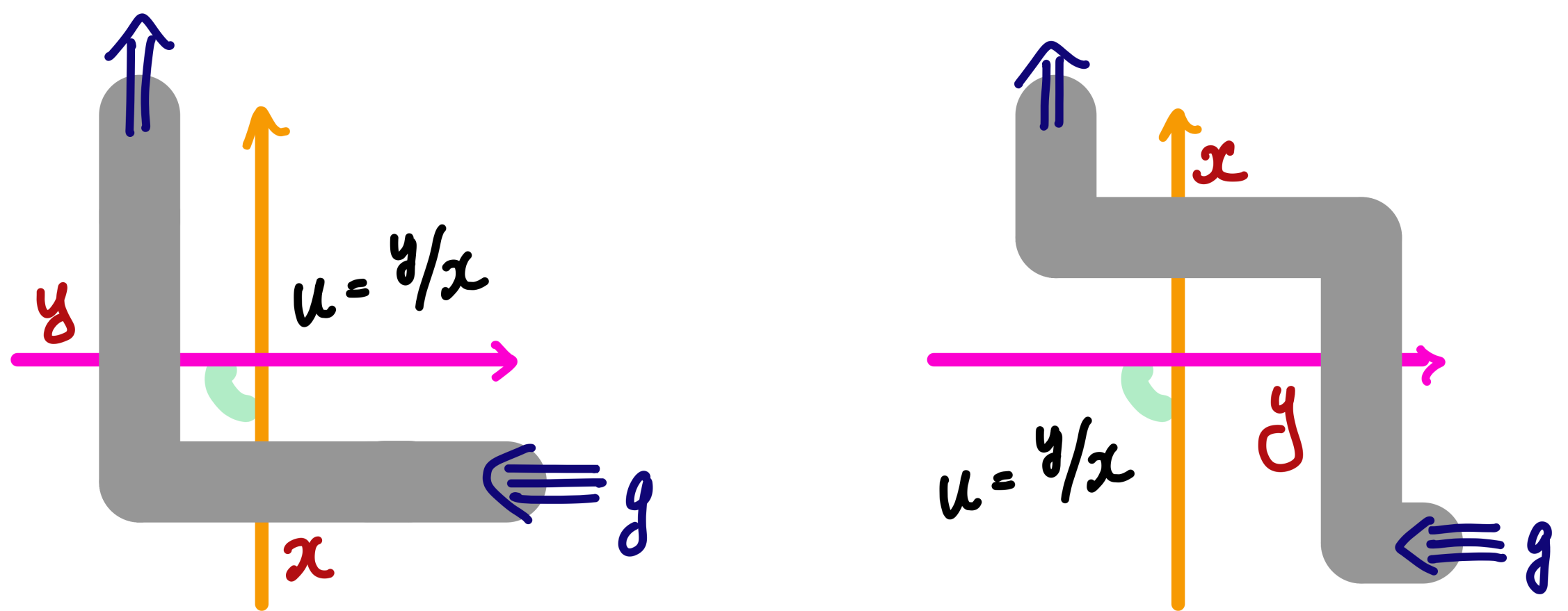
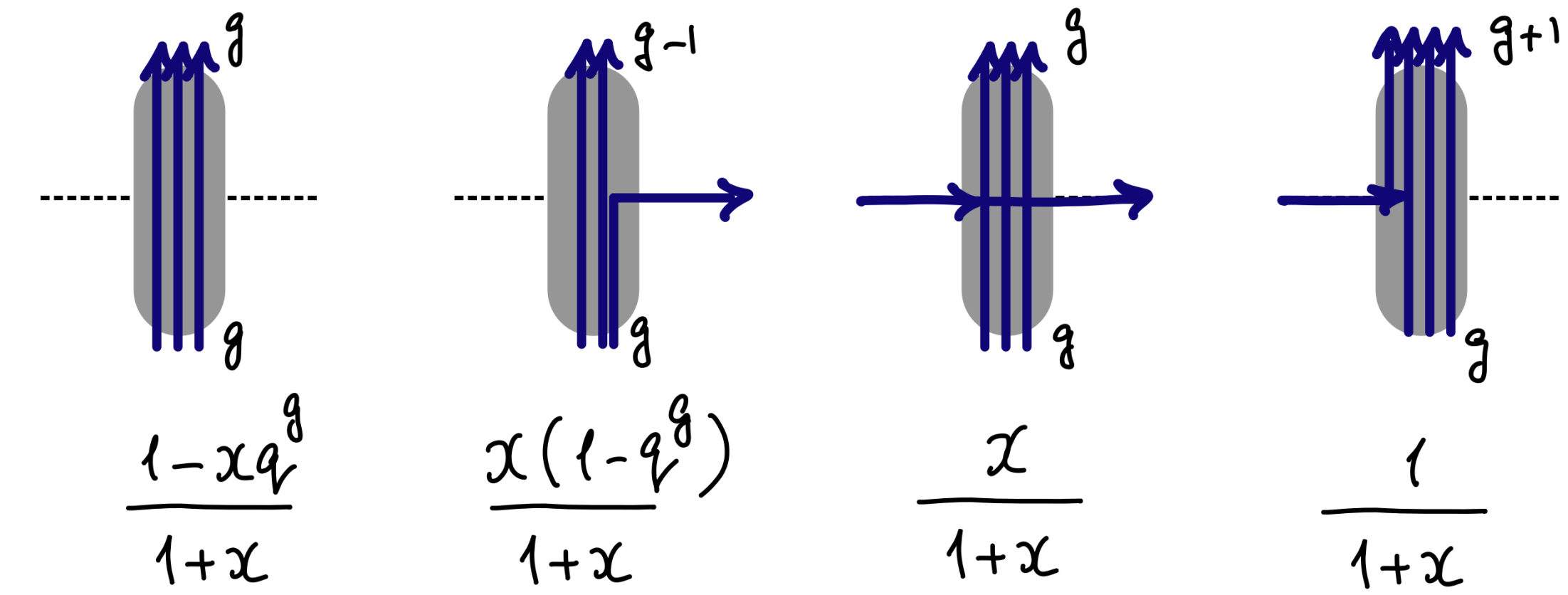
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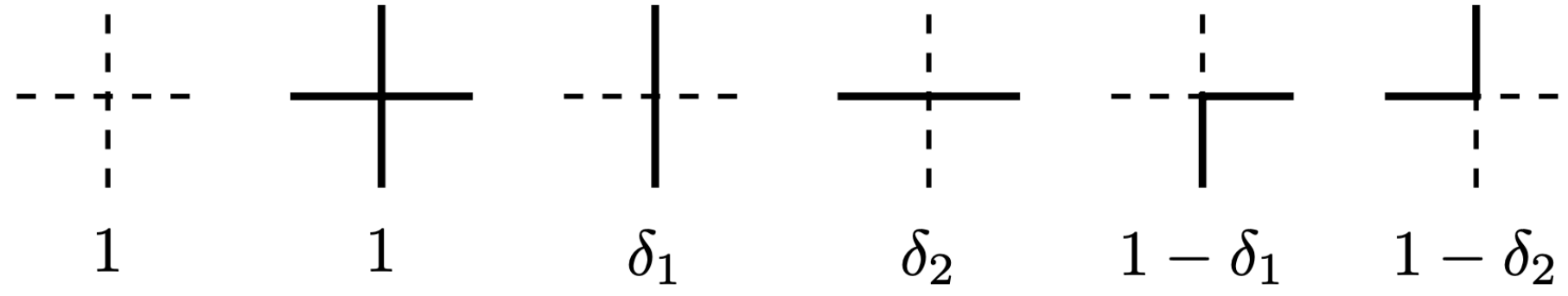


Stationarity via Yang-Baxter

- For $g = +\infty$, the right output of the fat vertex is *Bernoulli* $(\frac{x}{x+1})$, independent of the bottom and the left inputs.
- The Yang-Baxter equation is equivalent to the previous “Burke” computation: $\rho_v = \frac{x}{x+1}$,

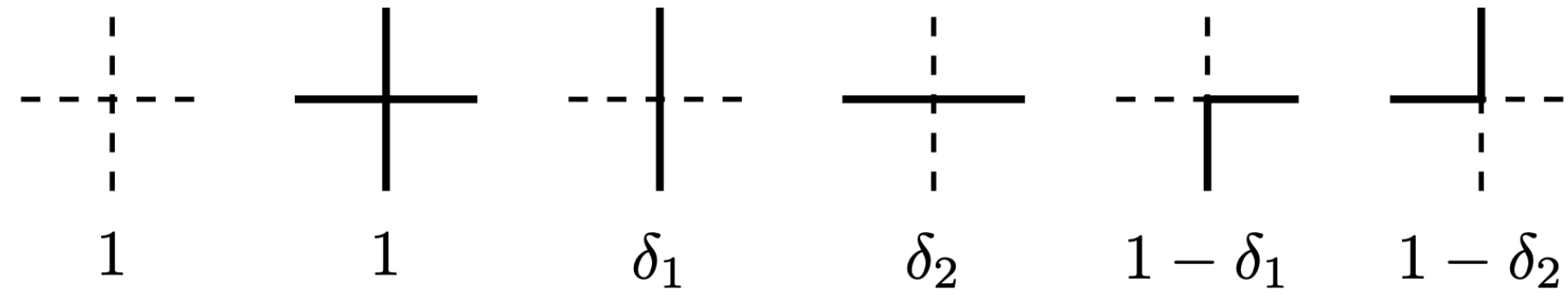
$$\rho_h = \frac{ux}{ux + 1} \Rightarrow \rho_h = \frac{u\rho_v}{1 - \rho_v + u\rho_v}$$

Stationarity for the single-color stochastic six-vertex model

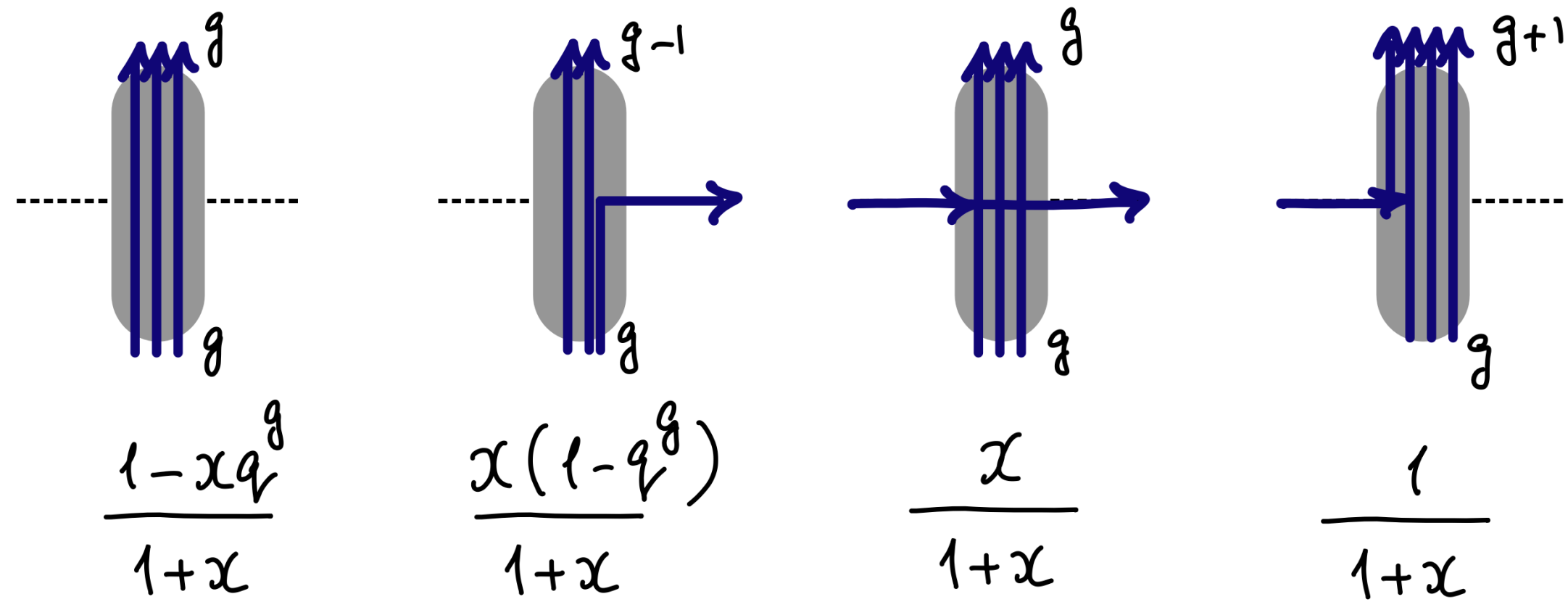


$$\rho_h = \frac{u\rho_v}{1 - \rho_v + u\rho_v} \quad u := \frac{1 - \delta_1}{1 - \delta_2}, \quad q := \delta_1/\delta_2$$

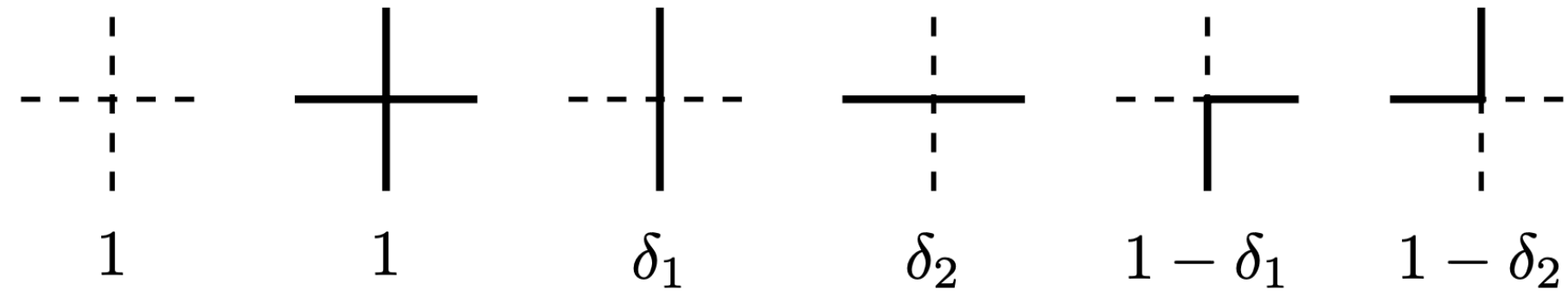
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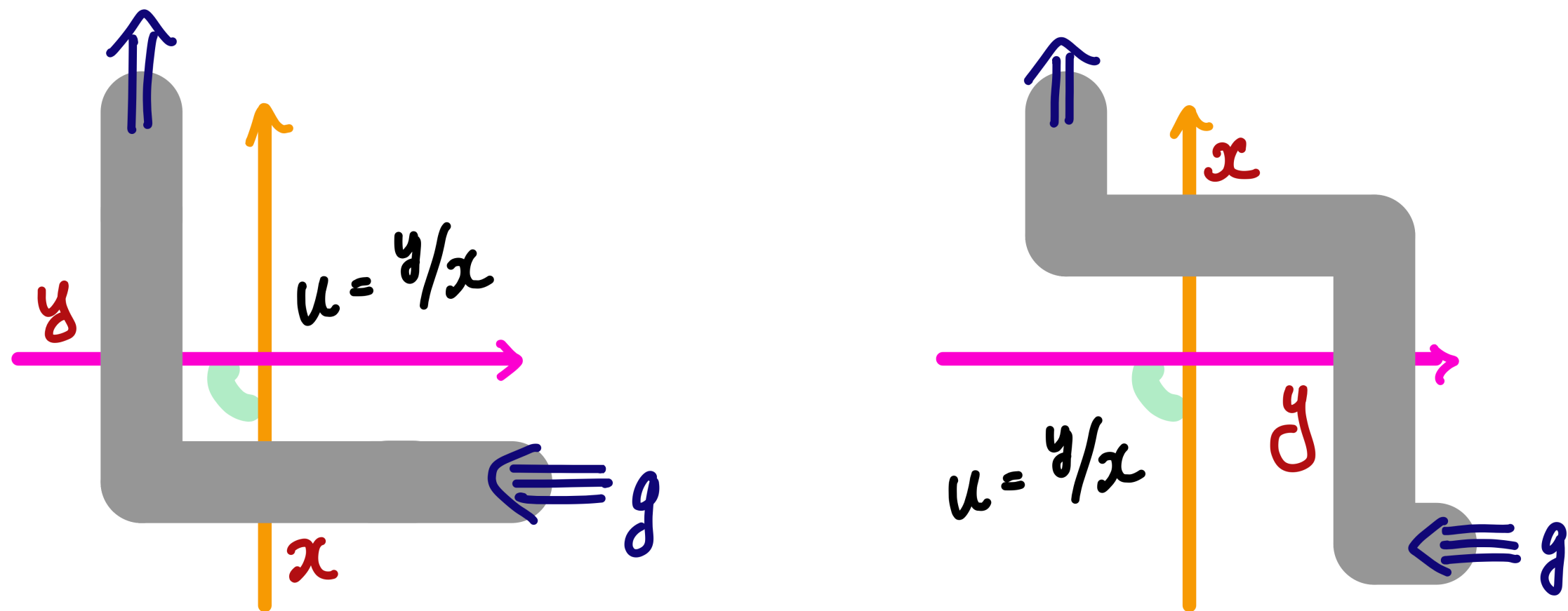
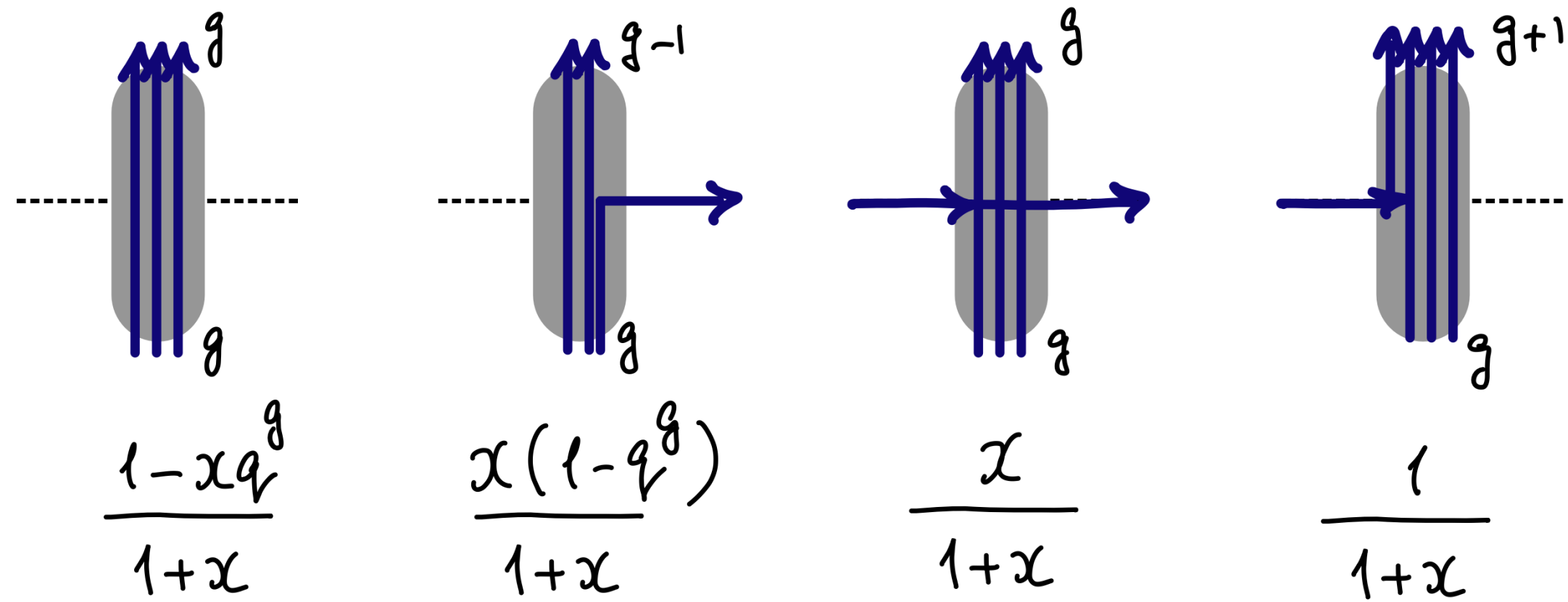
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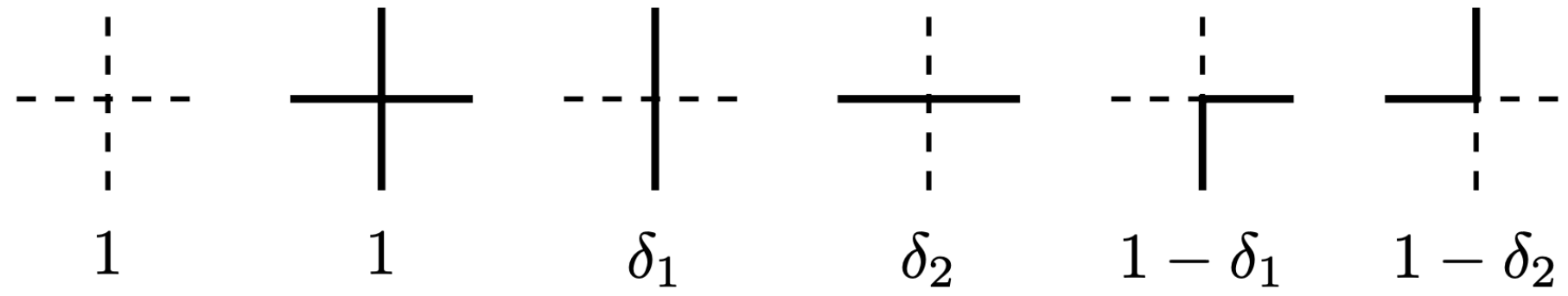
Stationarity for the single-color stochastic six-vertex model



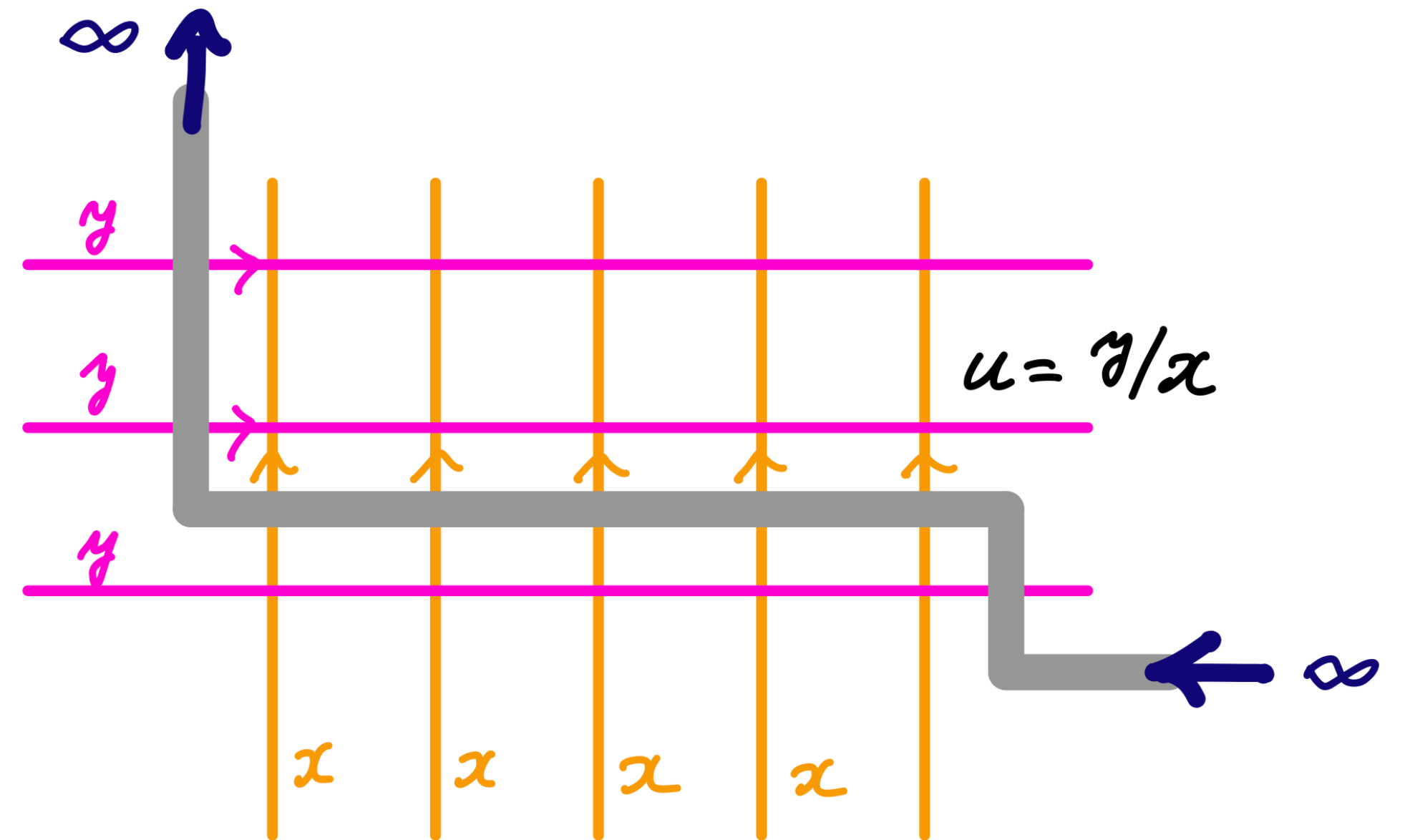
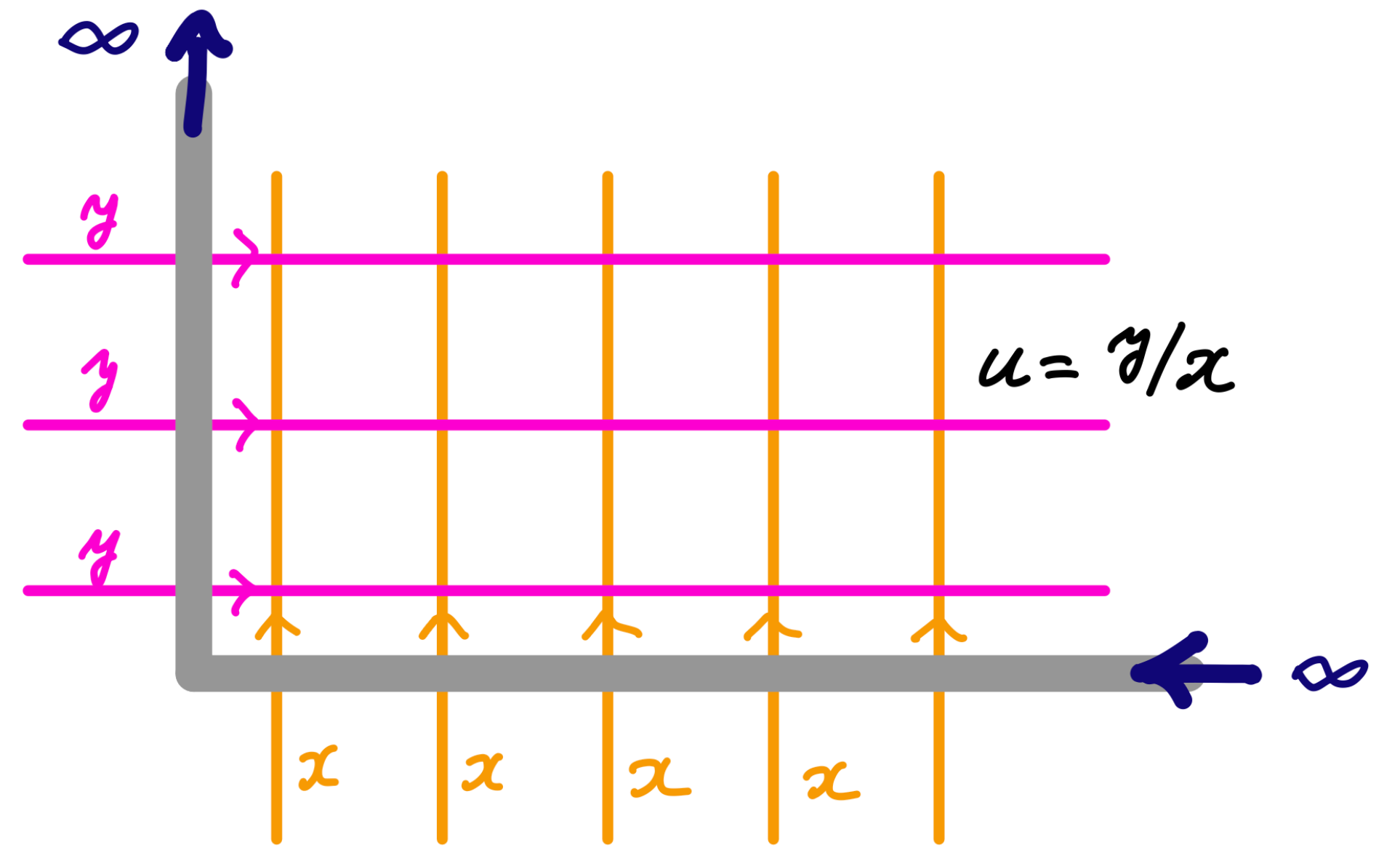
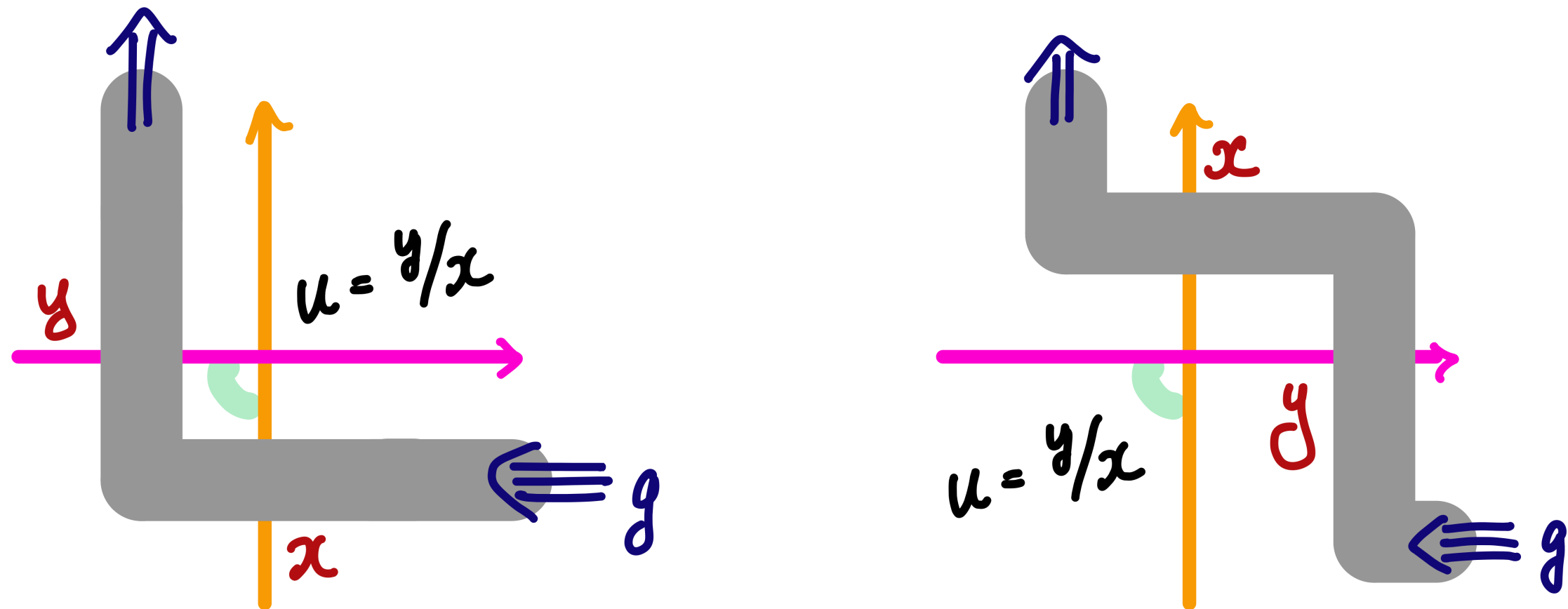
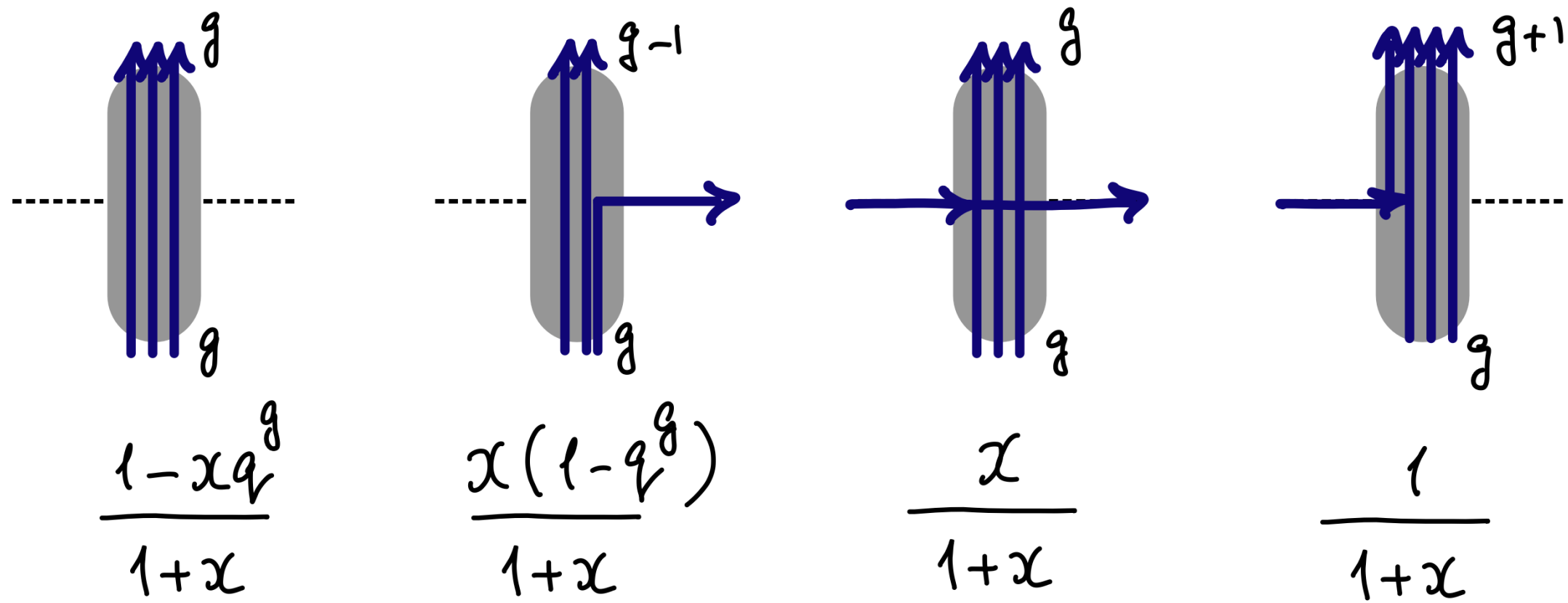
$$\rho_h = \frac{u\rho_v}{1 - \rho_v + u\rho_v} \quad u := \frac{1 - \delta_1}{1 - \delta_2}, \quad q := \delta_1/\delta_2$$



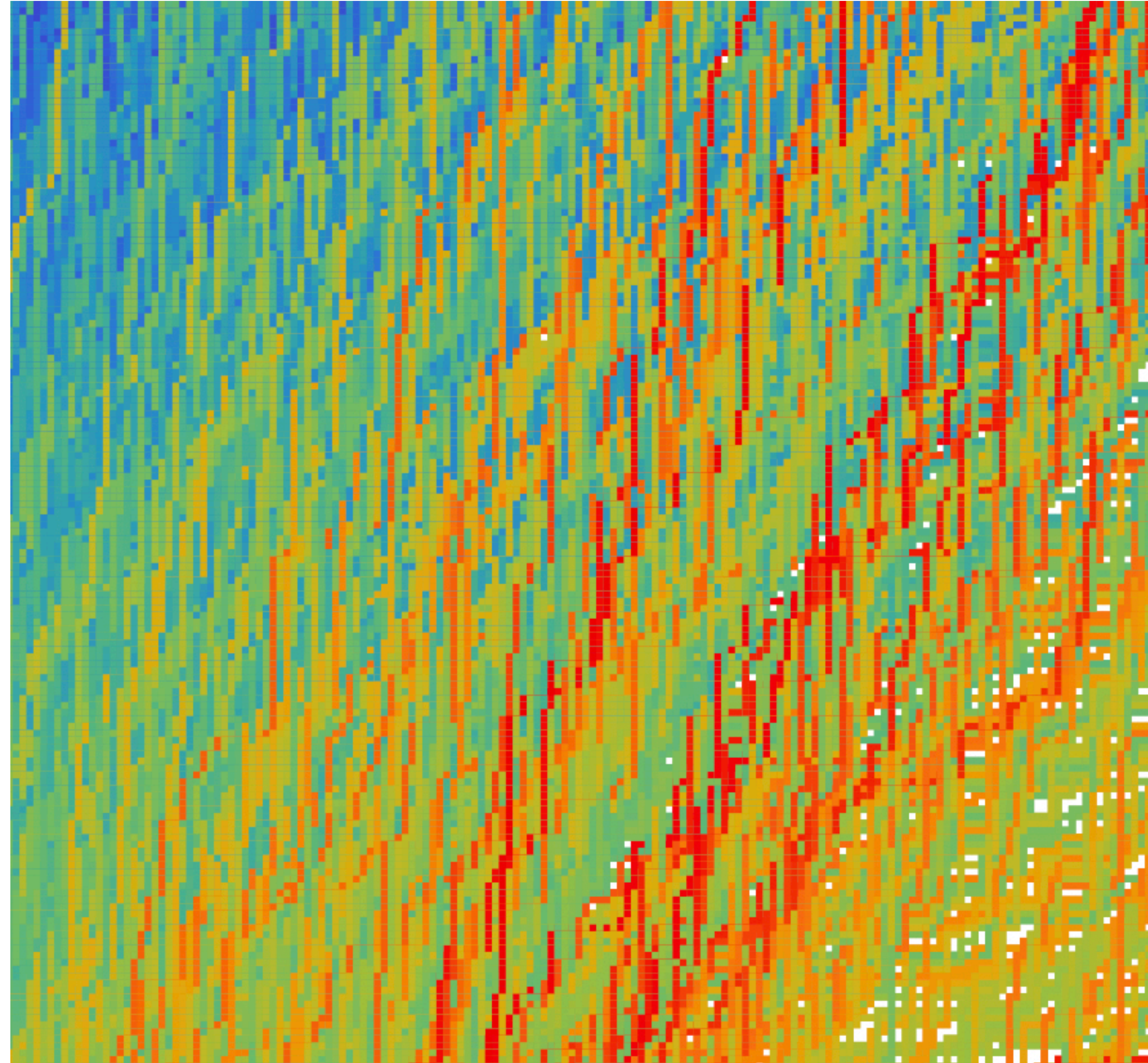
Stationarity for the single-color stochastic six-vertex model



$$\rho_h = \frac{u\rho_v}{1 - \rho_v + u\rho_v} \quad u := \frac{1 - \delta_1}{1 - \delta_2}, \quad q := \delta_1/\delta_2$$

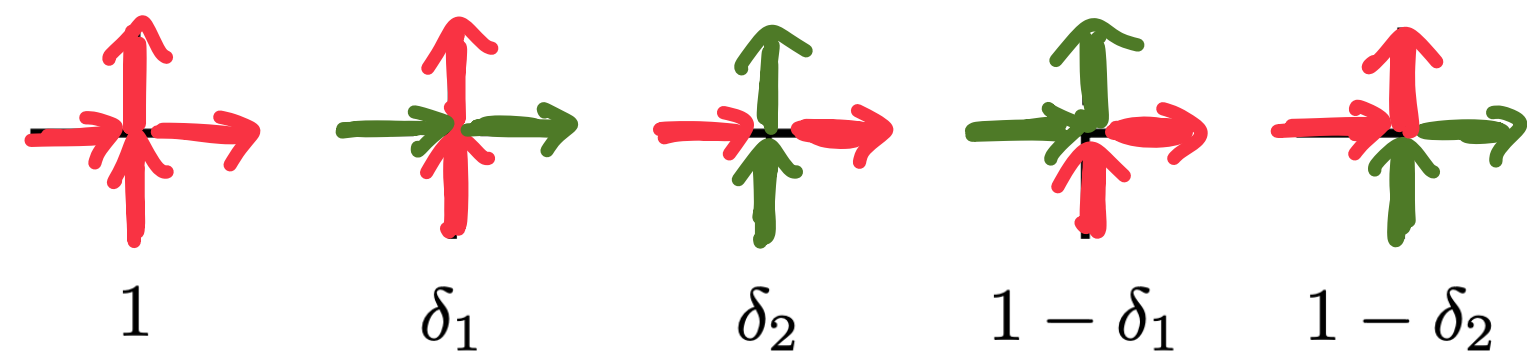


Add color!



Colored stochastic six-vertex model (converges to colored ASEP)

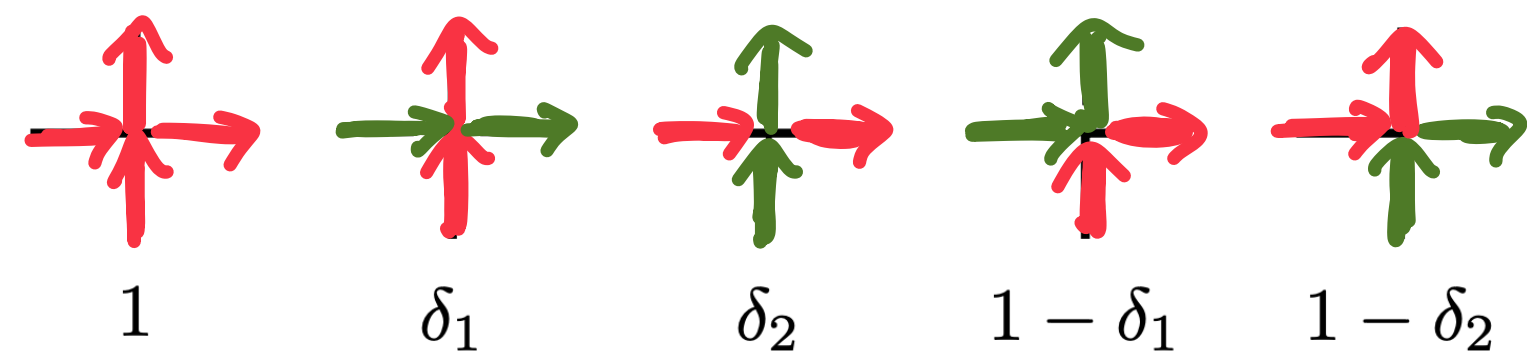
Red > Green



$$u := \frac{1 - \delta_1}{1 - \delta_2}, \quad q := \delta_1 / \delta_2$$

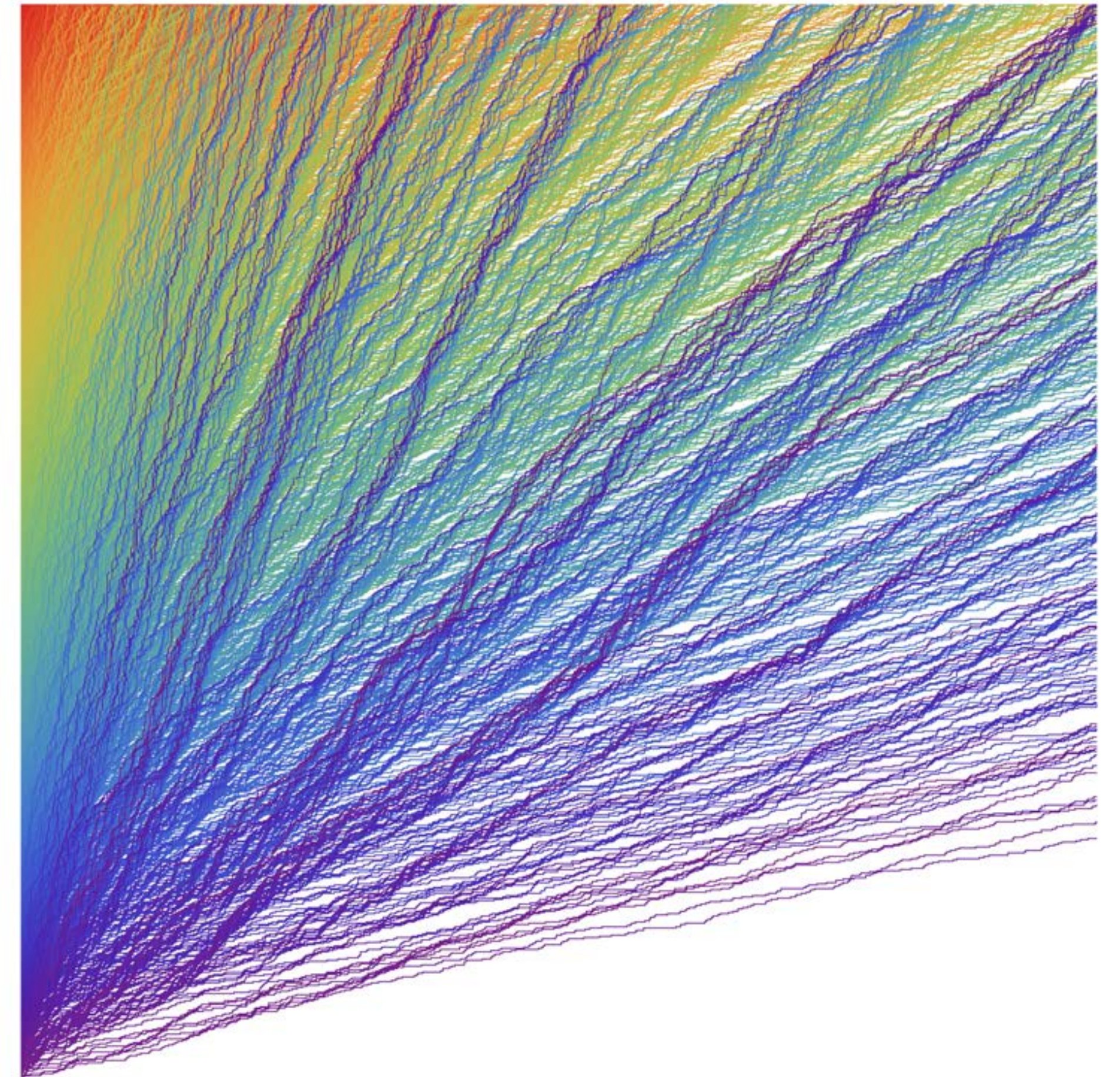
Colored stochastic six-vertex model (converges to colored ASEP)

Red > Green



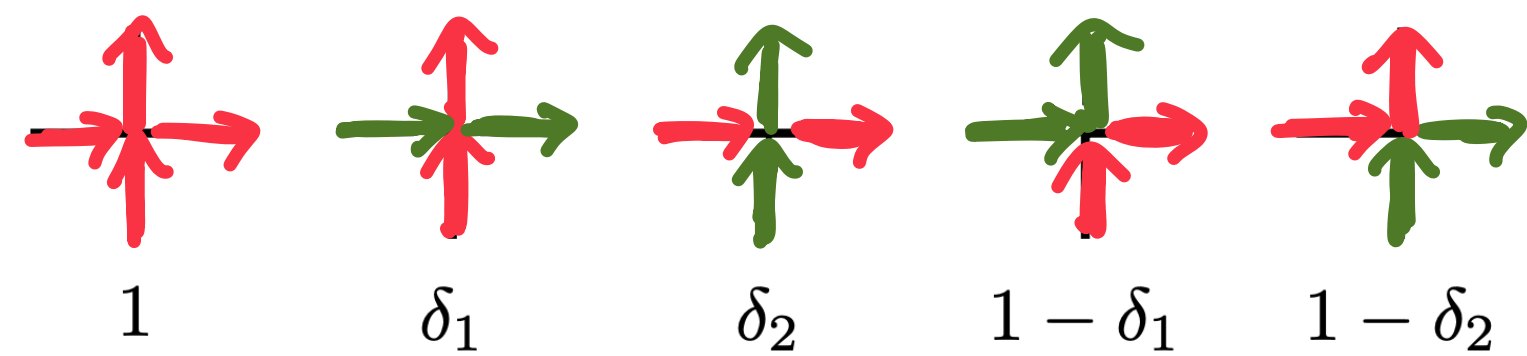
$$u := \frac{1 - \delta_1}{1 - \delta_2},$$

$$q := \delta_1 / \delta_2$$



Colored stochastic six-vertex model (converges to colored ASEP)

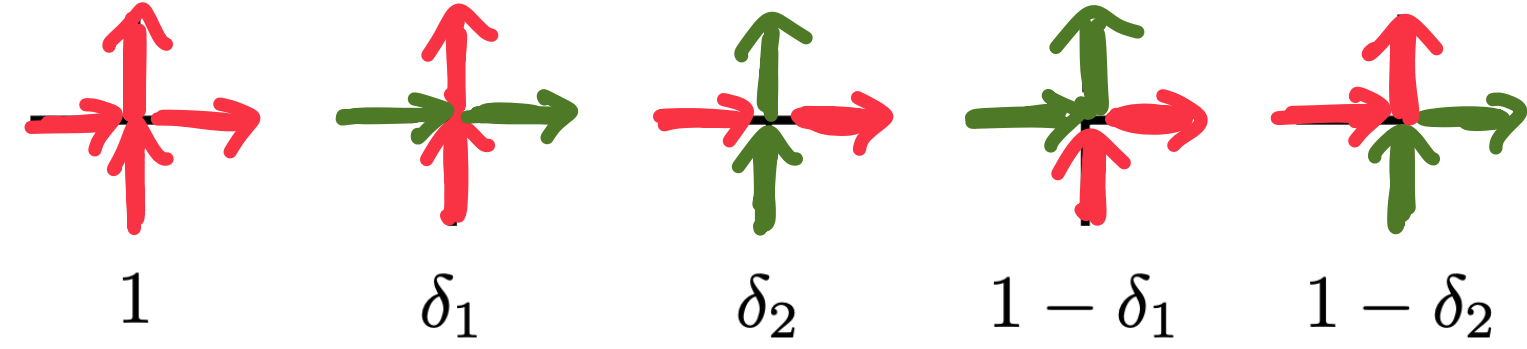
Red > Green



$$u := \frac{1 - \delta_1}{1 - \delta_2}, \quad q := \delta_1 / \delta_2$$

Colored stochastic six-vertex model (converges to colored ASEP)

Red > Green

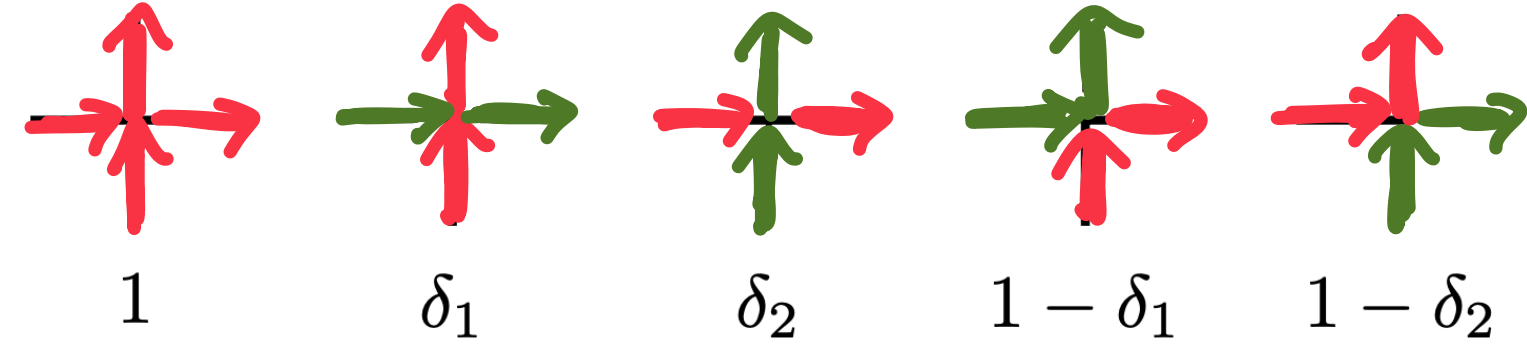


$$u := \frac{1 - \delta_1}{1 - \delta_2}, \quad q := \delta_1 / \delta_2$$

- **Fusion and Yang-Baxter equation.**

Colored stochastic six-vertex model (converges to colored ASEP)

Red > Green



$$u := \frac{1 - \delta_1}{1 - \delta_2}, \quad q := \delta_1 / \delta_2$$

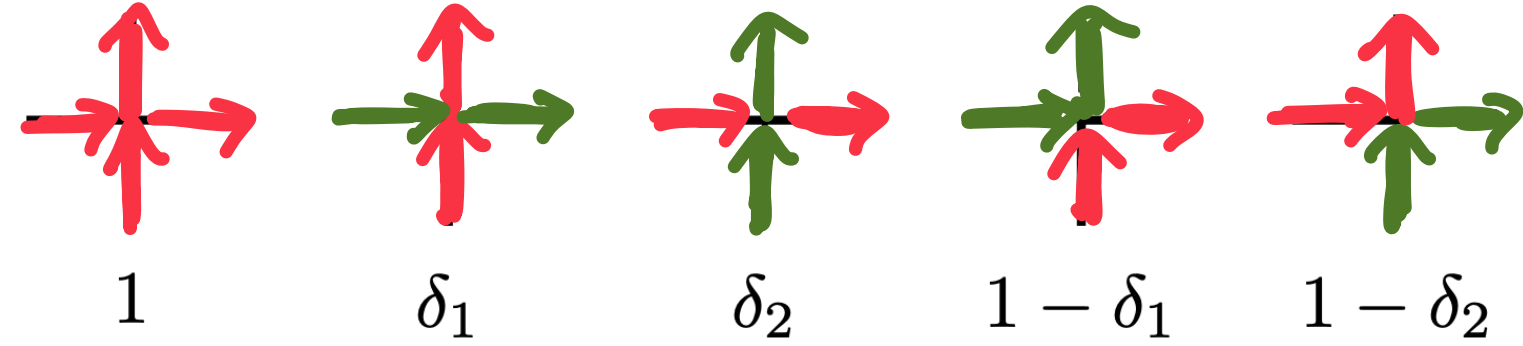
- **Fusion and Yang-Baxter equation.**

Higher spin, higher rank stochastic weights.

Related to $U_q(\widehat{sl}_{n+1})$; $1 \leq k < \ell \leq n$

Colored stochastic six-vertex model (converges to colored ASEP)

Red > Green

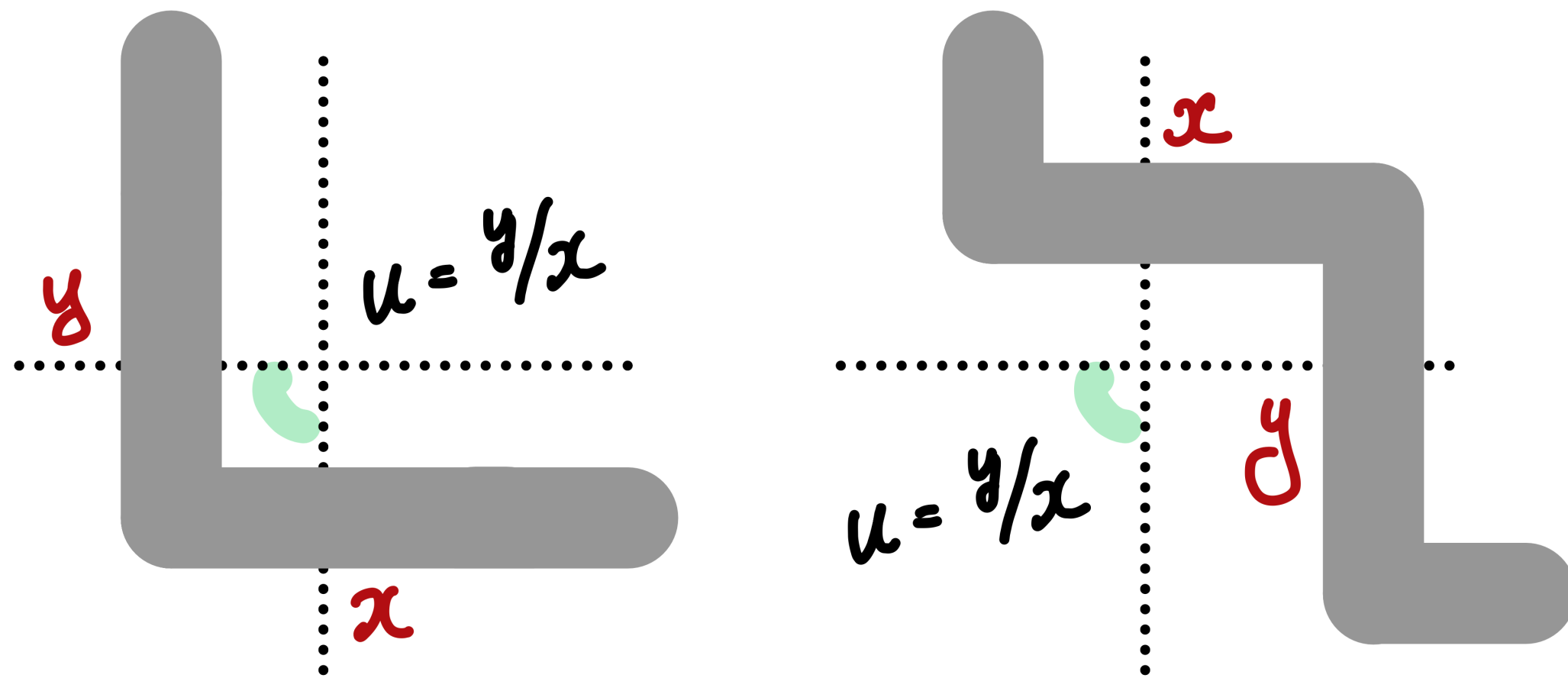


$$u := \frac{1 - \delta_1}{1 - \delta_2}, \quad q := \delta_1 / \delta_2$$

- Fusion and Yang-Baxter equation.**

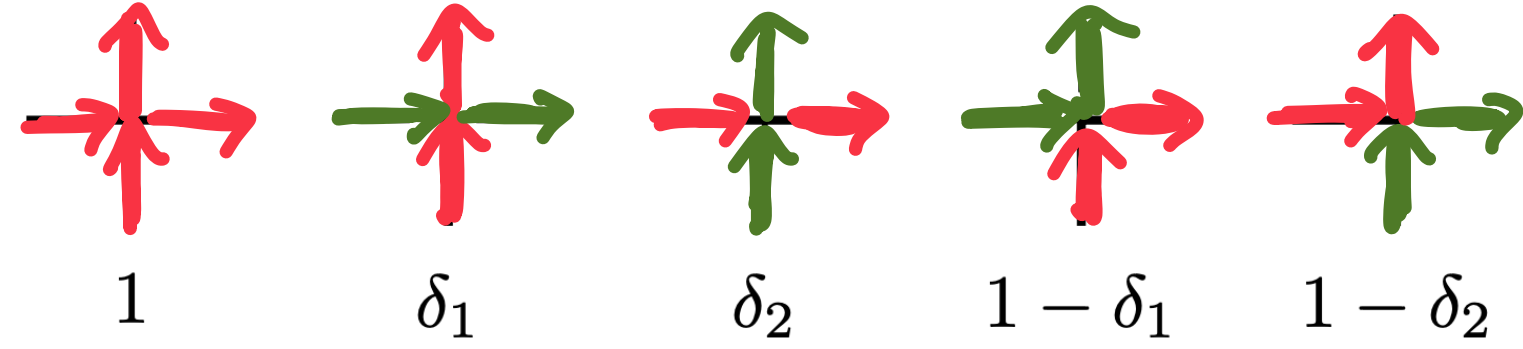
Higher spin, higher rank stochastic weights.

Related to $U_q(\widehat{sl}_{n+1})$; $1 \leq k < \ell \leq n$



Colored stochastic six-vertex model (converges to colored ASEP)

Red > Green

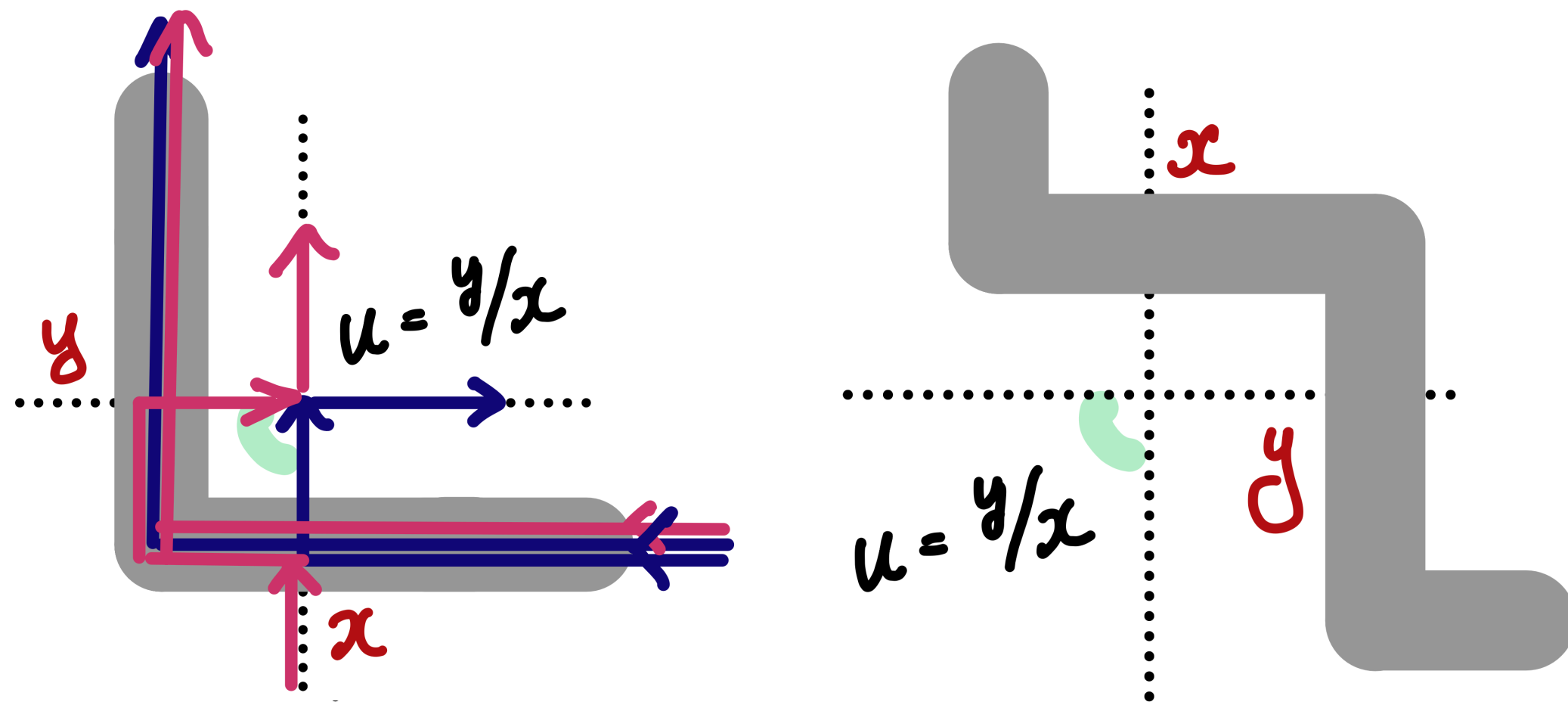


$$u := \frac{1 - \delta_1}{1 - \delta_2}, \quad q := \delta_1 / \delta_2$$

- Fusion and Yang-Baxter equation.**

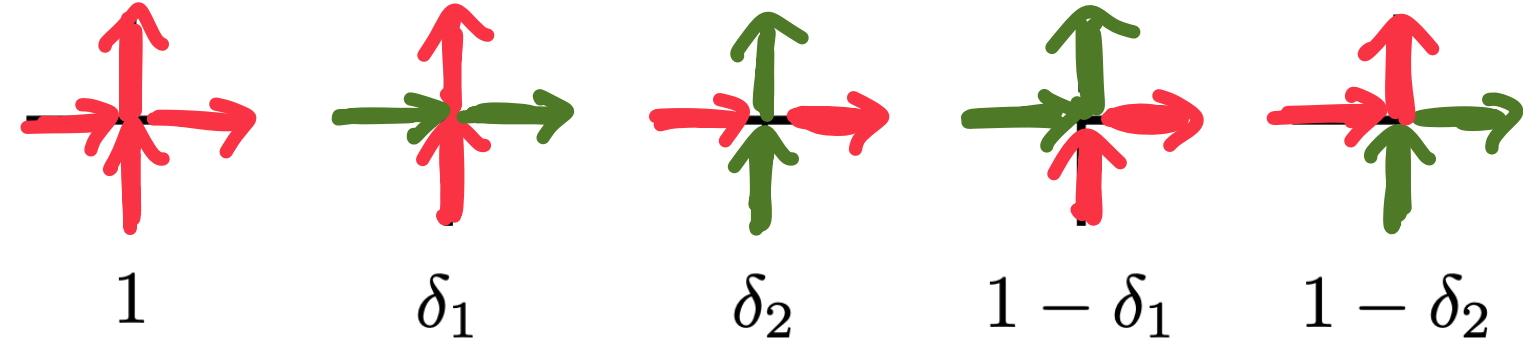
Higher spin, higher rank stochastic weights.

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Colored stochastic six-vertex model (converges to colored ASEP)

Red > Green

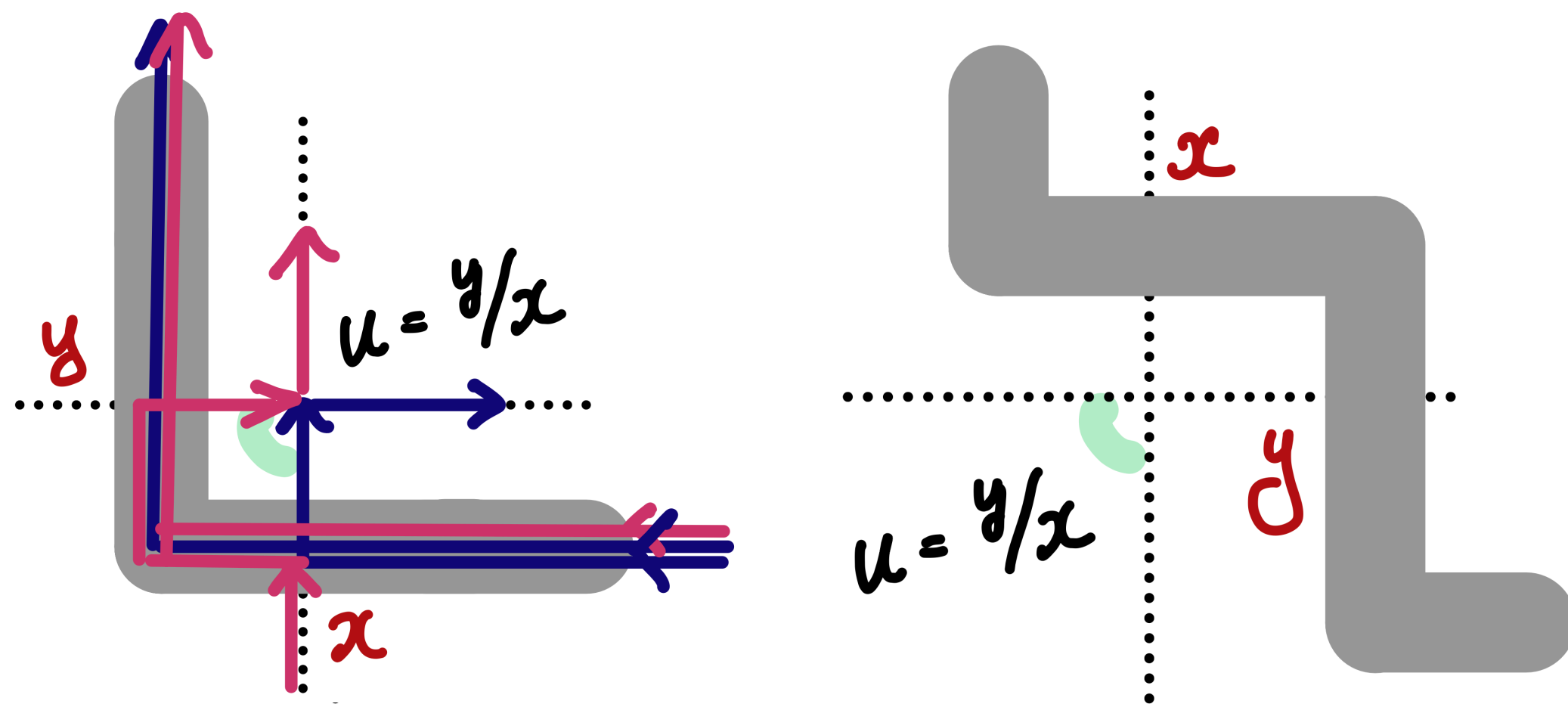


$$u := \frac{1 - \delta_1}{1 - \delta_2}, \quad q := \delta_1 / \delta_2$$

- Fusion and Yang-Baxter equation.**

Higher spin, higher rank stochastic weights.

Related to $U_q(\widehat{sl}_{n+1})$; $1 \leq k < \ell \leq n$

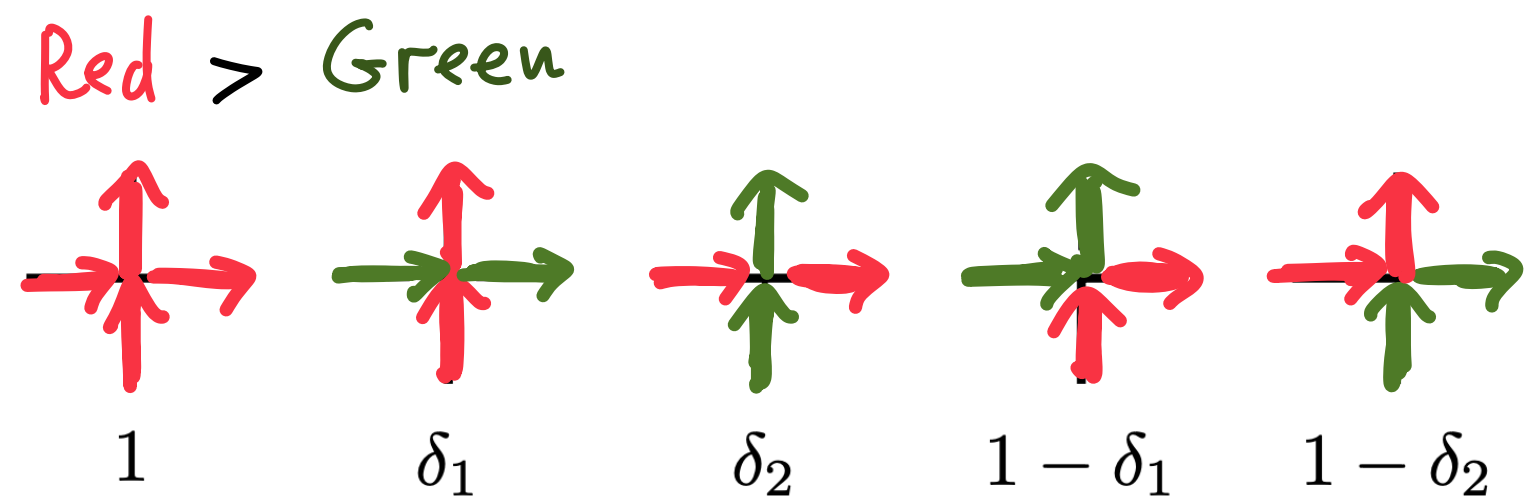


- Set the number of arrows of a given**

color m to $+\infty$. We get $\mathbb{W}_{S_m, x_m}^{(-m)}$ from

the beginning (up to simple factors).

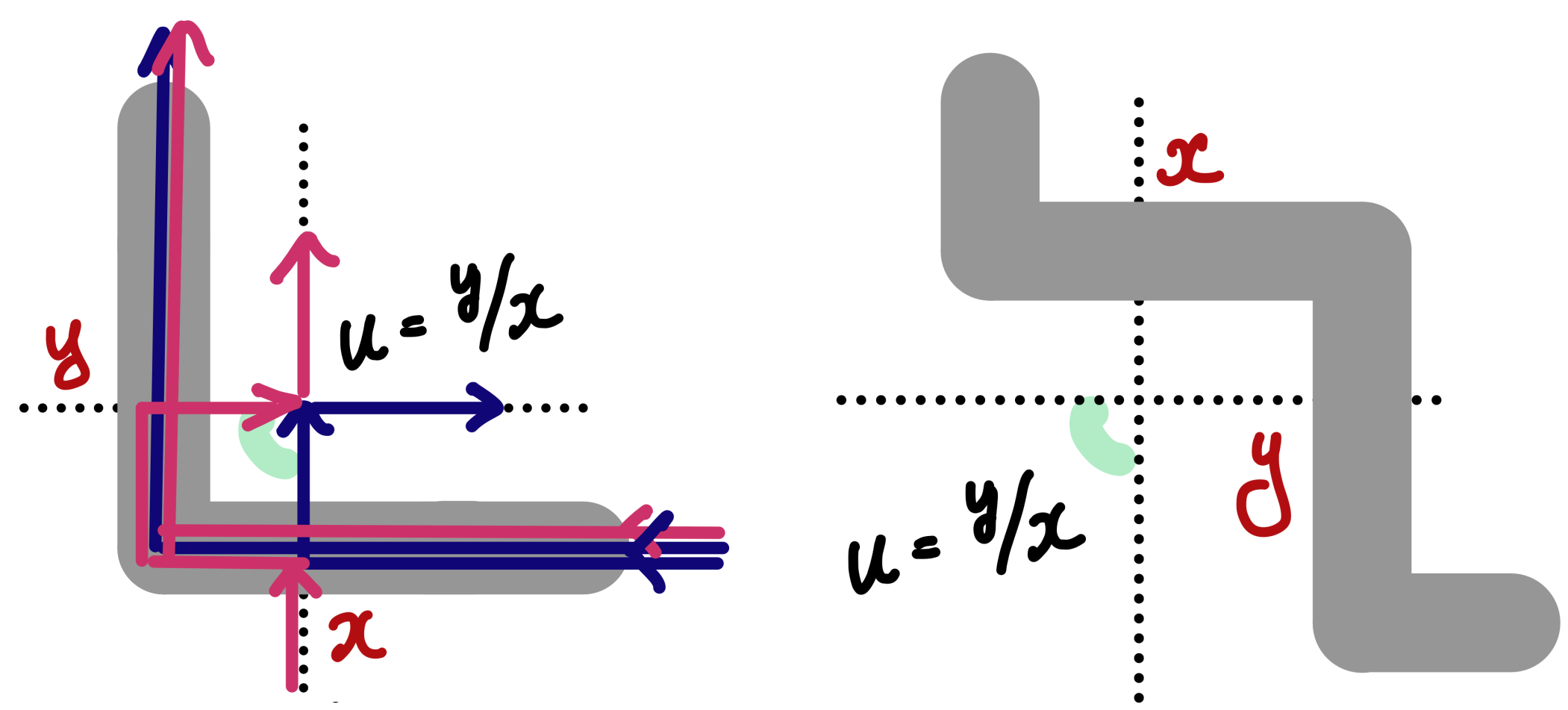
Colored stochastic six-vertex model (converges to colored ASEP)



$$u := \frac{1 - \delta_1}{1 - \delta_2}, \quad q := \delta_1 / \delta_2$$

- Fusion and Yang-Baxter equation.**

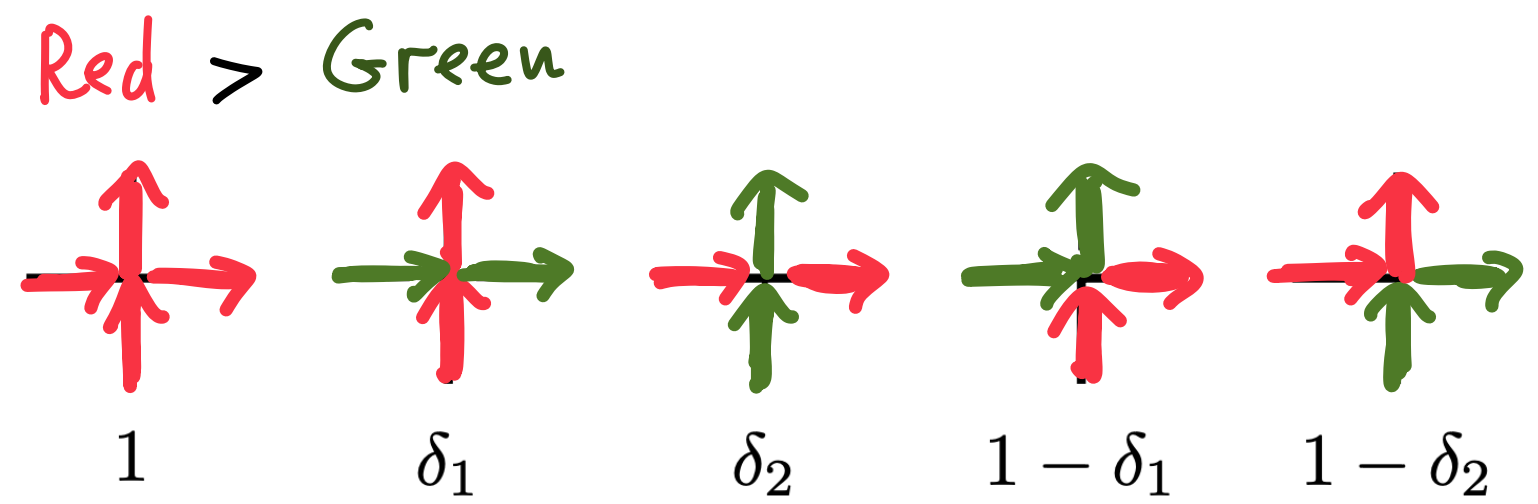
Higher spin, higher rank stochastic weights.
 Related to $U_q(\widehat{sl}_{n+1})$; $1 \leq k < \ell \leq n$



$\begin{array}{c} \mathbf{A} \\ \text{---} \\ \mathbf{A} \end{array}$ $\frac{1 + xq^{ \mathbf{A} }}{1 + x}$	$\begin{array}{c} \mathbf{A} \\ \text{---} \\ \mathbf{A} \end{array}$ $\frac{(x + \nu q^{A_k}) q^{A_{[k+1,n]}}}{1 + x}$	$\begin{array}{c} \mathbf{A}_k^- \\ \text{---} \\ \mathbf{A} \end{array}$ $\frac{x(1 - q^{A_k}) q^{A_{[k+1,n]}}}{1 + x}$
$\begin{array}{c} \mathbf{A}_k^+ \\ \text{---} \\ \mathbf{A} \end{array}$ $\frac{1 - \nu q^{ \mathbf{A} }}{1 + x}$	$\begin{array}{c} \mathbf{A}_{k\ell}^{+-} \\ \text{---} \\ \mathbf{A} \end{array}$ $\frac{x(1 - q^{A_\ell}) q^{A_{[\ell+1,n]}}}{1 + x}$	$\begin{array}{c} \mathbf{A}_{\ell k}^{+-} \\ \text{---} \\ \mathbf{A} \end{array}$ $\frac{\nu(1 - q^{A_k}) q^{A_{[k+1,n]}}}{1 + x}$

- Set the number of arrows of a given color m to $+\infty$. We get $\mathbb{W}_{S_m, x_m}^{(-m)}$ from the beginning (up to simple factors).

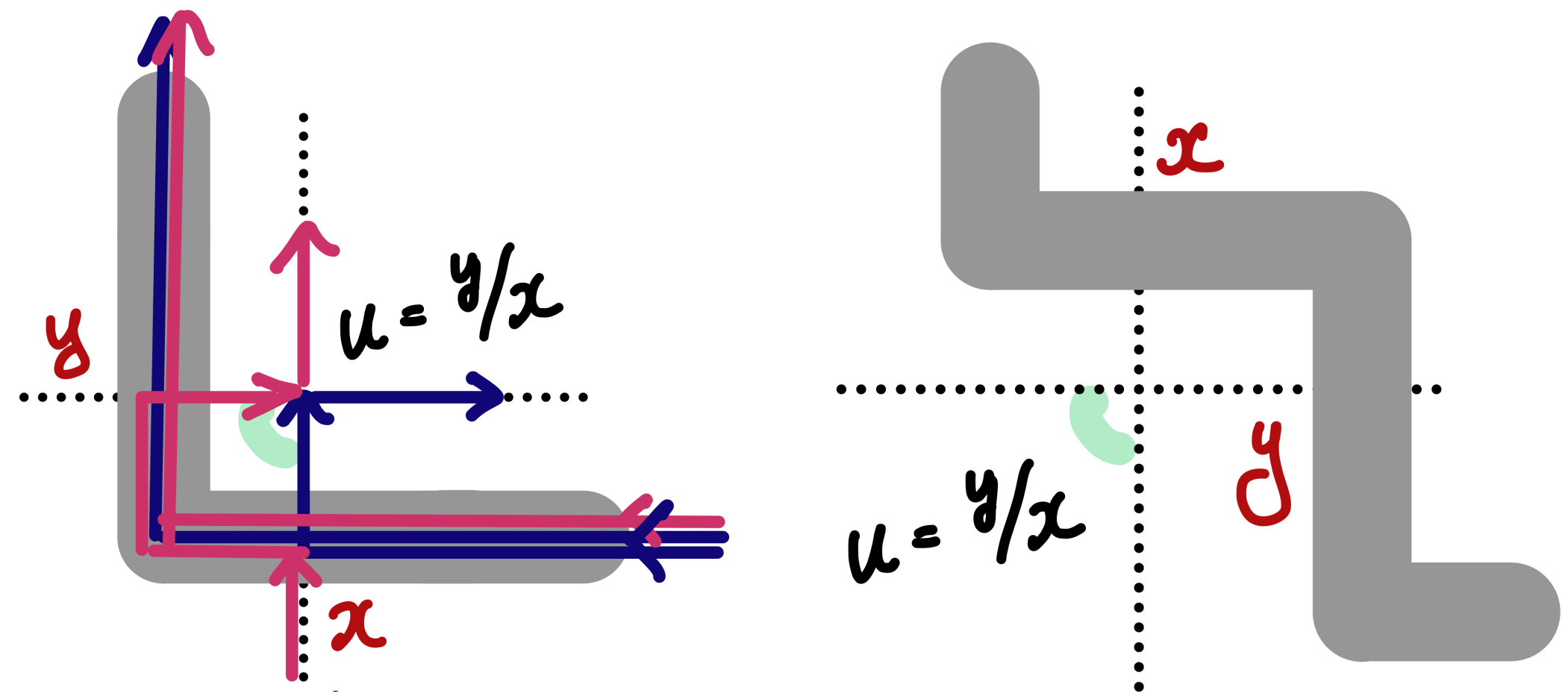
Colored stochastic six-vertex model (converges to colored ASEP)



$$u := \frac{1 - \delta_1}{1 - \delta_2}, \quad q := \delta_1 / \delta_2$$

- Fusion and Yang-Baxter equation.**

Higher spin, higher rank stochastic weights.
 Related to $U_q(\widehat{sl}_{n+1})$; $1 \leq k < \ell \leq n$



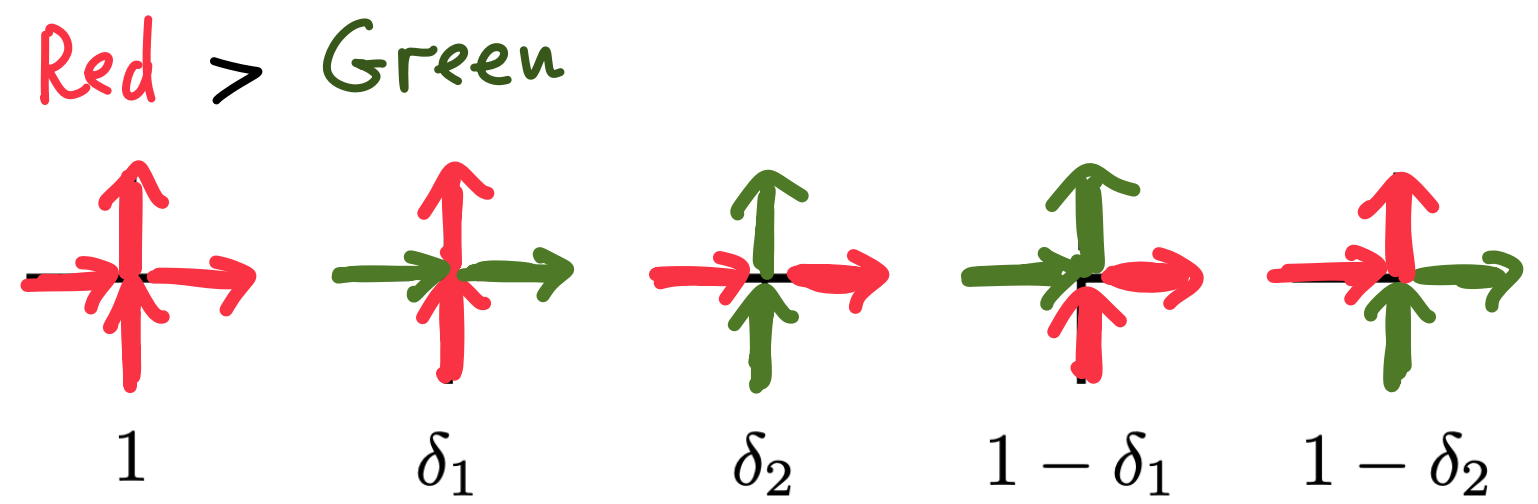
$\begin{array}{c} \mathbf{A} \\ \text{---} \\ \mathbf{A} \end{array}$ $\frac{1 + xq^{ \mathbf{A} }}{1 + x}$	$\begin{array}{c} \mathbf{A} \\ \text{---} \\ \mathbf{A} \end{array}$ $\frac{(x + \nu q^{A_k}) q^{A_{[k+1,n]}}}{1 + x}$	$\begin{array}{c} \mathbf{A}_k^- \\ \text{---} \\ \mathbf{A} \end{array}$ $\frac{x(1 - q^{A_k}) q^{A_{[k+1,n]}}}{1 + x}$
$\begin{array}{c} \mathbf{A}_k^+ \\ \text{---} \\ \mathbf{A} \end{array}$ $\frac{1 - \nu q^{ \mathbf{A} }}{1 + x}$	$\begin{array}{c} \mathbf{A}_{k\ell}^{+-} \\ \text{---} \\ \mathbf{A} \end{array}$ $\frac{x(1 - q^{A_\ell}) q^{A_{[\ell+1,n]}}}{1 + x}$	$\begin{array}{c} \mathbf{A}_{\ell k}^{+-} \\ \text{---} \\ \mathbf{A} \end{array}$ $\frac{\nu(1 - q^{A_k}) q^{A_{[k+1,n]}}}{1 + x}$

- Set the number of arrows of a given**

color m to $+\infty$. We get $\mathbb{W}_{S_m, x_m}^{(-m)}$ from the beginning (up to simple factors).

(Fused weights preserve the incoming/outgoing arrows before sending color m to infinity)

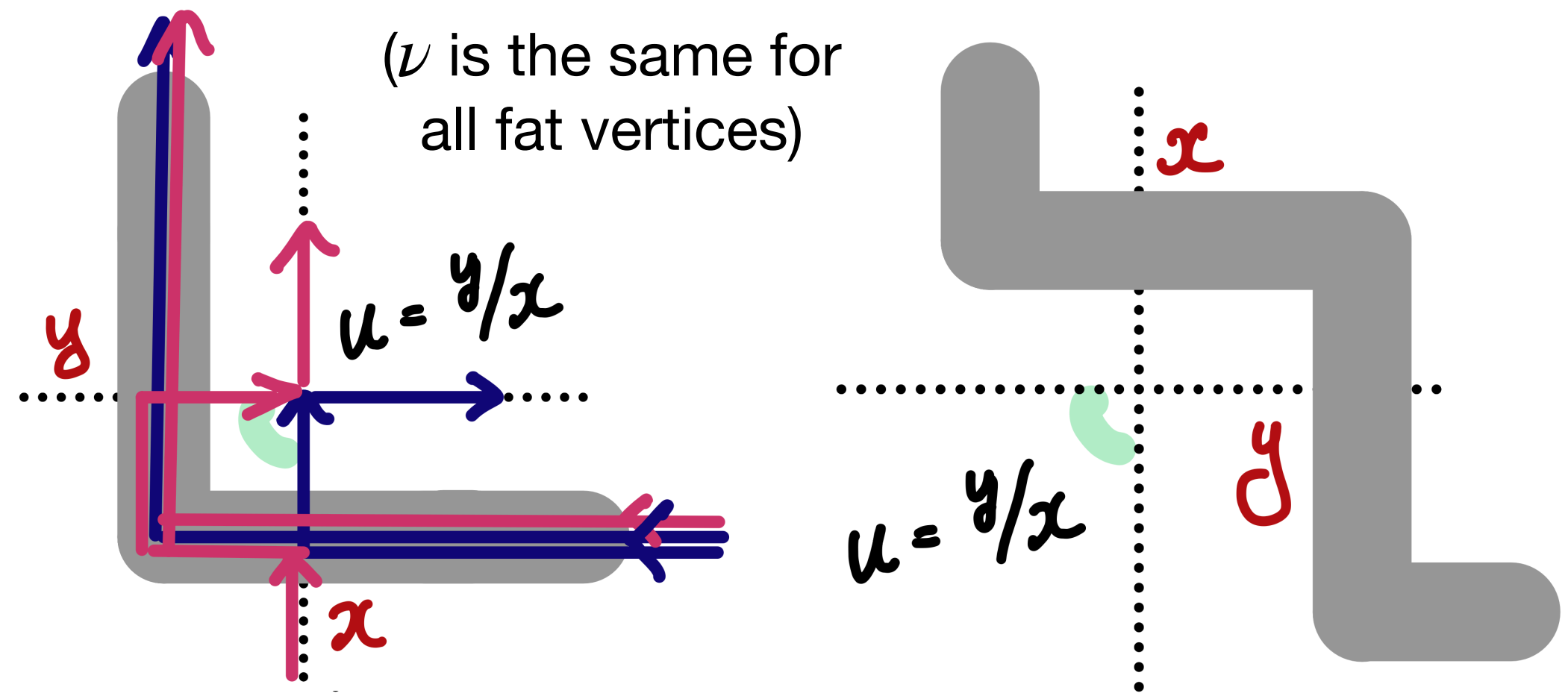
Colored stochastic six-vertex model (converges to colored ASEP)



$$u := \frac{1 - \delta_1}{1 - \delta_2}, \quad q := \delta_1 / \delta_2$$

- Fusion and Yang-Baxter equation.**

Higher spin, higher rank stochastic weights.
 Related to $U_q(\widehat{sl}_{n+1})$; $1 \leq k < \ell \leq n$



$\begin{array}{c} \mathbf{A} \\ \\ 0 \text{---} \mathbf{A} \text{---} 0 \\ \\ \mathbf{A} \end{array}$ $\frac{1 + xq^{ \mathbf{A} }}{1 + x}$	$\begin{array}{c} \mathbf{A} \\ \\ k \text{---} \mathbf{A} \text{---} k \\ \\ \mathbf{A} \end{array}$ $\frac{(x + \nu q^{A_k}) q^{A_{[k+1,n]}}}{1 + x}$	$\begin{array}{c} \mathbf{A}_k^- \\ \\ 0 \text{---} \mathbf{A} \text{---} k \\ \\ \mathbf{A} \end{array}$ $\frac{x(1 - q^{A_k}) q^{A_{[k+1,n]}}}{1 + x}$
$\begin{array}{c} \mathbf{A}_k^+ \\ \\ k \text{---} \mathbf{A} \text{---} 0 \\ \\ \mathbf{A} \end{array}$ $\frac{1 - \nu q^{ \mathbf{A} }}{1 + x}$	$\begin{array}{c} \mathbf{A}_{k\ell}^{+-} \\ \\ k \text{---} \mathbf{A} \text{---} \ell \\ \\ \mathbf{A} \end{array}$ $\frac{x(1 - q^{A_\ell}) q^{A_{[\ell+1,n]}}}{1 + x}$	$\begin{array}{c} \mathbf{A}_{\ell k}^{+-} \\ \\ \ell \text{---} \mathbf{A} \text{---} k \\ \\ \mathbf{A} \end{array}$ $\frac{\nu(1 - q^{A_k}) q^{A_{[k+1,n]}}}{1 + x}$

- Set the number of arrows of a given**

color m to $+\infty$. We get $\mathbb{W}_{S_m, x_m}^{(-m)}$ from the beginning (up to simple factors).

(Fused weights preserve the incoming/outgoing arrows before sending color m to infinity)

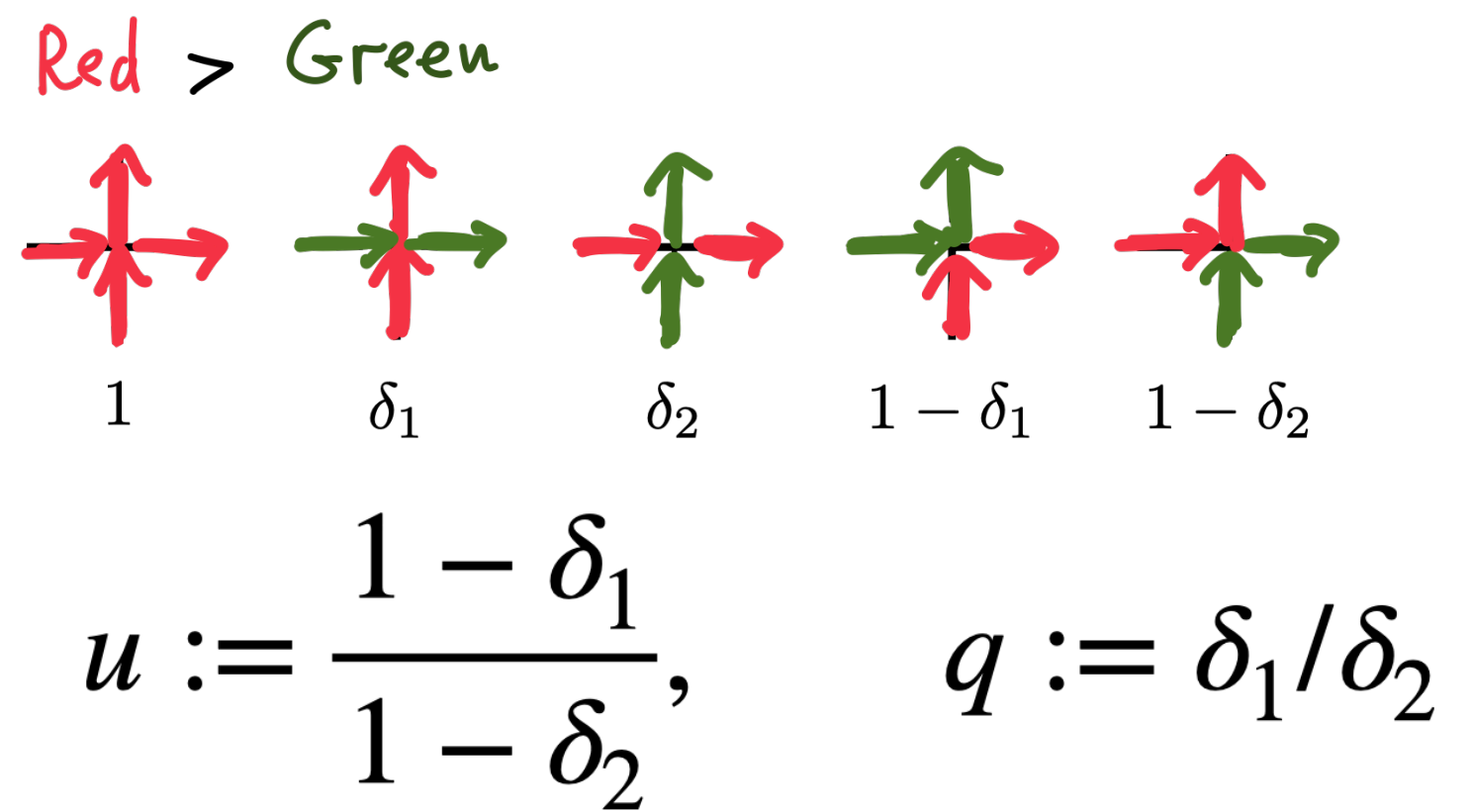
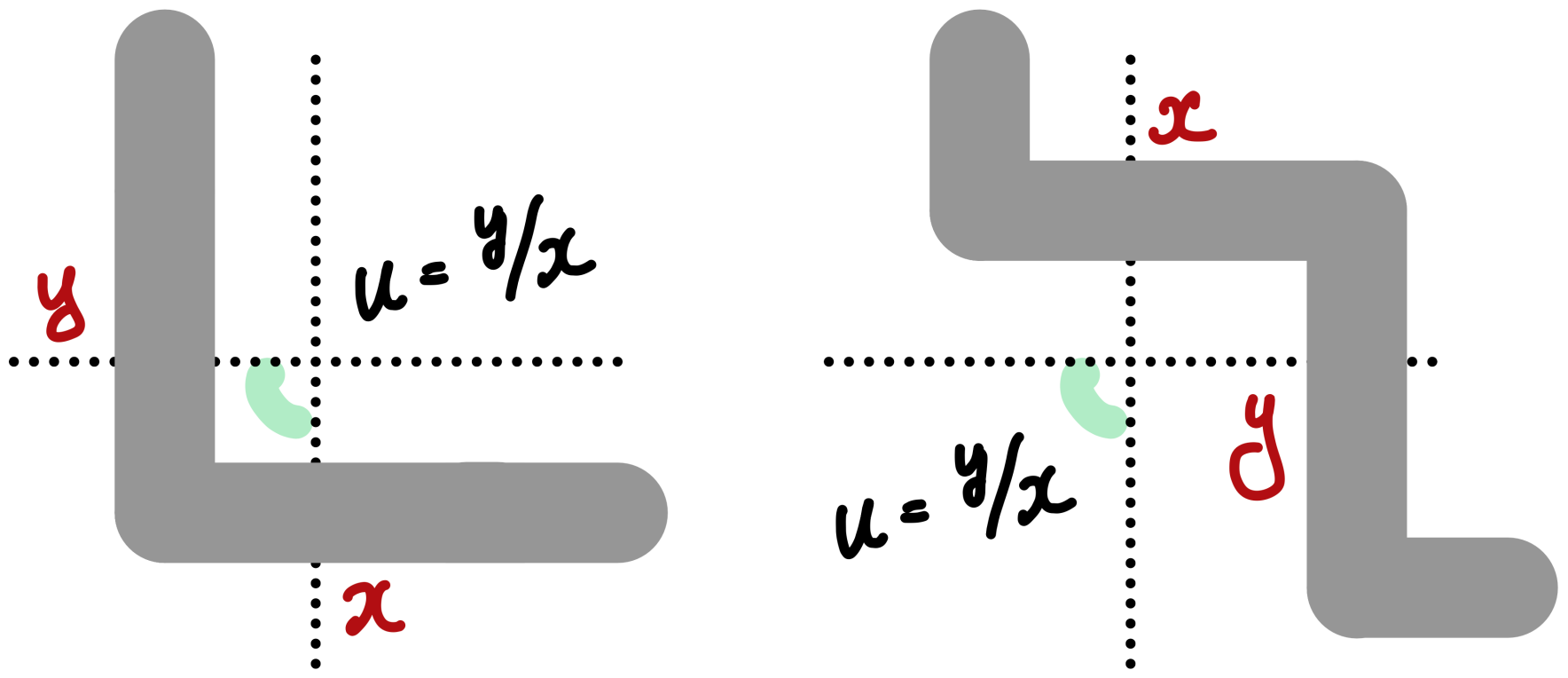
Colored stochastic six-vertex model. Color m goes to infinity

- Set the number of arrows of a given

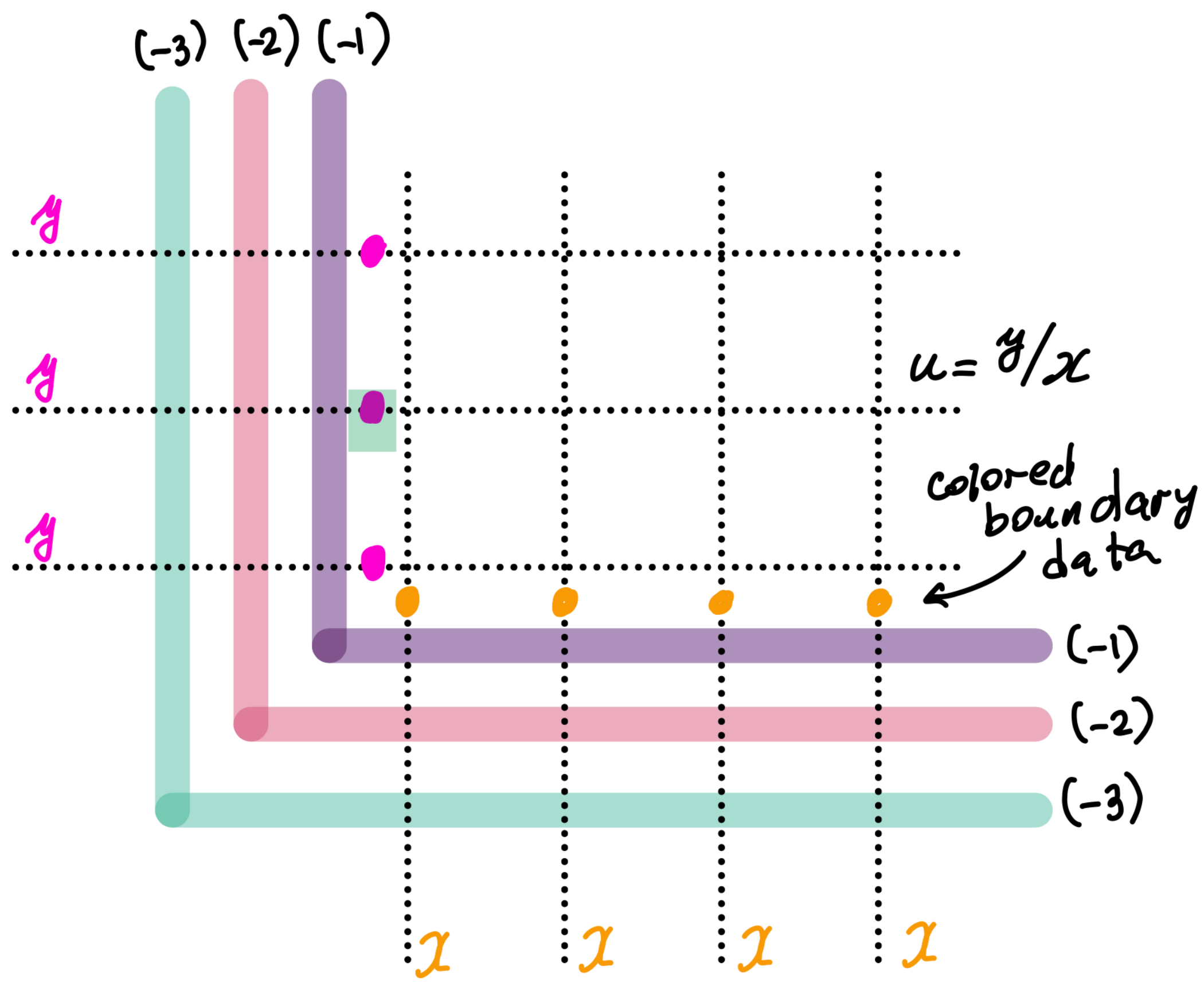
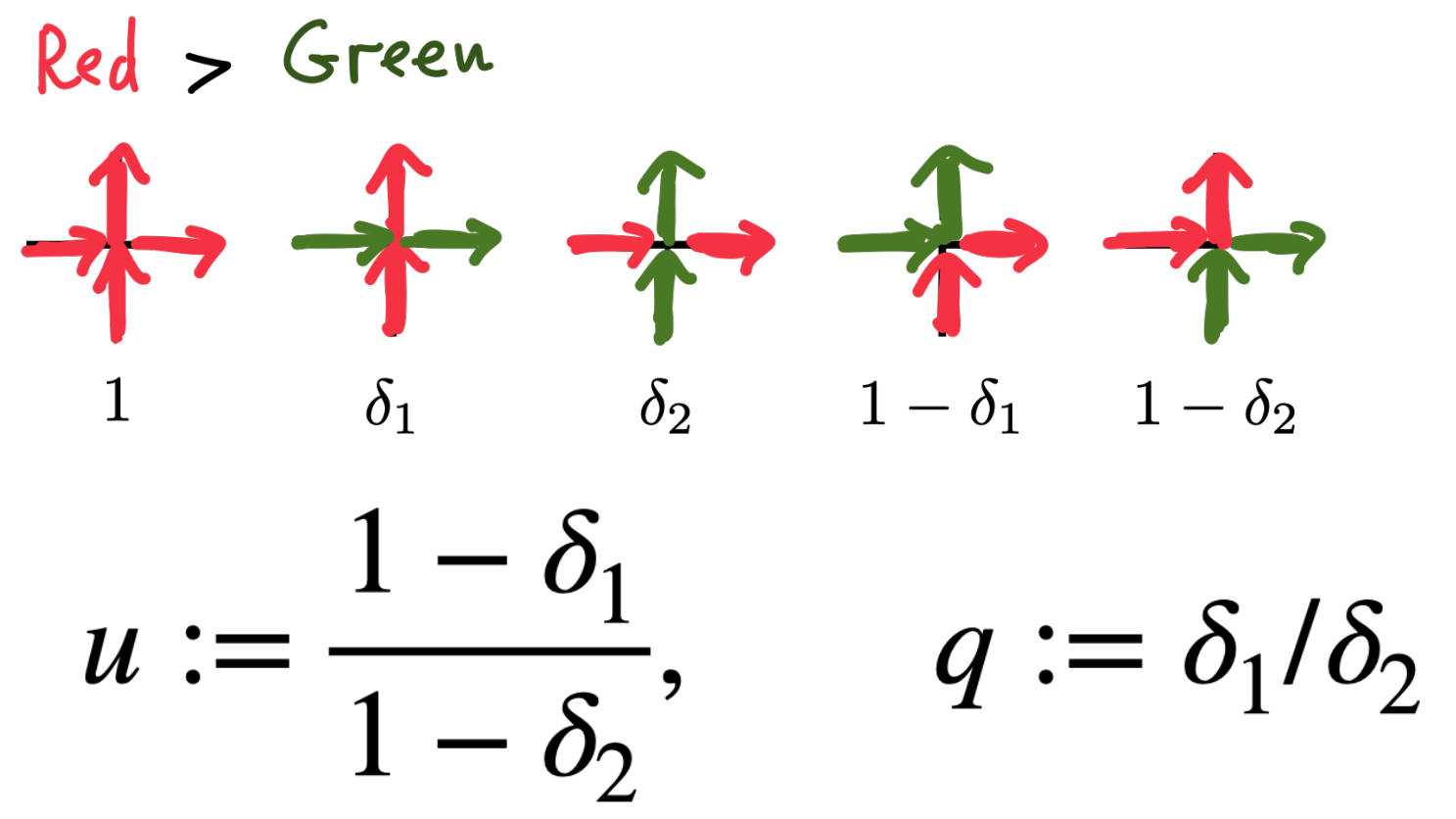
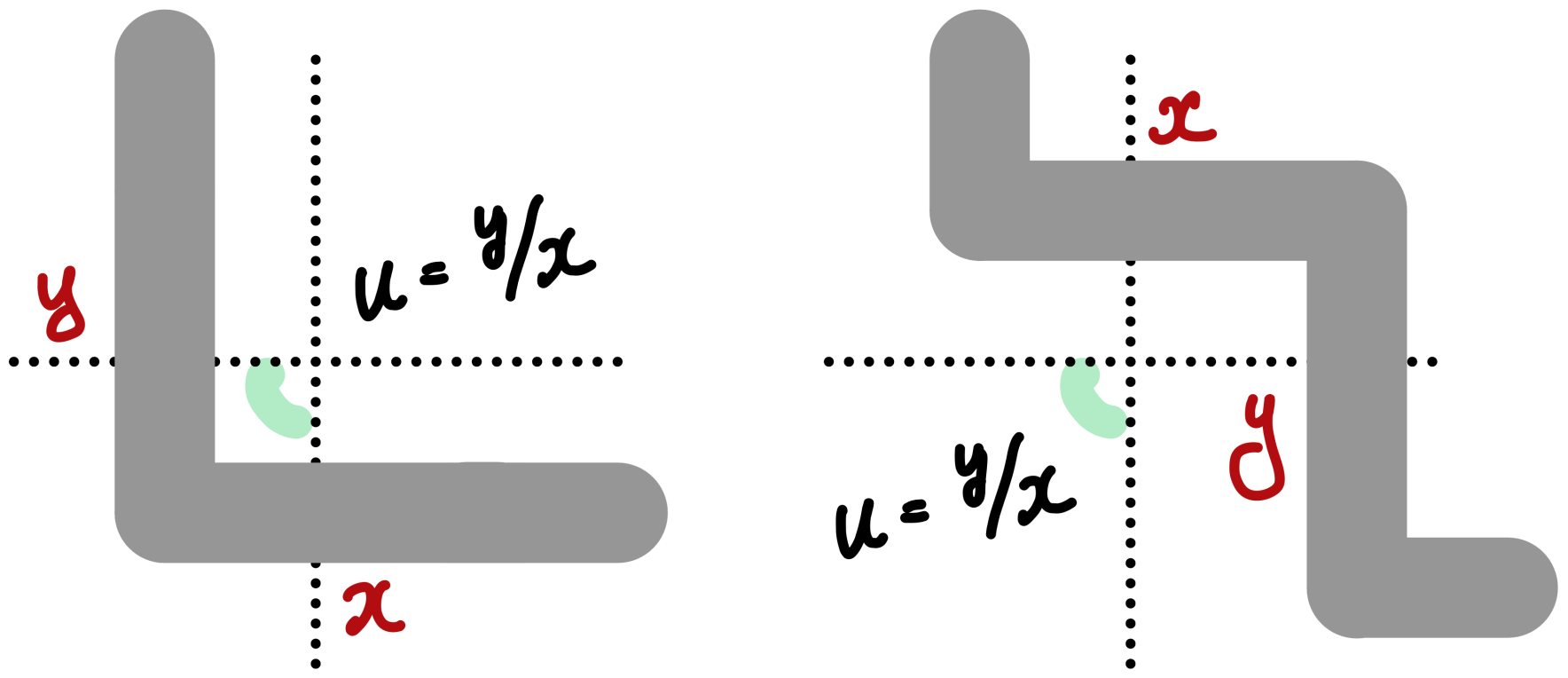
color m to $+\infty$. We get $\mathbb{W}_x^{(-m)}$: $m < k < \ell \leq n$

$\begin{array}{c} \mathbf{A} \\ \\ 0 \text{ --- } \mathbf{A} \text{ --- } 0 \\ \\ \mathbf{A} \end{array}$ $\frac{1}{1+x}$	$\begin{array}{c} \mathbf{A} \\ \\ k \text{ --- } \mathbf{A} \text{ --- } k \\ \\ \mathbf{A} \end{array}$ $\frac{x q^{\mathbf{A}_{[k+1,n]}}}{1+x}$	$\begin{array}{c} \mathbf{A}_k^- \\ \\ 0 \text{ --- } \mathbf{A} \text{ --- } k \\ \\ \mathbf{A} \end{array}$ $\frac{x(1 - q^{\mathbf{A}_k}) q^{\mathbf{A}_{[k+1,n]}}}{1+x}$	$\begin{array}{c} \mathbf{A} \\ \\ 0 \text{ --- } \mathbf{A} \text{ --- } m \\ \\ \mathbf{A} \end{array}$ $\frac{x q^{\mathbf{A}_{[m+1,n]}}}{1+x}$
$\begin{array}{c} \mathbf{A}_k^+ \\ \\ k \text{ --- } \mathbf{A} \text{ --- } 0 \\ \\ \mathbf{A} \end{array}$ $\frac{1}{1+x}$	$\begin{array}{c} \mathbf{A}_{k\ell}^{+-} \\ \\ k \text{ --- } \mathbf{A} \text{ --- } \ell \\ \\ \mathbf{A} \end{array}$ $\frac{x(1 - q^{\mathbf{A}_\ell}) q^{\mathbf{A}_{[\ell+1,n]}}}{1+x}$	$\begin{array}{c} \mathbf{A}_{\ell k}^{+-} \\ \\ \ell \text{ --- } \mathbf{A} \text{ --- } k \\ \\ \mathbf{A} \end{array}$ 0	$\begin{array}{c} \mathbf{A}_\ell^+ \\ \\ \ell \text{ --- } \mathbf{A} \text{ --- } m \\ \\ \mathbf{A} \end{array}$ 0

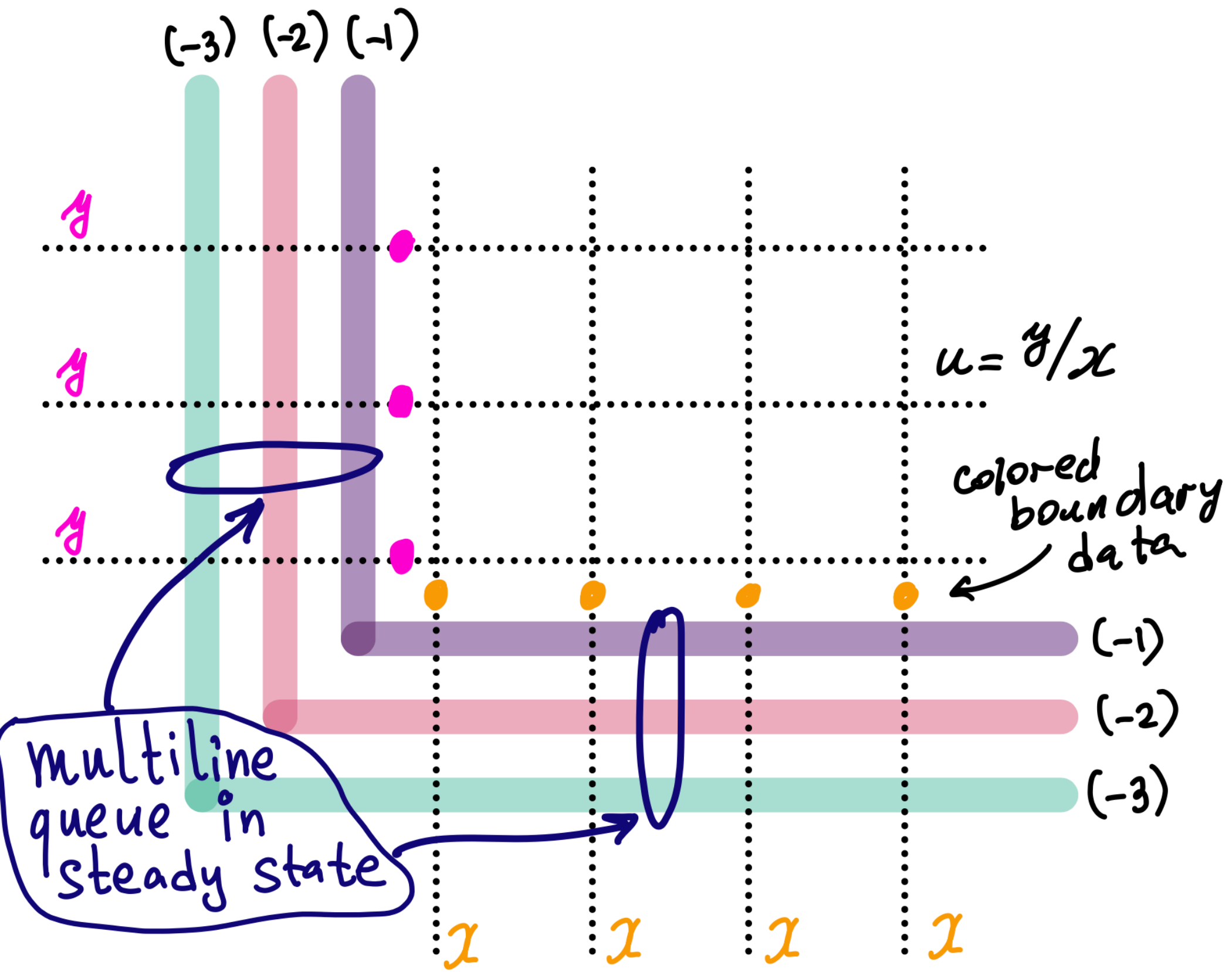
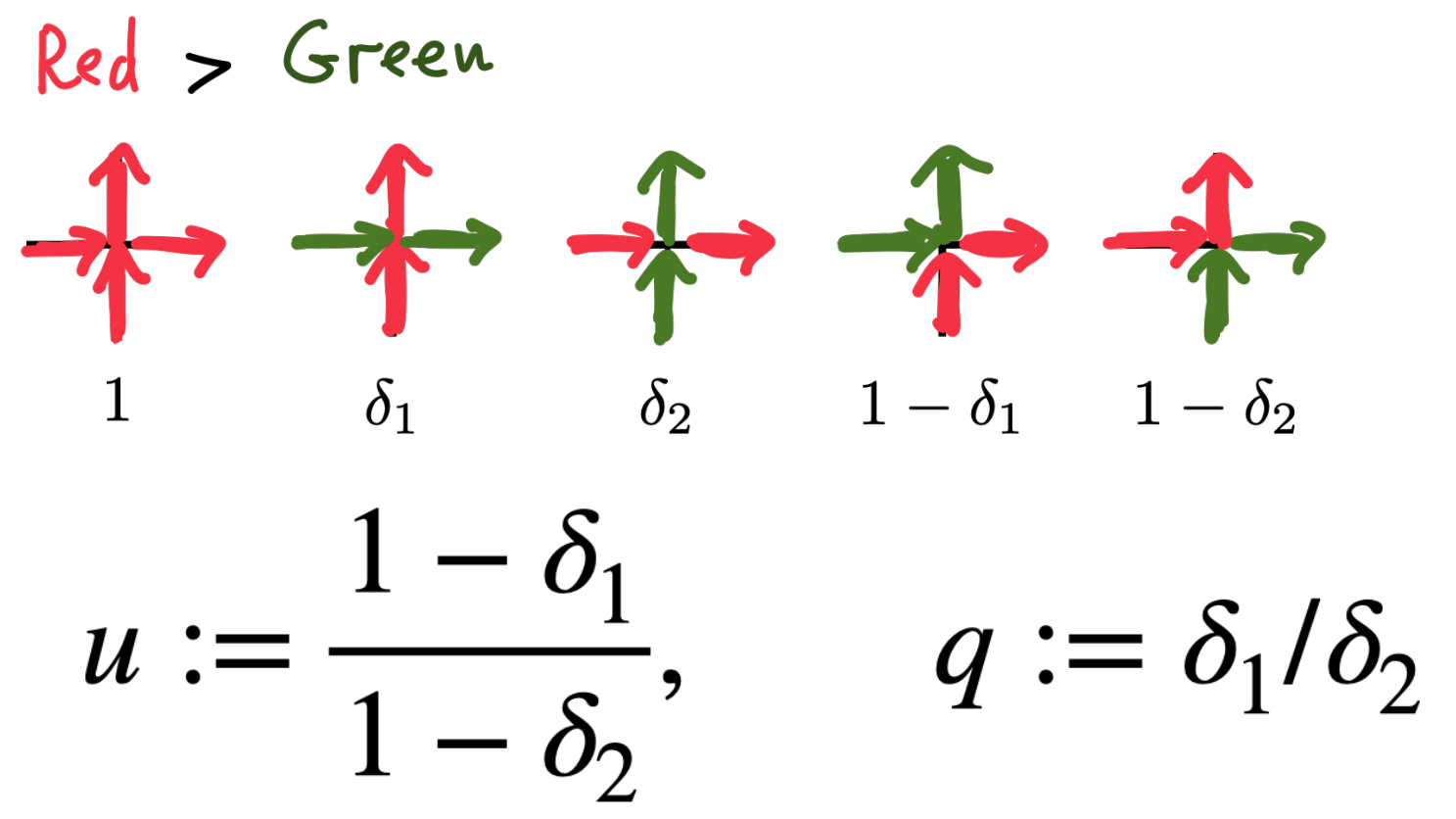
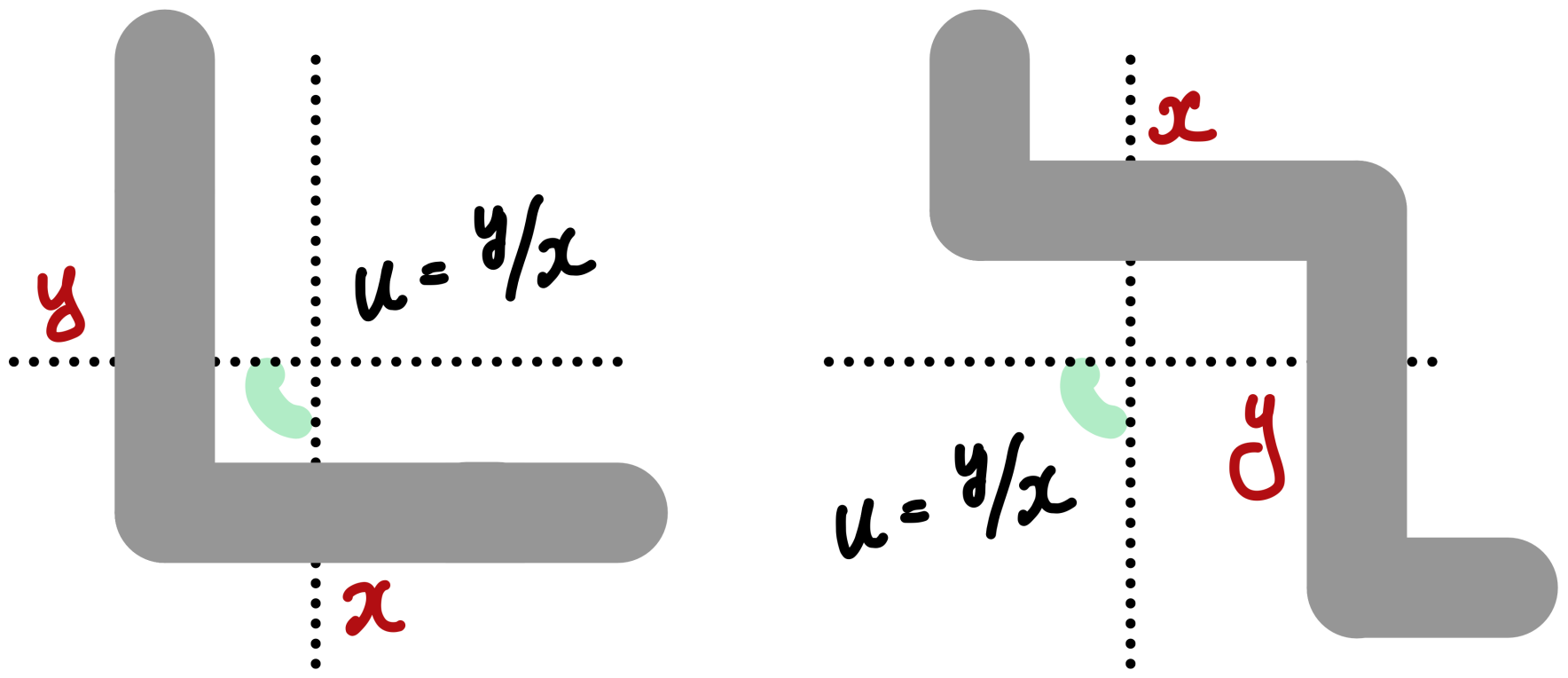
Colored stochastic six-vertex model. Many colors \Rightarrow many fat lines



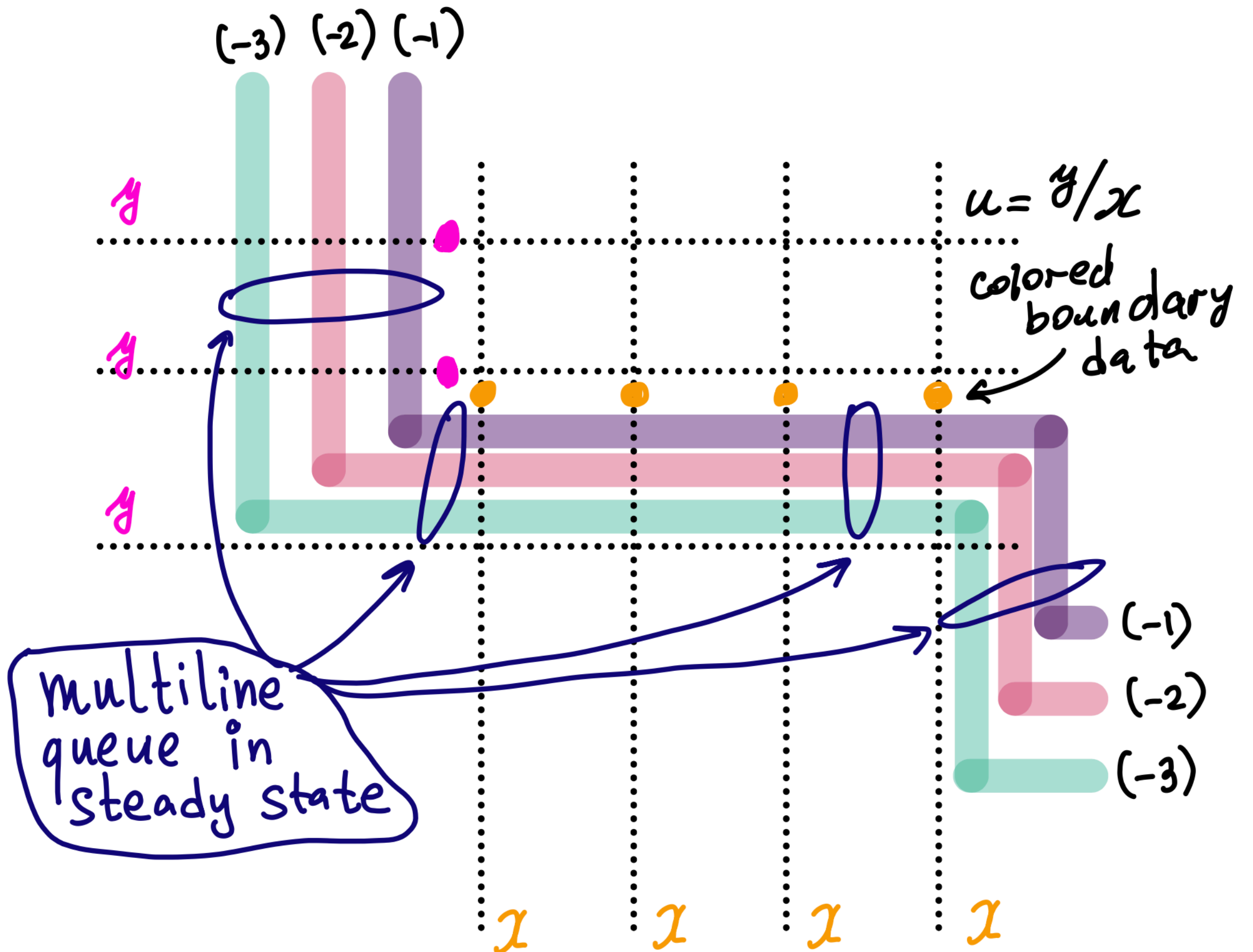
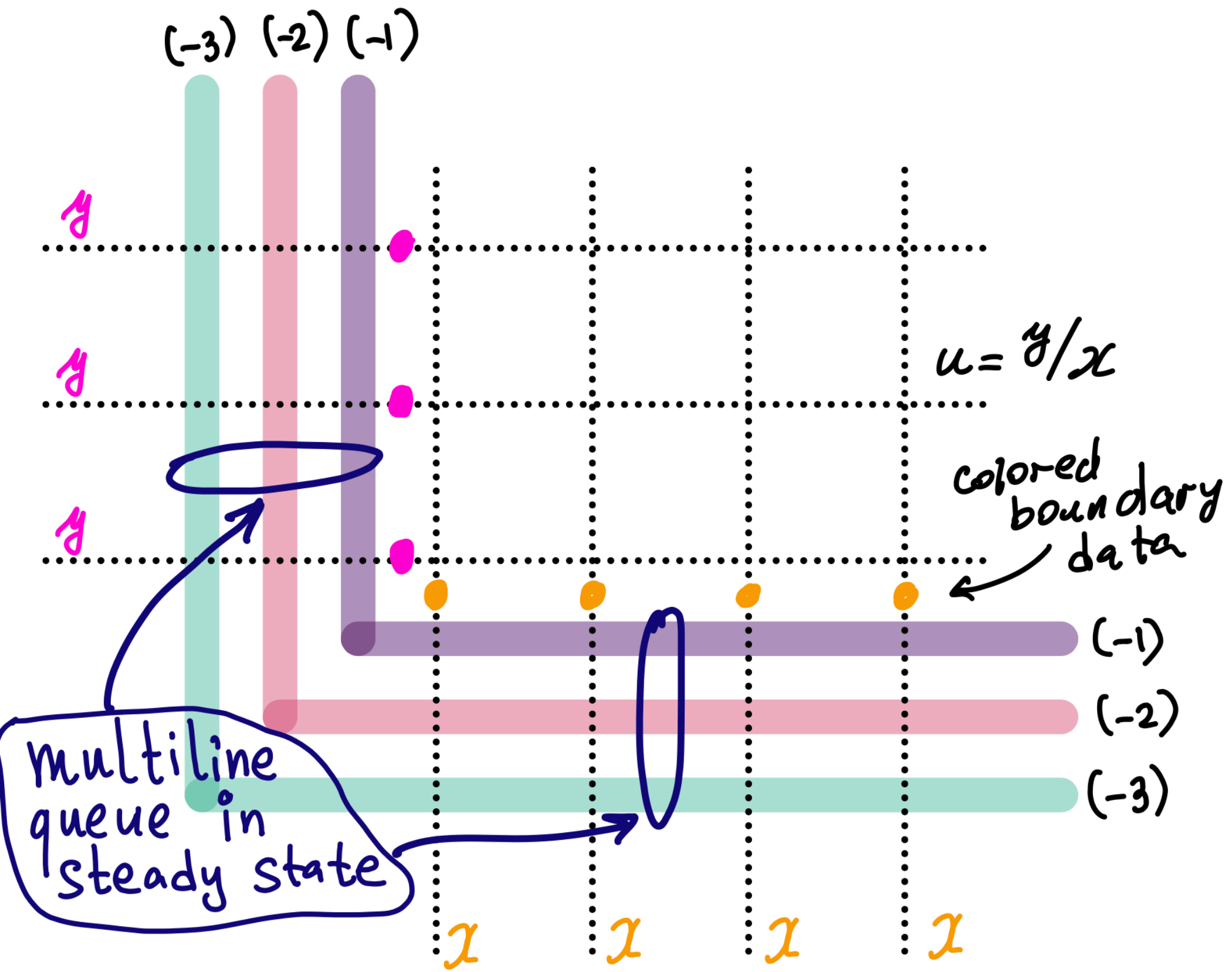
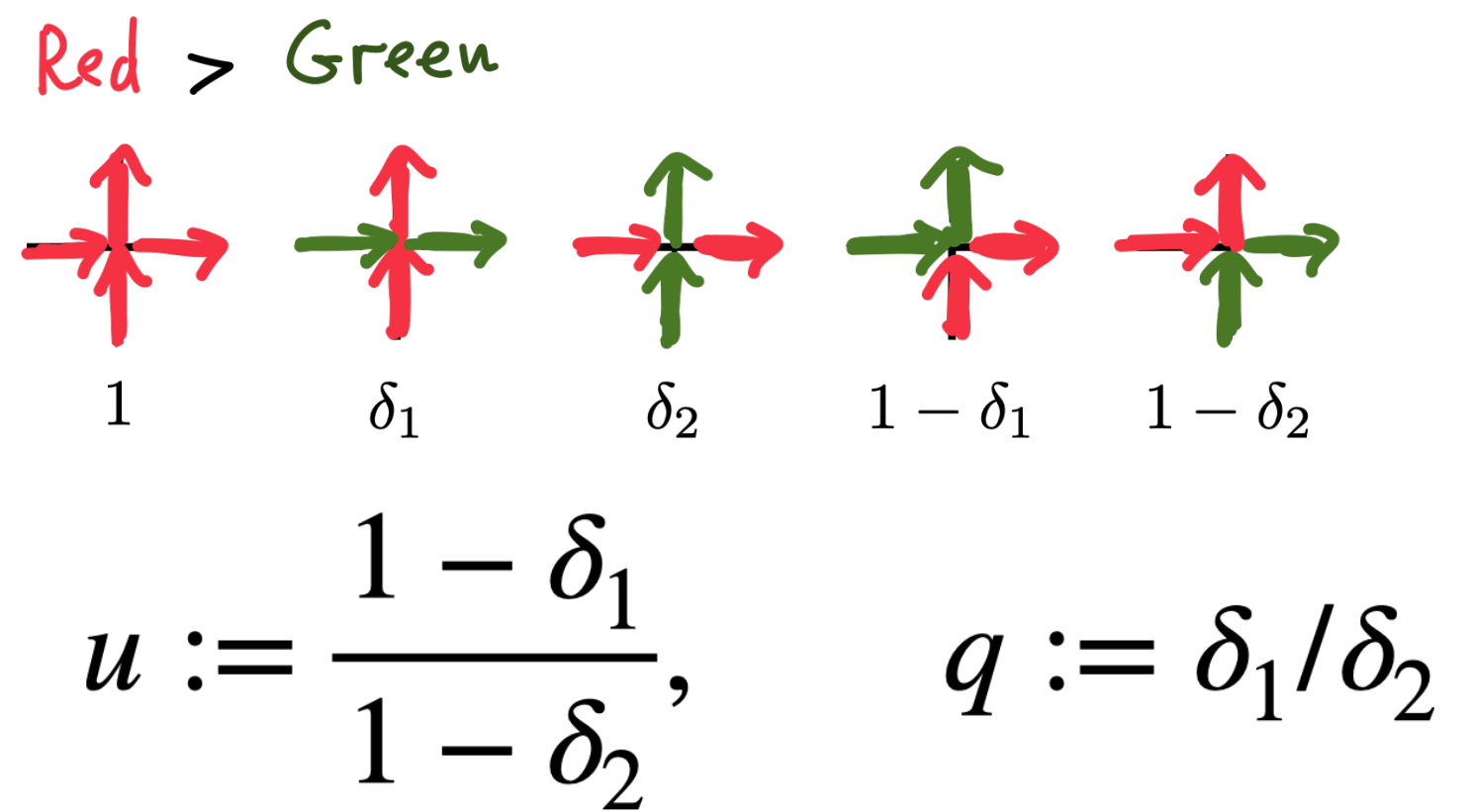
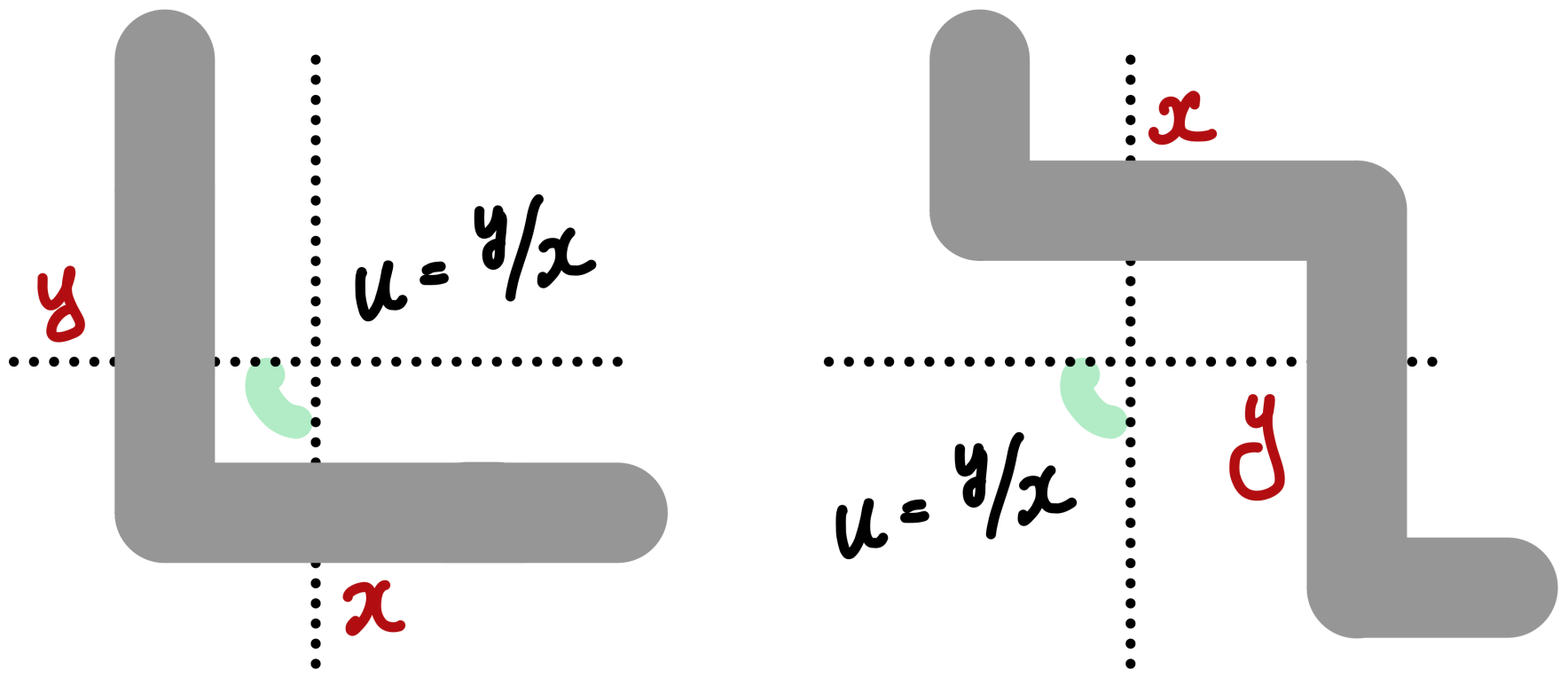
Colored stochastic six-vertex model. Many colors \Rightarrow many fat lines



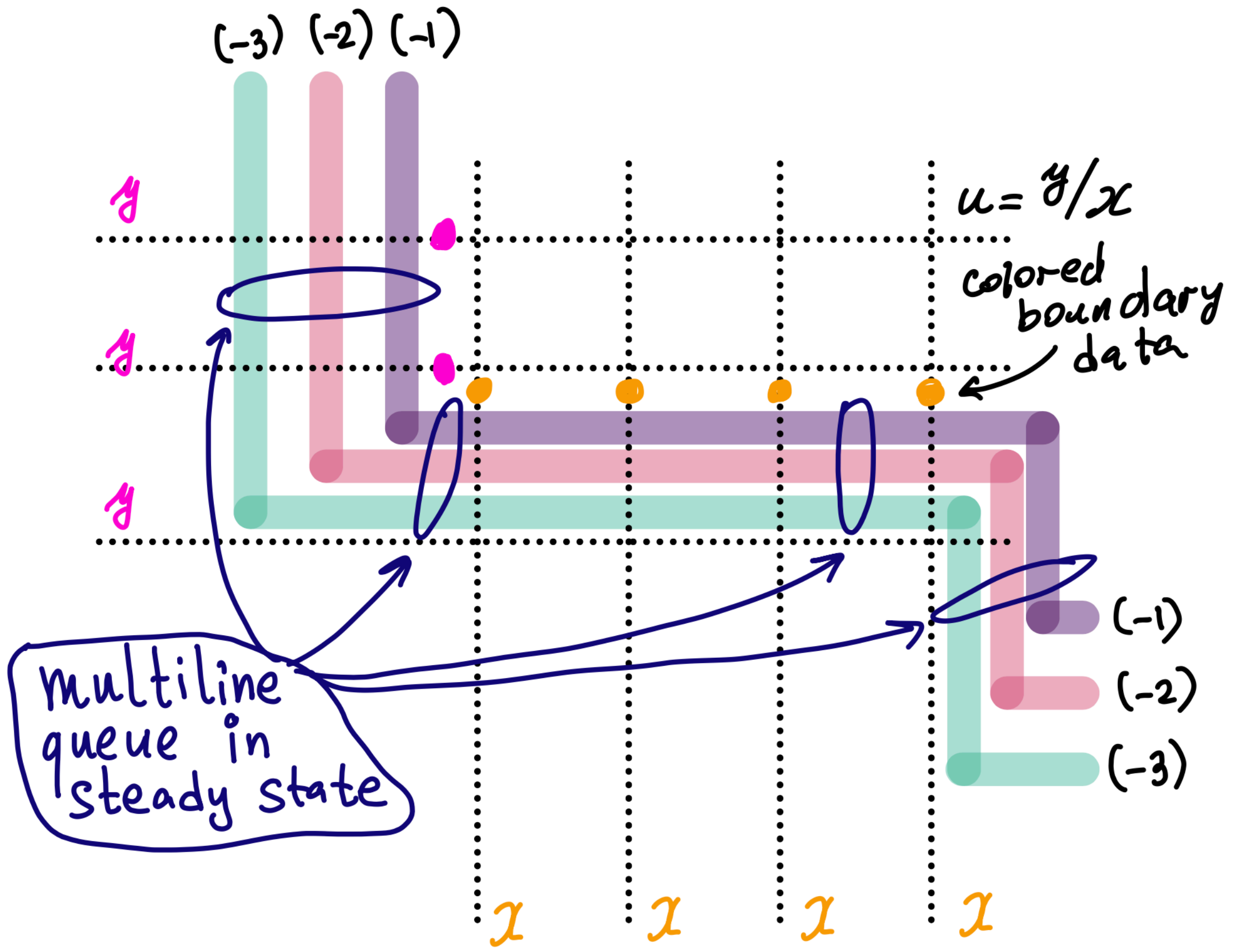
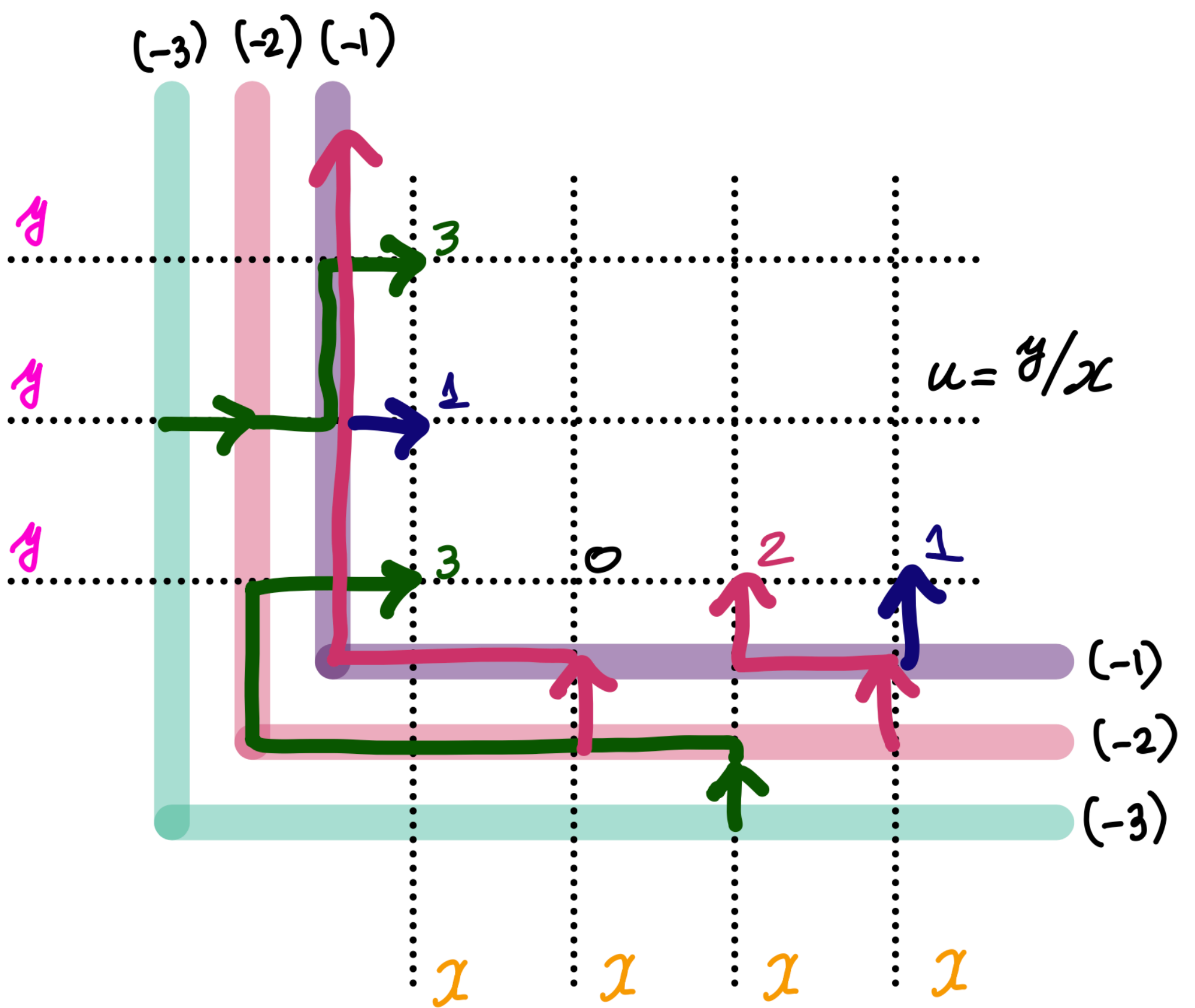
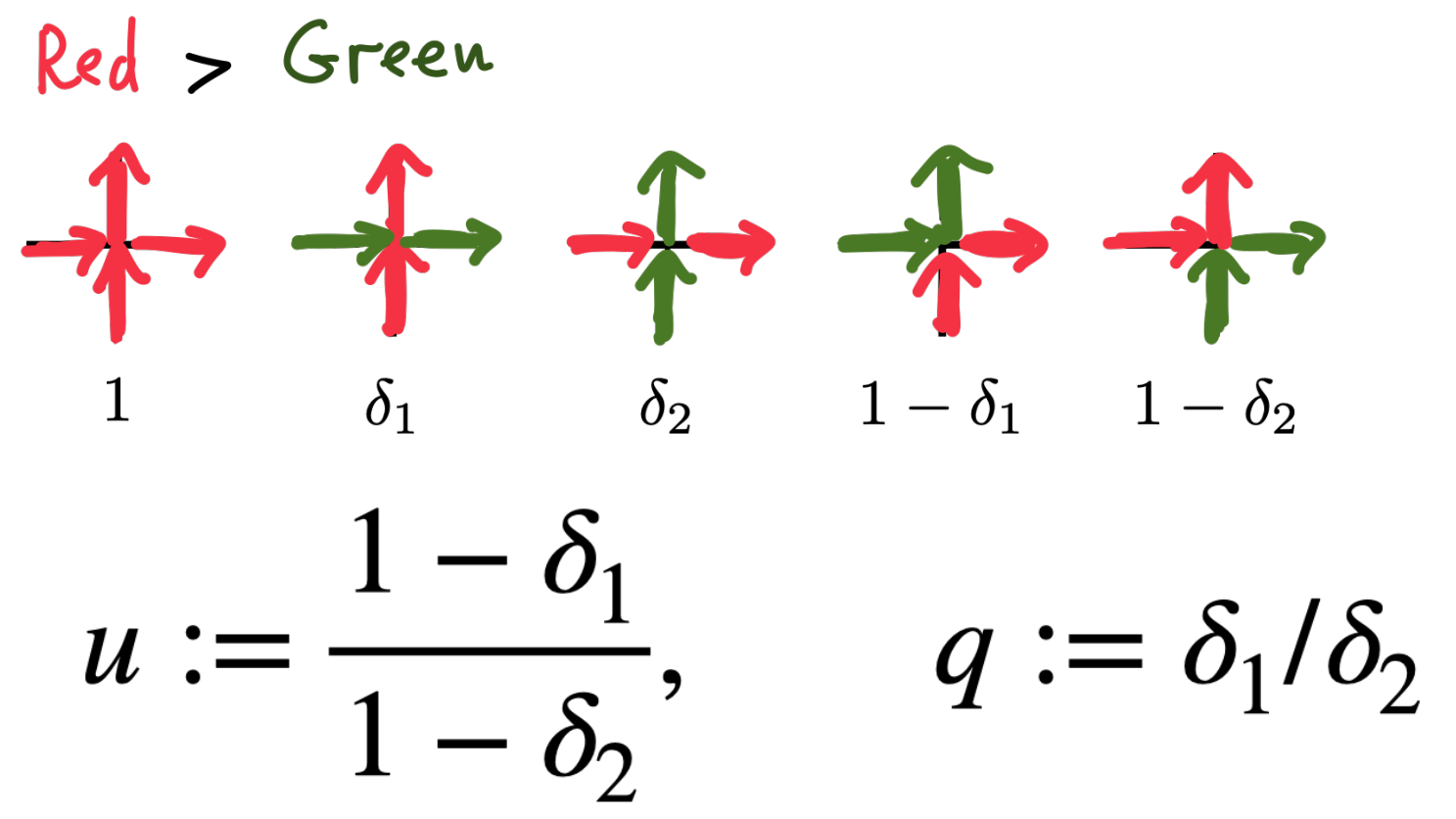
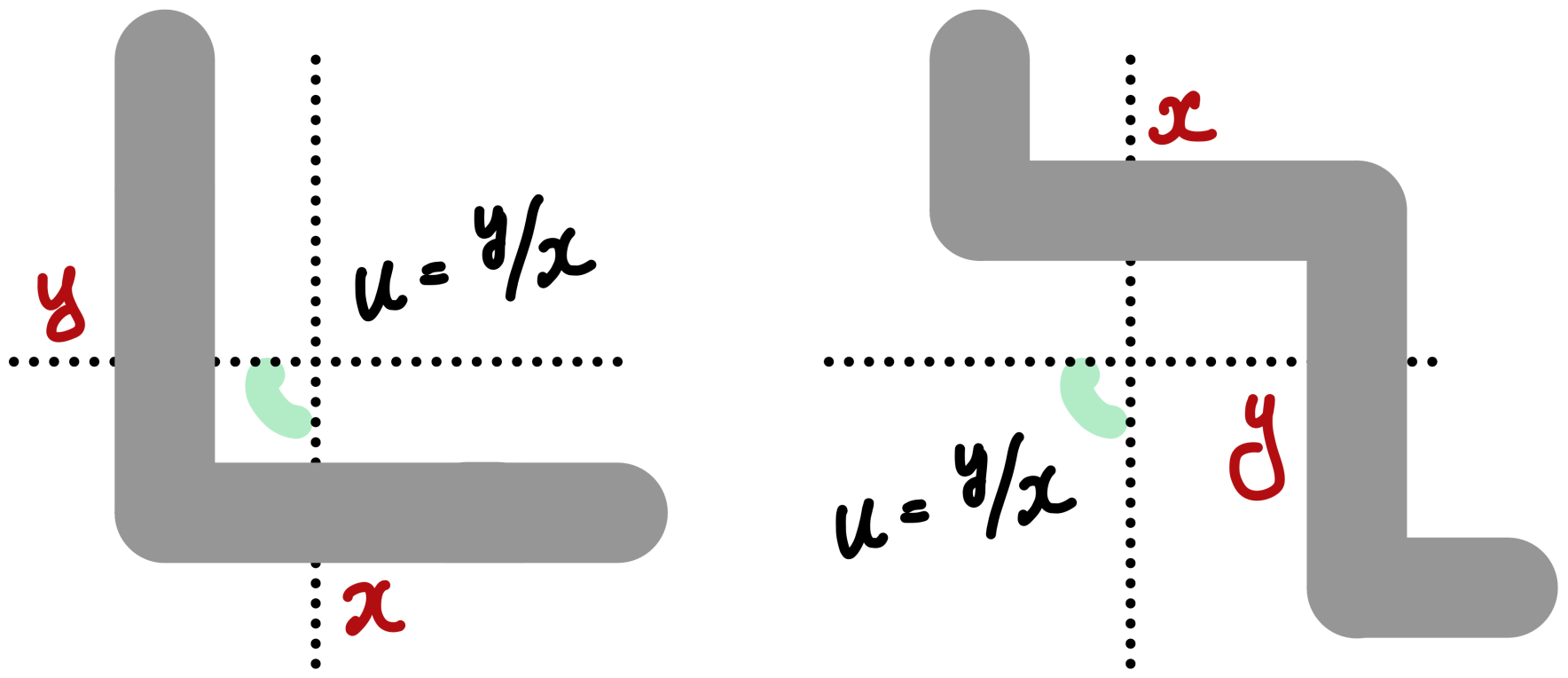
Colored stochastic six-vertex model. Many colors \Rightarrow many fat lines



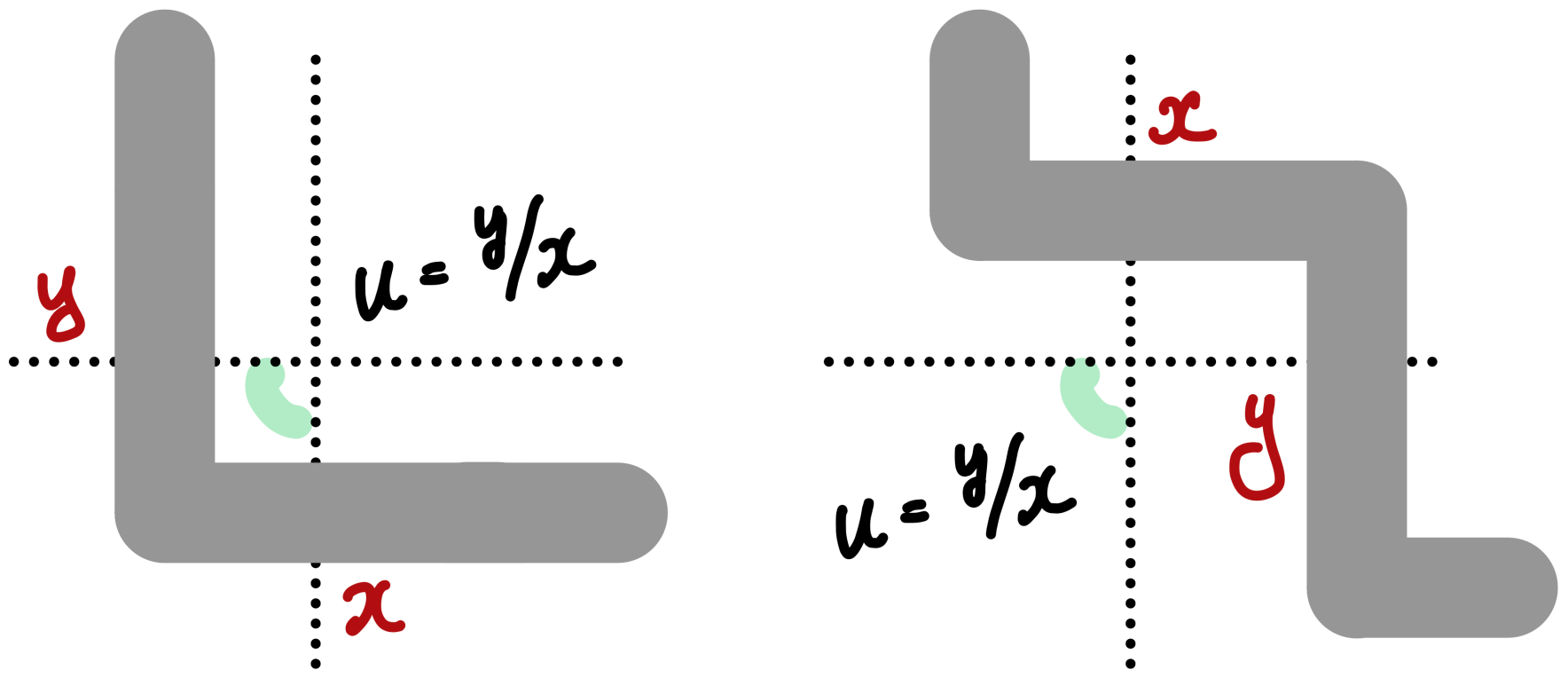
Colored stochastic six-vertex model. Many colors \Rightarrow many fat lines



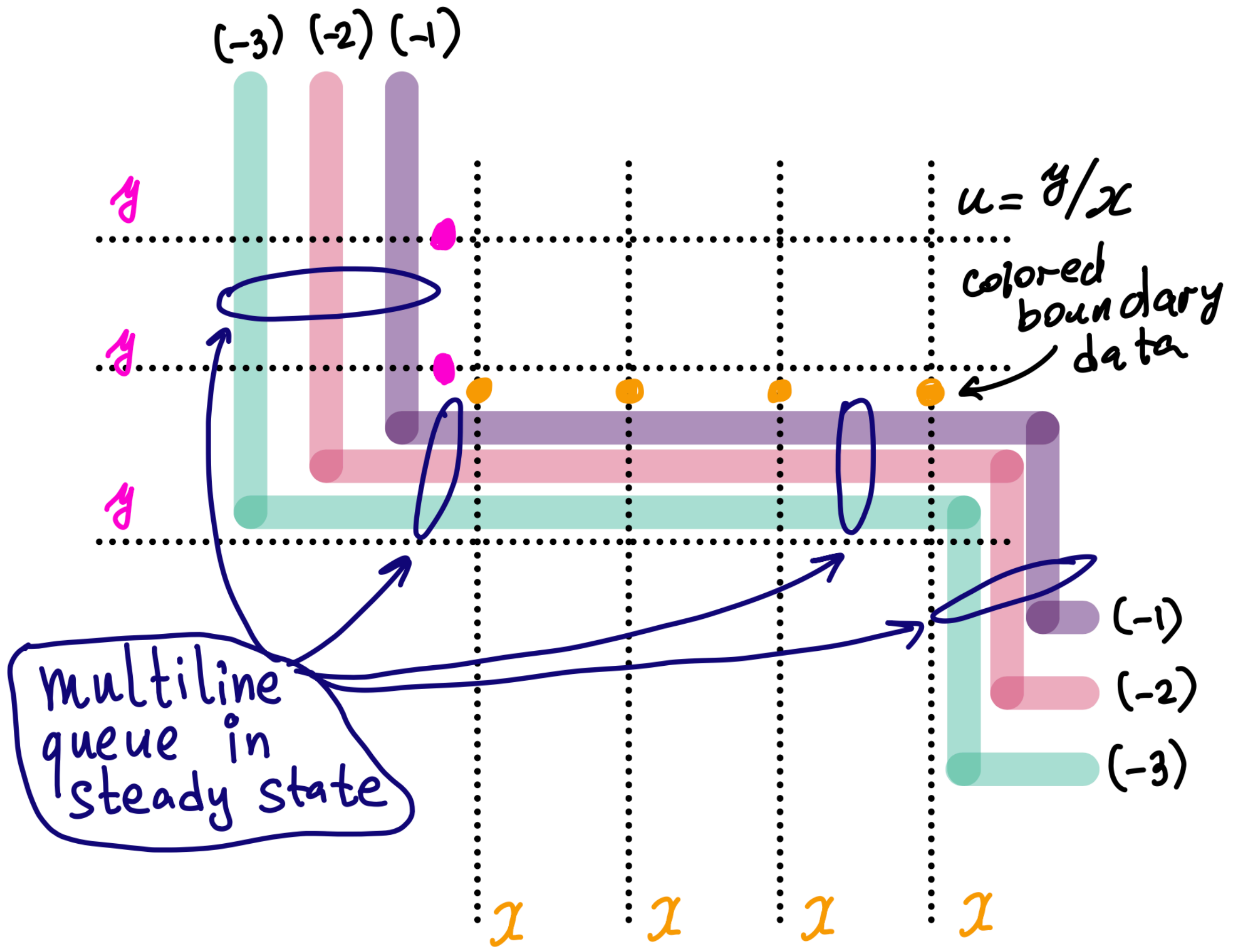
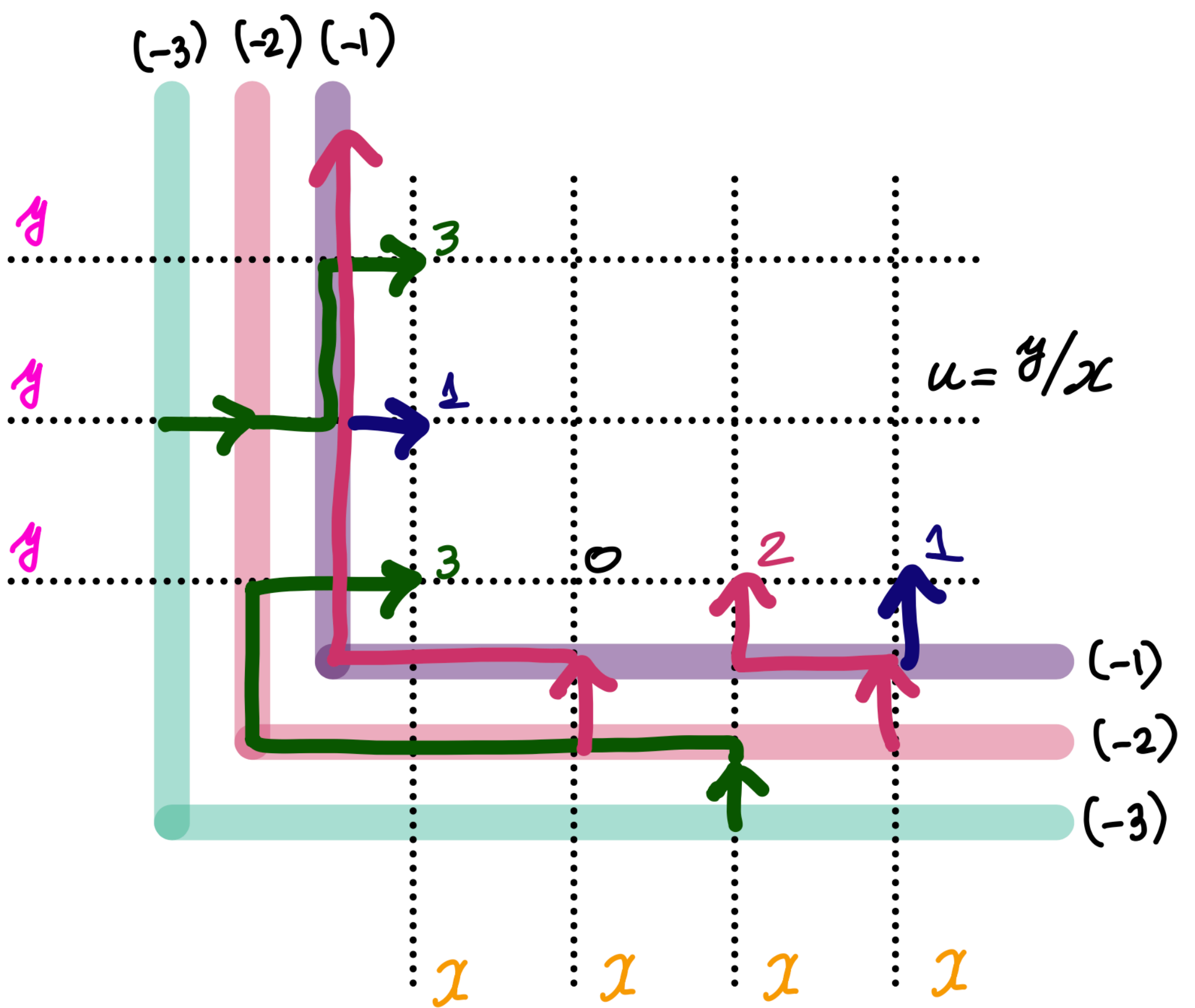
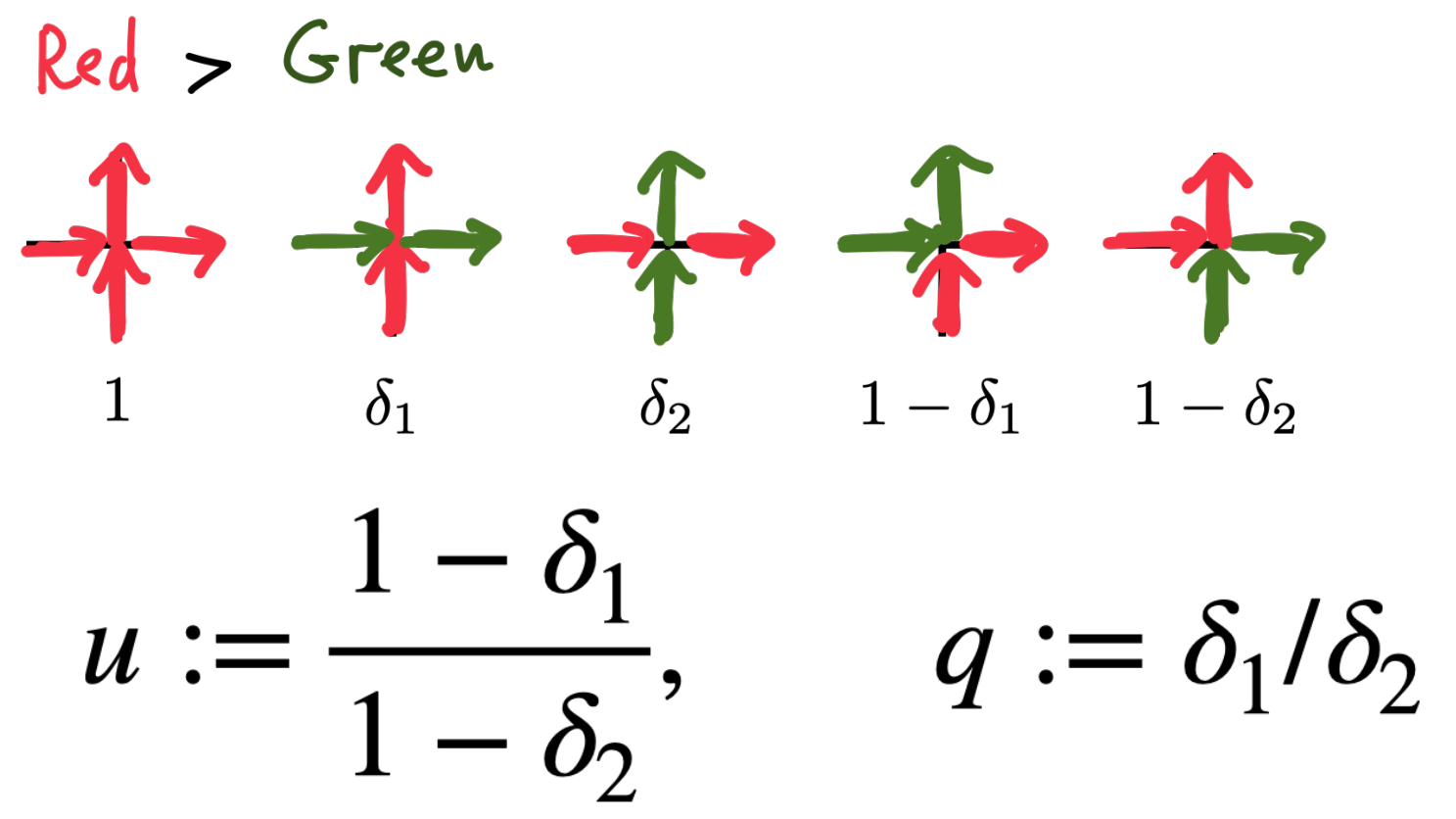
Colored stochastic six-vertex model. Many colors \Rightarrow many fat lines



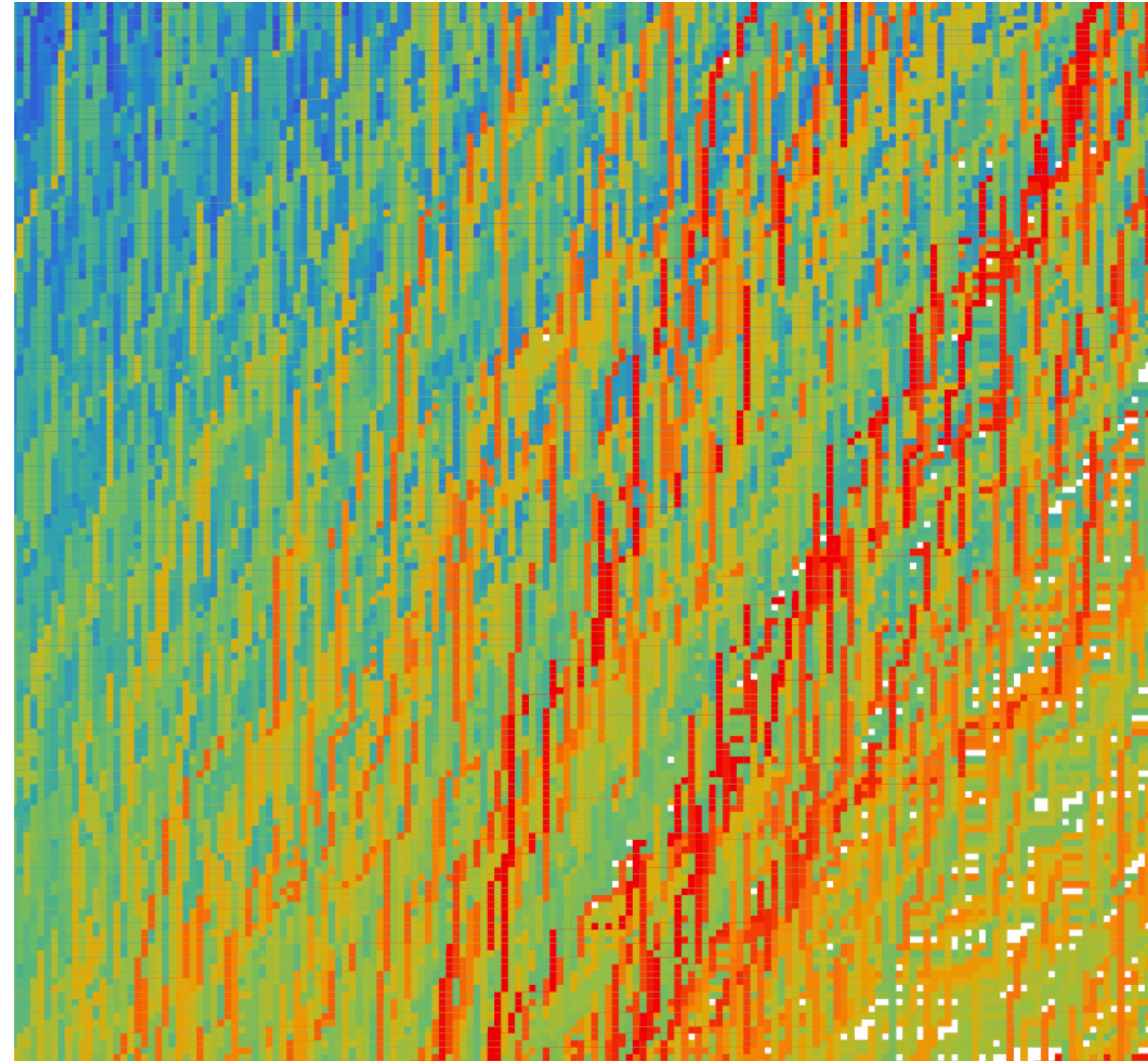
Colored stochastic six-vertex model. Many colors \Rightarrow many fat lines



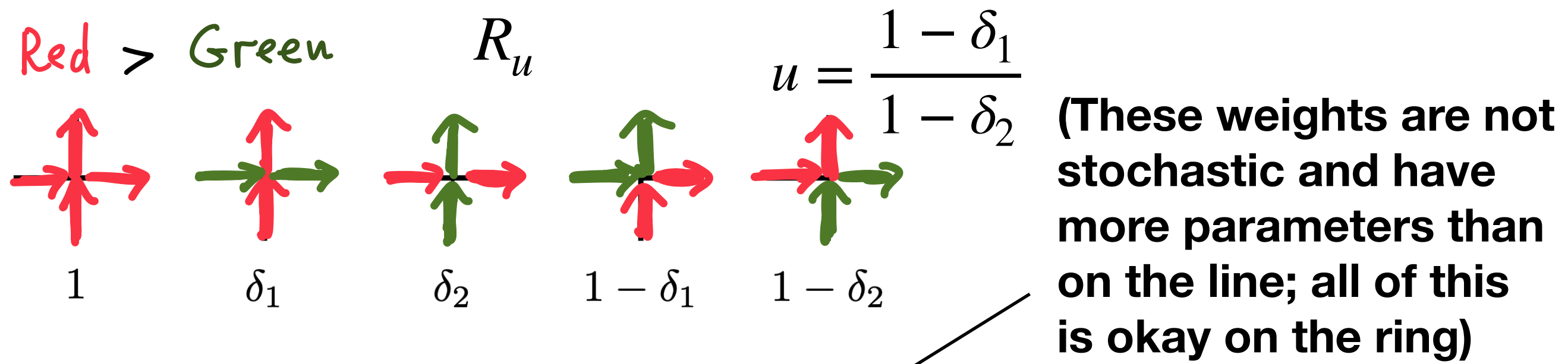
Implies mASEP stationary measure results on the line + multiline queues results)



Go to the ring!

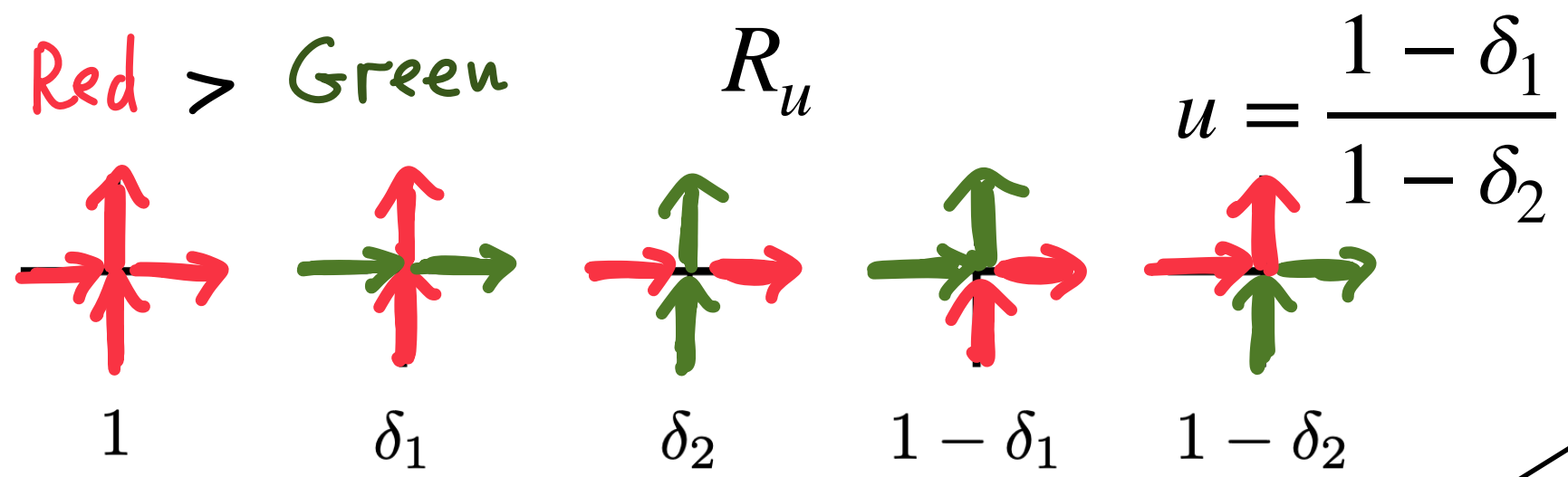


Yang-Baxter equation on the $n \times N$ cylinder



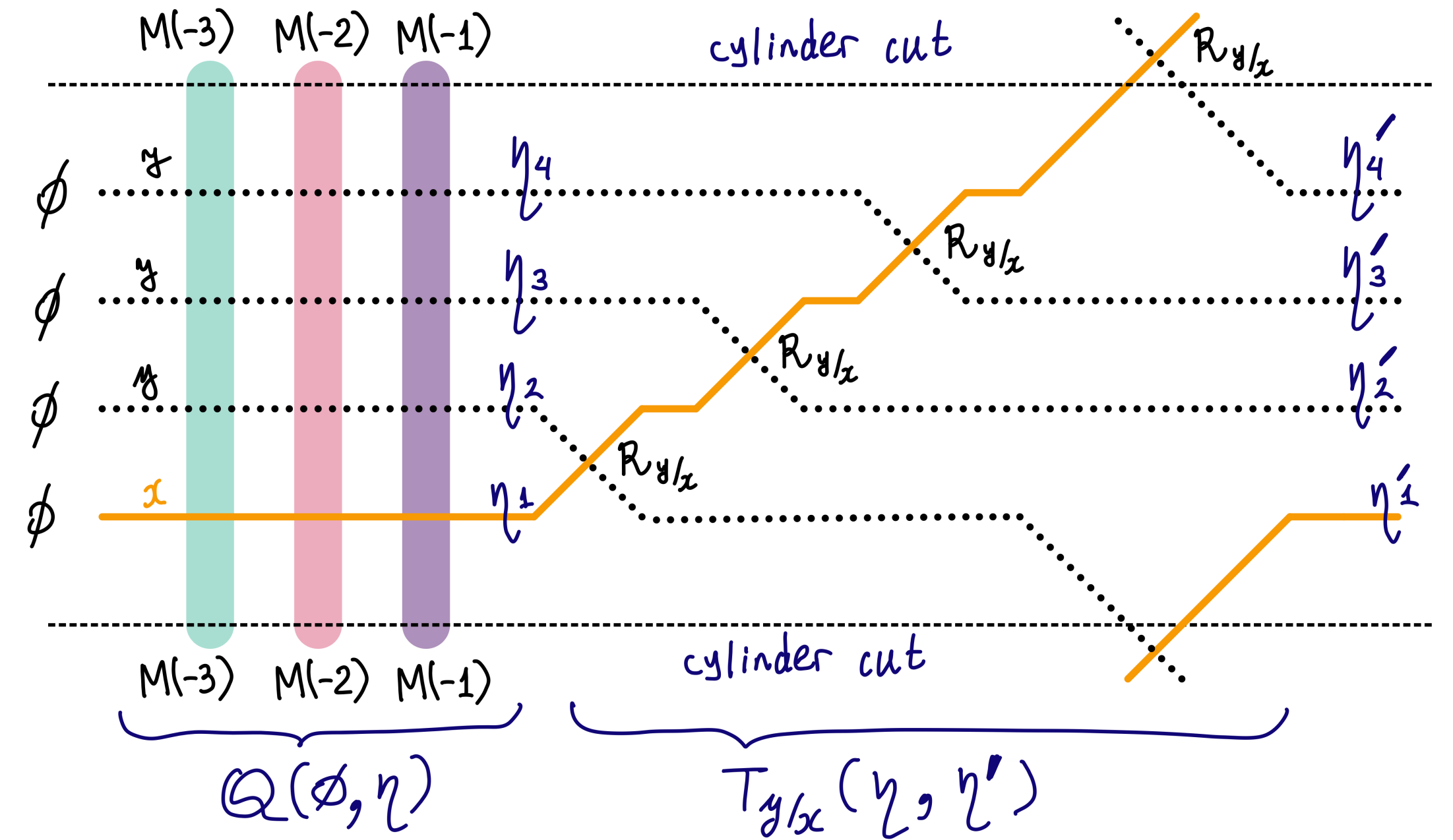
$\begin{array}{c} \mathbf{A} \\ \\ 0 \text{ --- } \text{ --- } 0 \\ \\ \mathbf{A} \\ 1 \end{array}$	$\begin{array}{c} \mathbf{A} \\ \\ k \text{ --- } \text{ --- } k \\ \\ \mathbf{A} \\ (x - sq^{A_k})q^{\mathbf{A}_{[k+1,n]}} \end{array}$	$\begin{array}{c} \mathbf{A}_k^- \\ \\ 0 \text{ --- } \text{ --- } k \\ \\ \mathbf{A} \\ x(1 - q^{A_k})q^{\mathbf{A}_{[k+1,n]}} \end{array}$	$\begin{array}{c} \mathbf{A} \\ \\ 0 \text{ --- } \text{ --- } m \\ \\ \mathbf{A} \\ xq^{\mathbf{A}_{[m+1,n]}} \end{array}$
$\begin{array}{c} \mathbf{A}_k^+ \\ \\ k \text{ --- } \text{ --- } 0 \\ \\ \mathbf{A} \\ 1 \end{array}$	$\begin{array}{c} \mathbf{A}_{k\ell}^{+-} \\ \\ k \text{ --- } \text{ --- } \ell \\ \\ \mathbf{A} \\ x(1 - q^{A_\ell})q^{\mathbf{A}_{[\ell+1,n]}} \end{array}$	$\begin{array}{c} \mathbf{A}_{\ell k}^{+-} \\ \\ \ell \text{ --- } \text{ --- } k \\ \\ \mathbf{A} \\ s(1 - q^{A_k})q^{\mathbf{A}_{[k+1,n]}} \end{array}$	$\begin{array}{c} \mathbf{A}_\ell^+ \\ \\ \ell \text{ --- } \text{ --- } m \\ \\ \mathbf{A} \\ sq^{\mathbf{A}_{[m+1,n]}} \end{array}$

Yang-Baxter equation on the $n \times N$ cylinder

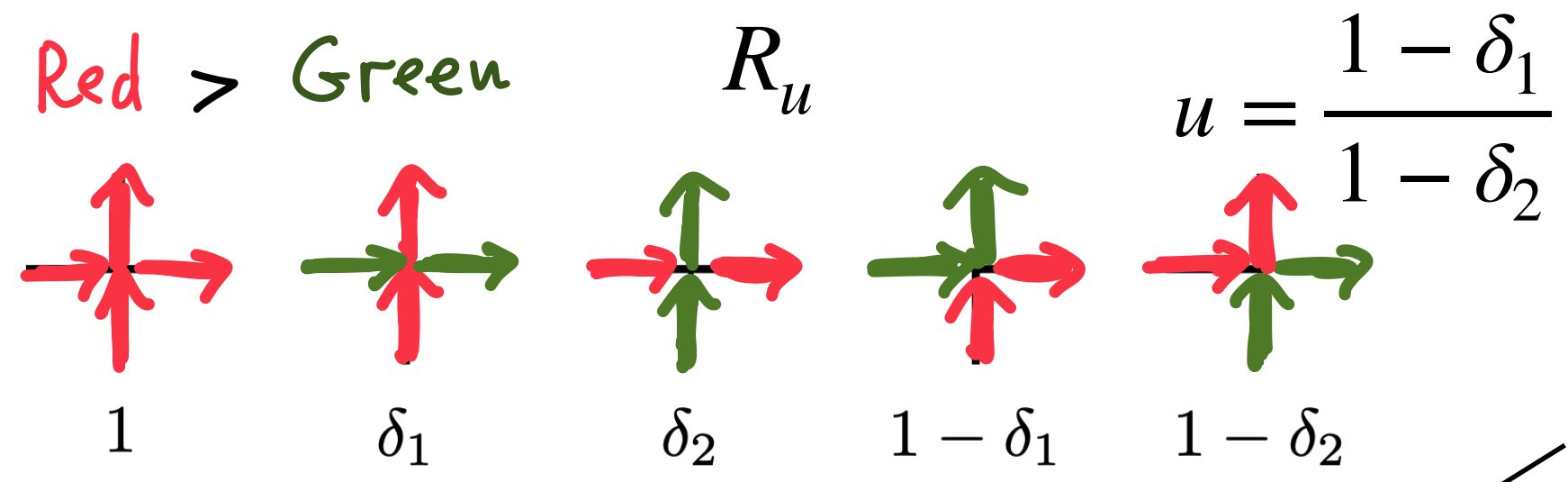


(These weights are not stochastic and have more parameters than on the line; all of this is okay on the ring)

$\begin{array}{c} \mathbf{A} \\ \\ 0 \text{---} \text{---} 0 \\ \\ \mathbf{A} \\ 1 \end{array}$	$\begin{array}{c} \mathbf{A} \\ \\ k \text{---} \text{---} k \\ \\ \mathbf{A} \\ (x - sq^{A_k}) q^{\mathbf{A}_{[k+1,n]}} \end{array}$	$\begin{array}{c} \mathbf{A}_k^- \\ \\ 0 \text{---} \text{---} k \\ \\ \mathbf{A} \\ x(1 - q^{A_k}) q^{\mathbf{A}_{[k+1,n]}} \end{array}$	$\begin{array}{c} \mathbf{A} \\ \\ 0 \text{---} \text{---} m \\ \\ \mathbf{A} \\ xq^{\mathbf{A}_{[m+1,n]}} \end{array}$
$\begin{array}{c} \mathbf{A}_k^+ \\ \\ k \text{---} \text{---} 0 \\ \\ \mathbf{A} \\ 1 \end{array}$	$\begin{array}{c} \mathbf{A}_{k\ell}^{+-} \\ \\ k \text{---} \text{---} \ell \\ \\ \mathbf{A} \\ x(1 - q^{A_\ell}) q^{\mathbf{A}_{[\ell+1,n]}} \end{array}$	$\begin{array}{c} \mathbf{A}_{\ell k}^{+-} \\ \\ \ell \text{---} \text{---} k \\ \\ \mathbf{A} \\ s(1 - q^{A_k}) q^{\mathbf{A}_{[k+1,n]}} \end{array}$	$\begin{array}{c} \mathbf{A}_\ell^+ \\ \\ \ell \text{---} \text{---} m \\ \\ \mathbf{A} \\ sq^{\mathbf{A}_{[m+1,n]}} \end{array}$

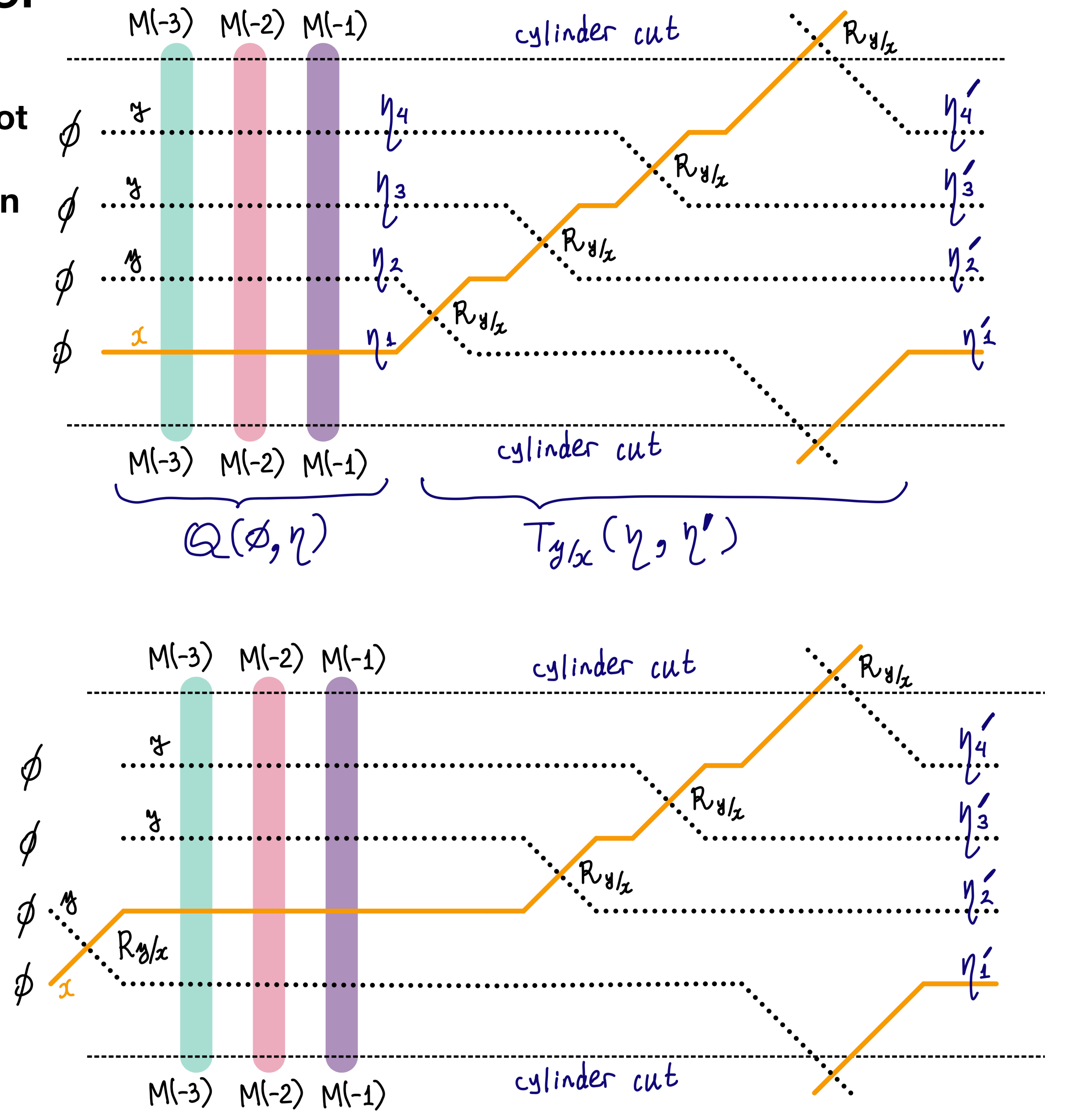


Yang-Baxter equation on the $n \times N$ cylinder

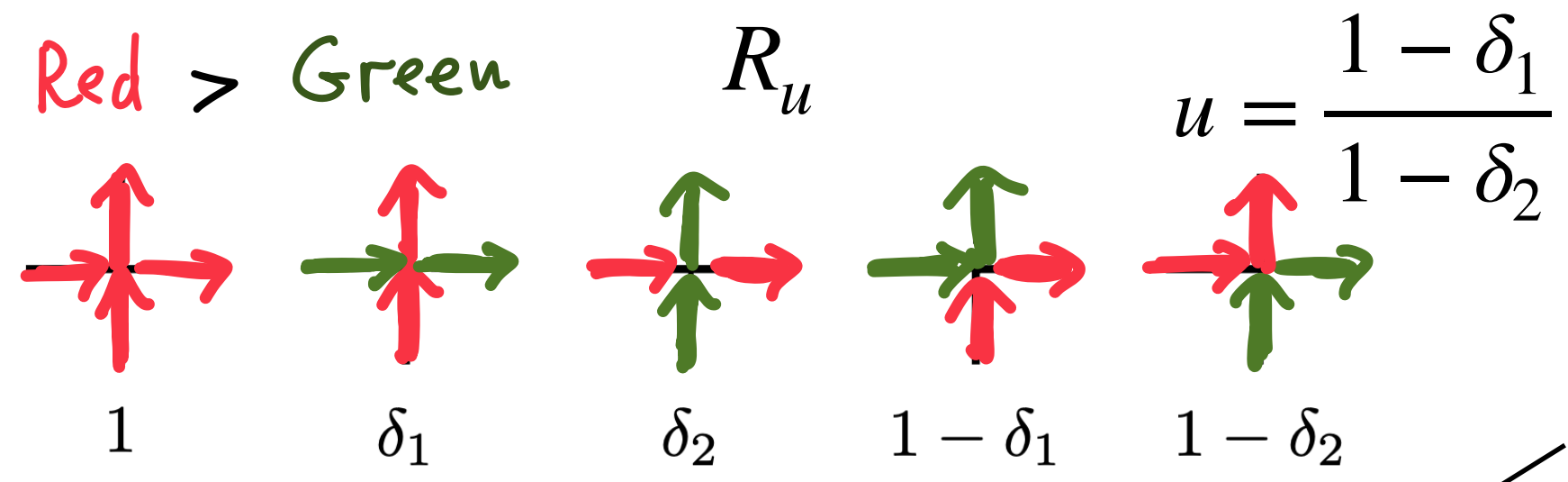


(These weights are not stochastic and have more parameters than on the line; all of this is okay on the ring)

<p>1</p>	<p>$(x - sq^{A_k})q^{A_{[k+1,n]}}$</p>	<p>$x(1 - q^{A_k})q^{A_{[k+1,n]}}$</p>	<p>$xq^{A_{[m+1,n]}}$</p>
<p>1</p>	<p>$x(1 - q^{A_l})q^{A_{[l+1,n]}}$</p>	<p>$s(1 - q^{A_k})q^{A_{[k+1,n]}}$</p>	<p>$sq^{A_{[m+1,n]}}$</p>

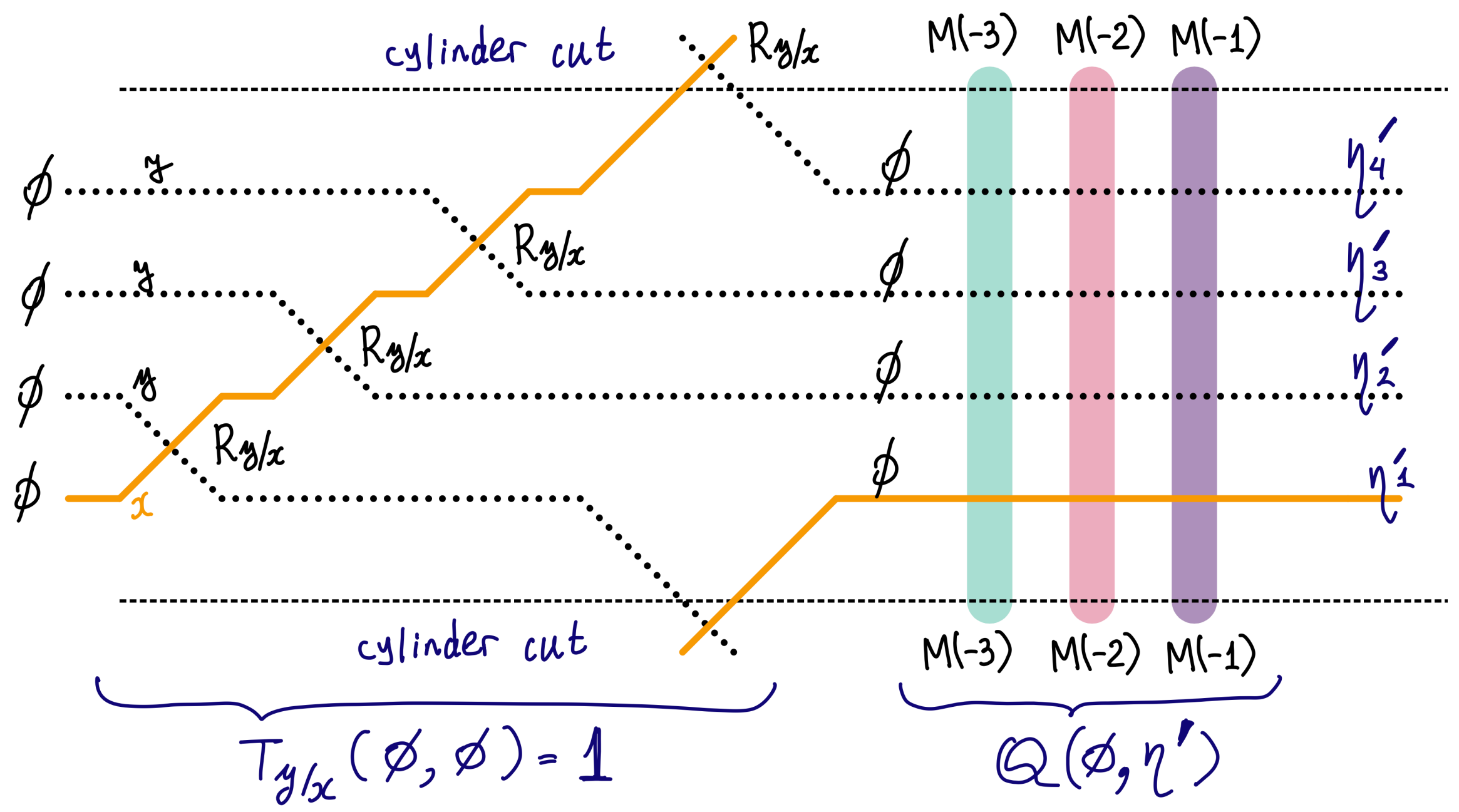
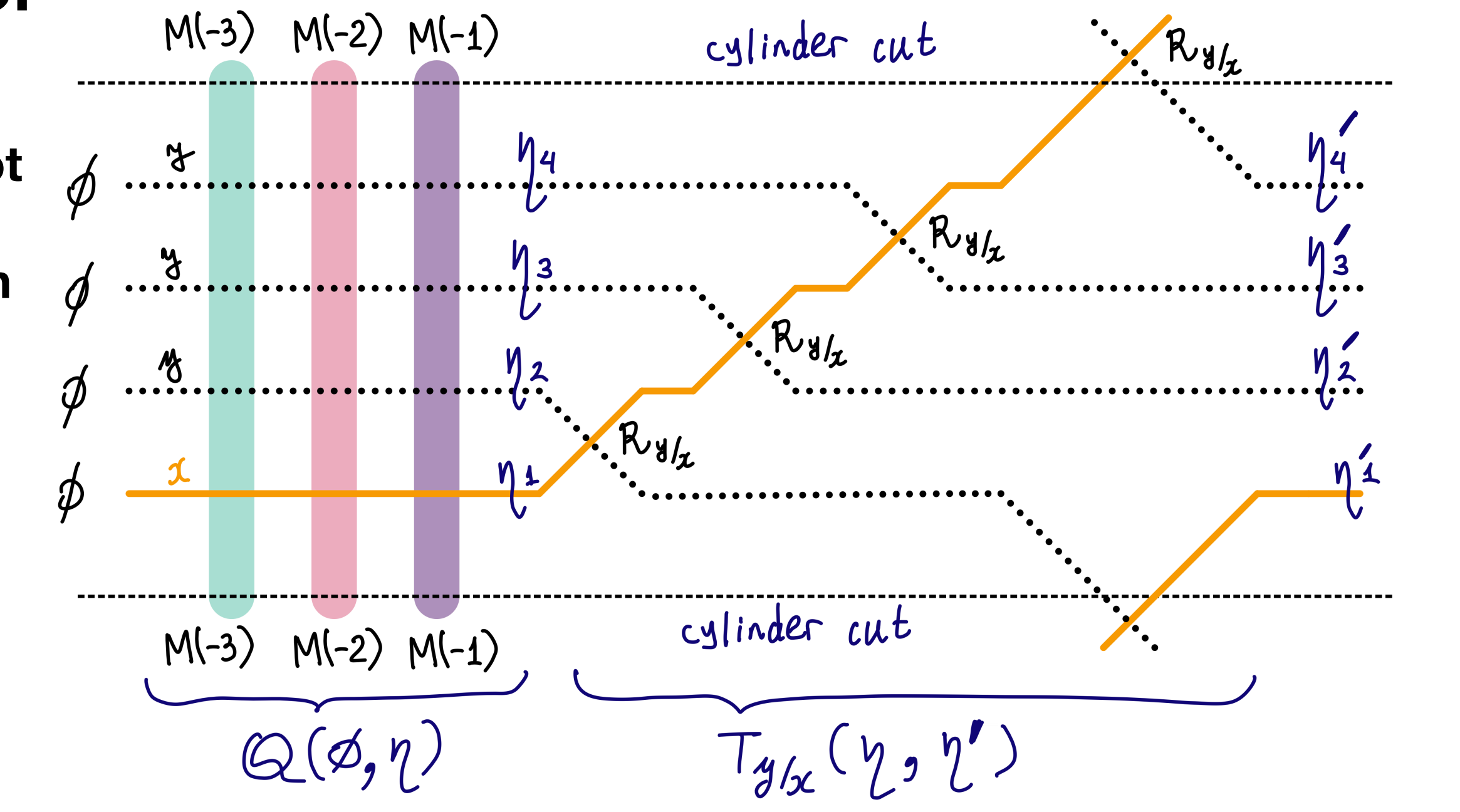


Yang-Baxter equation on the $n \times N$ cylinder



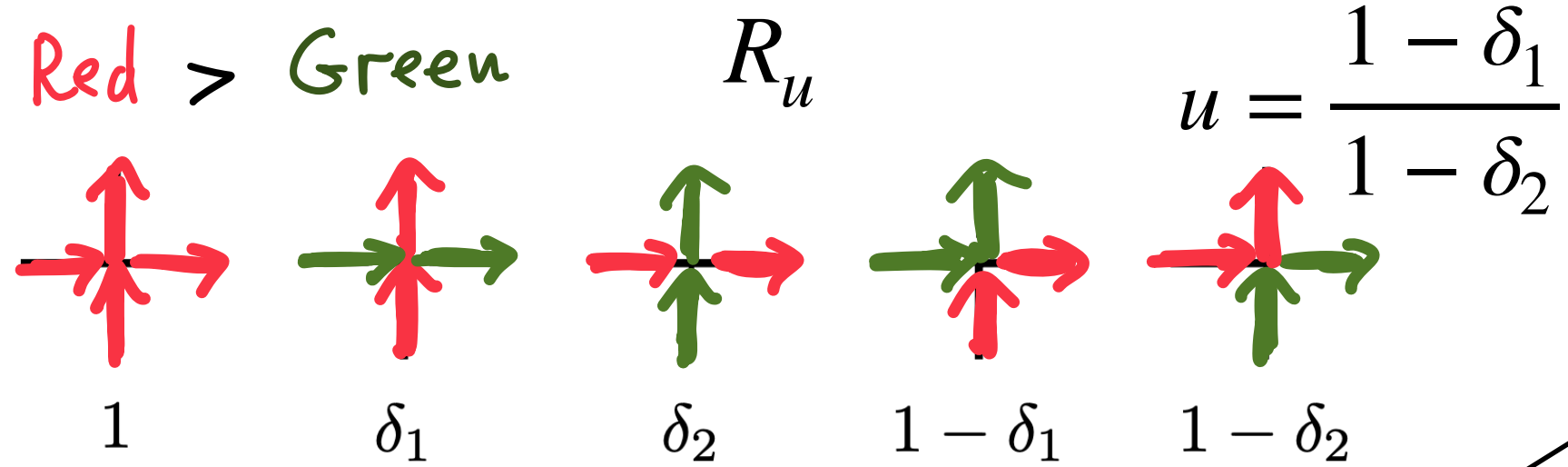
(These weights are not stochastic and have more parameters than on the line; all of this is okay on the ring)

<p>1</p>	<p>$(x - sq^{A_k})q^{A_{[k+1,n]}}$</p>	<p>$x(1 - q^{A_k})q^{A_{[k+1,n]}}$</p>	<p>$xq^{A_{[m+1,n]}}$</p>
<p>1</p>	<p>$x(1 - q^{A_l})q^{A_{[l+1,n]}}$</p>	<p>$s(1 - q^{A_k})q^{A_{[k+1,n]}}$</p>	<p>$sq^{A_{[m+1,n]}}$</p>



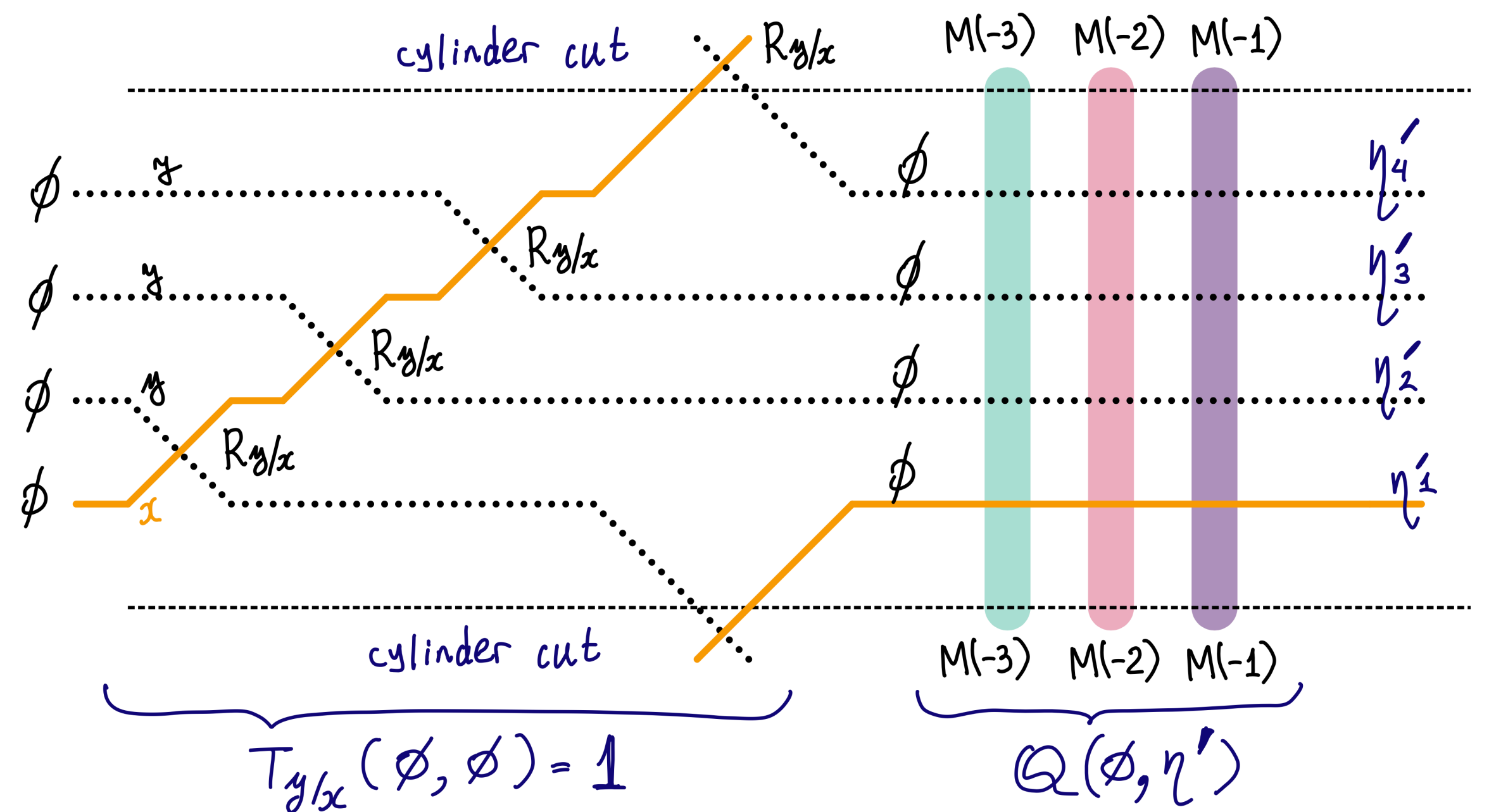
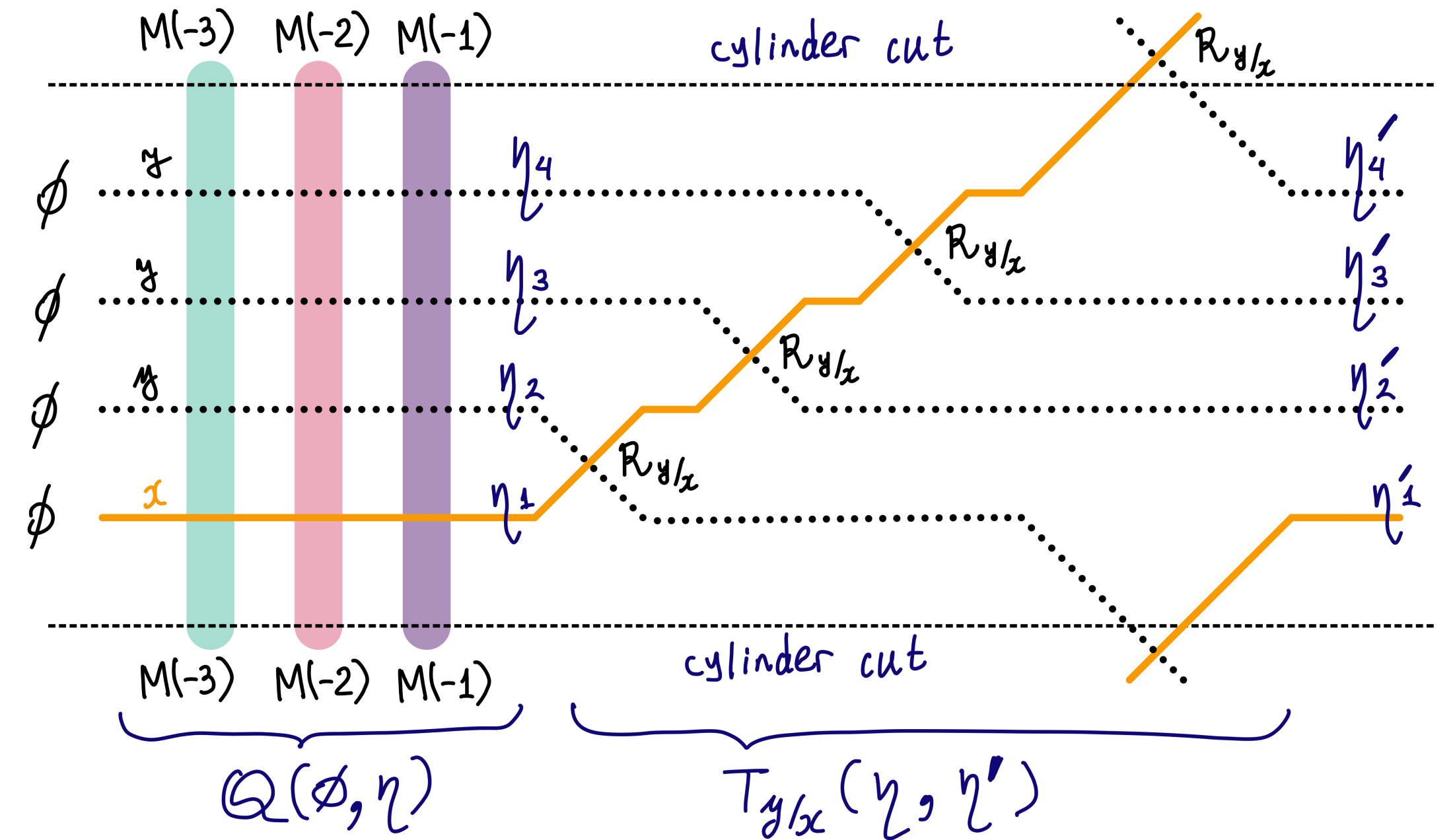
Yang-Baxter equation on the $n \times N$ cylinder

Red > Green



$$u = \frac{1 - \delta_1}{1 - \delta_2}$$

(These weights are not stochastic and have more parameters than on the line; all of this is okay on the ring)

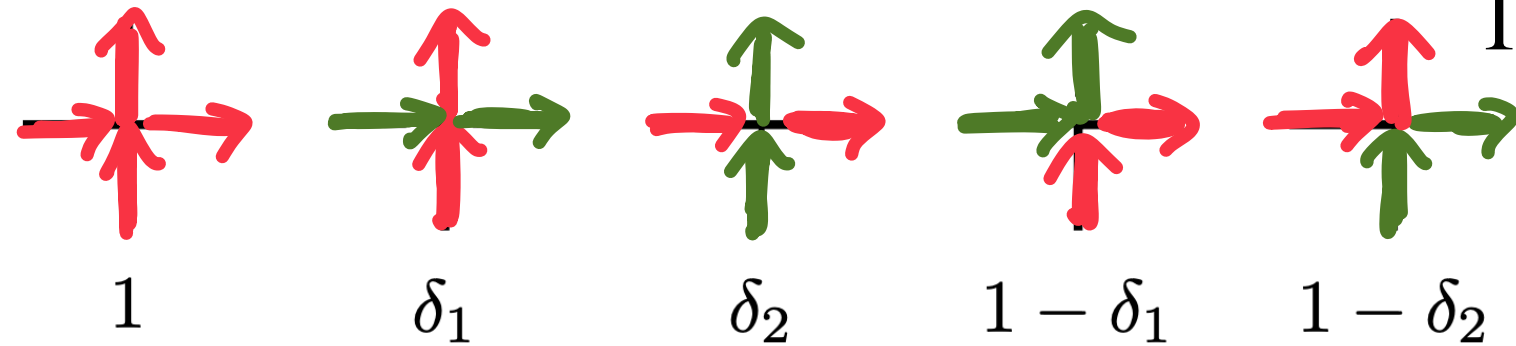


Commutation relation on the cylinder

$$\sum_{\eta} \mathcal{Q}(\emptyset, \eta) T_{y/x}(\eta, \eta') = T_{y/x}(\emptyset, \emptyset) \mathcal{Q}(\emptyset, \eta') = \mathcal{Q}(\emptyset, \eta')$$

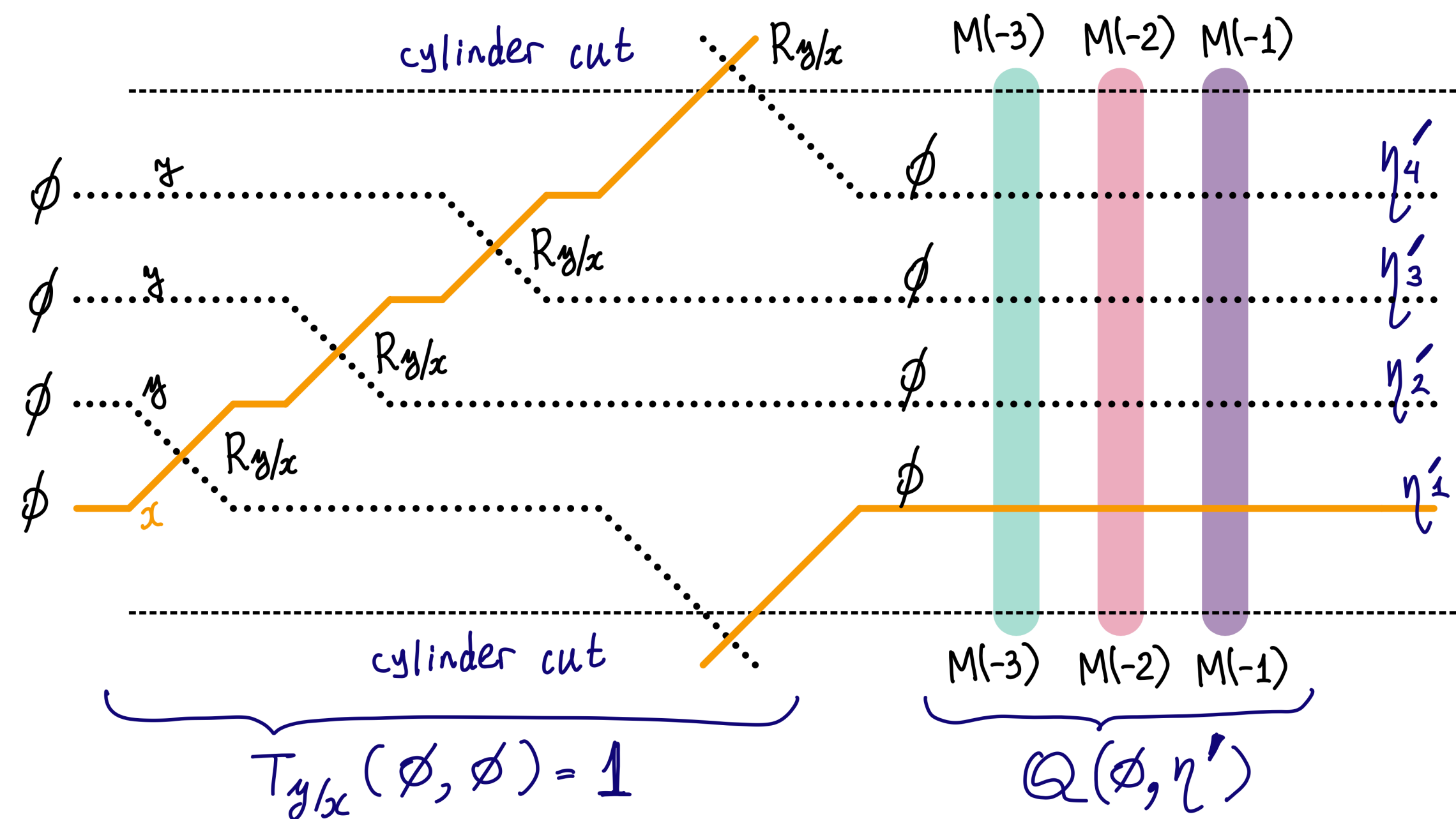
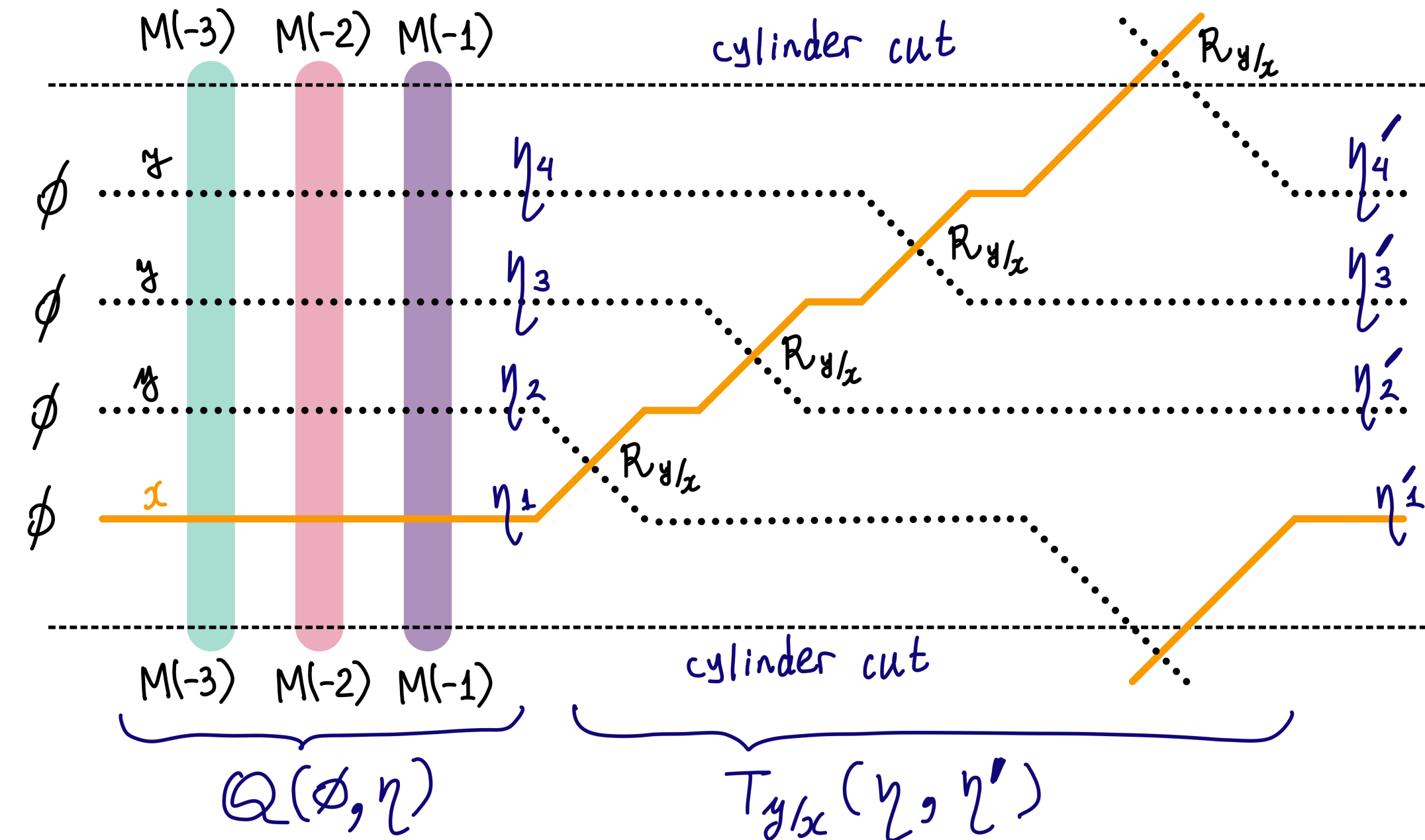
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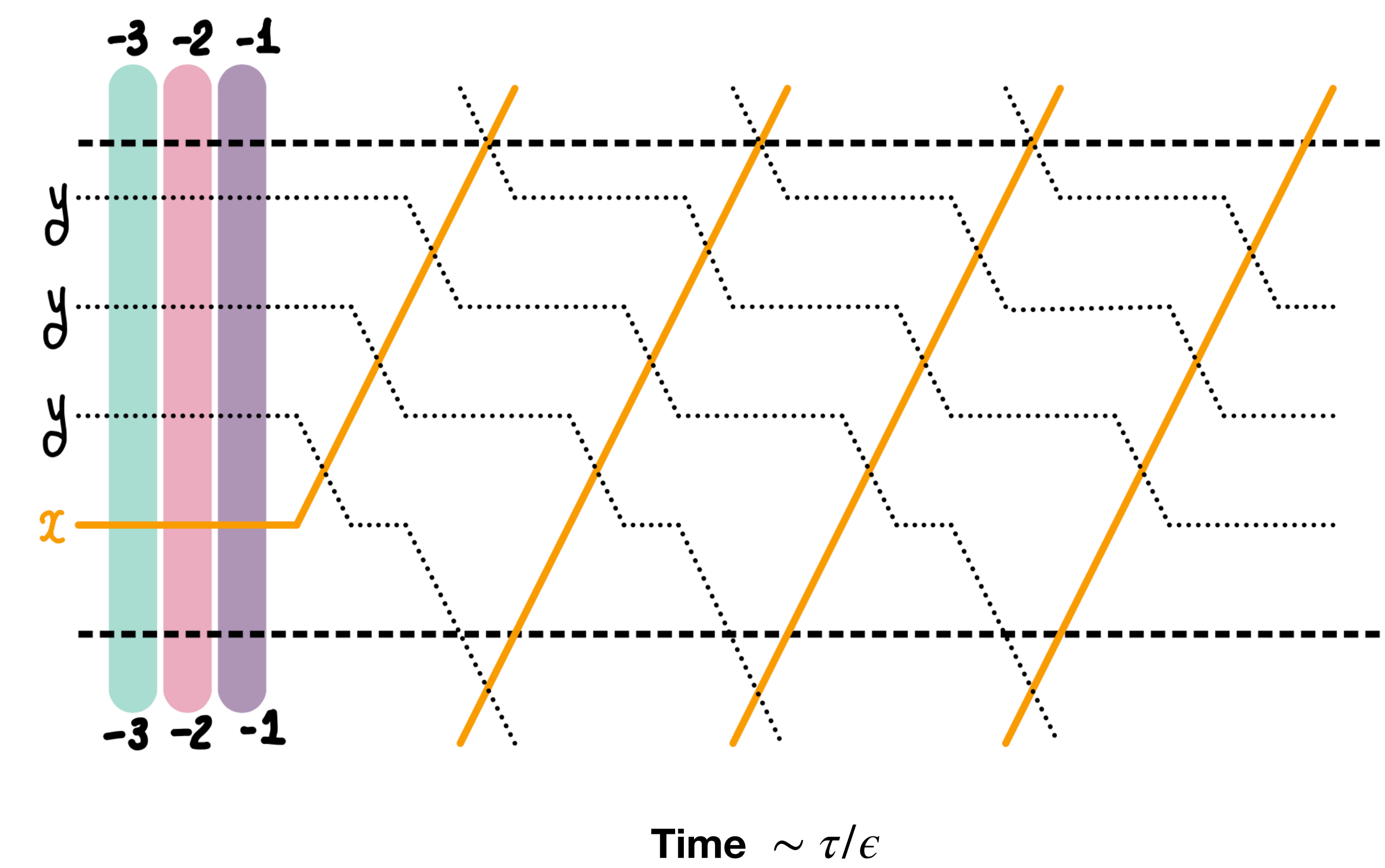
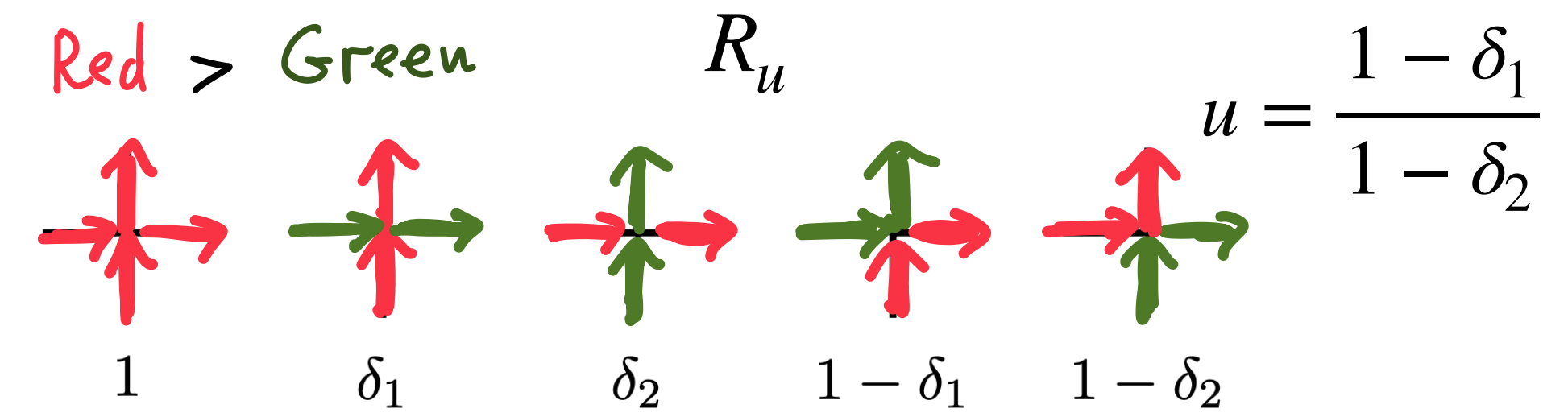
Commutation relation on the cylinder

$$\sum_{\eta} \mathcal{Q}(\emptyset, \eta) T_{y/x}(\eta, \eta') = T_{y/x}(\emptyset, \emptyset) \mathcal{Q}(\emptyset, \eta') = \mathcal{Q}(\emptyset, \eta')$$

(Bethe Ansatz: construct eigenvalue of T as a partition function)

Limit to the mASEP, $y/x = 1 - \epsilon$, continuous time

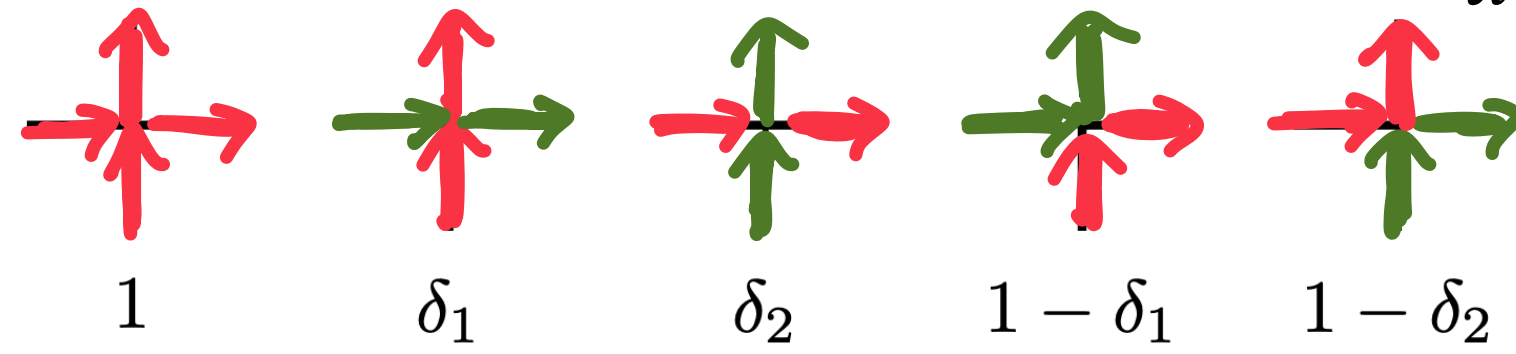
mASEP limit $\delta_1, \delta_2 \rightarrow 0, q = \delta_1/\delta_2$



Limit to the mASEP, $y/x = 1 - \epsilon$, continuous time

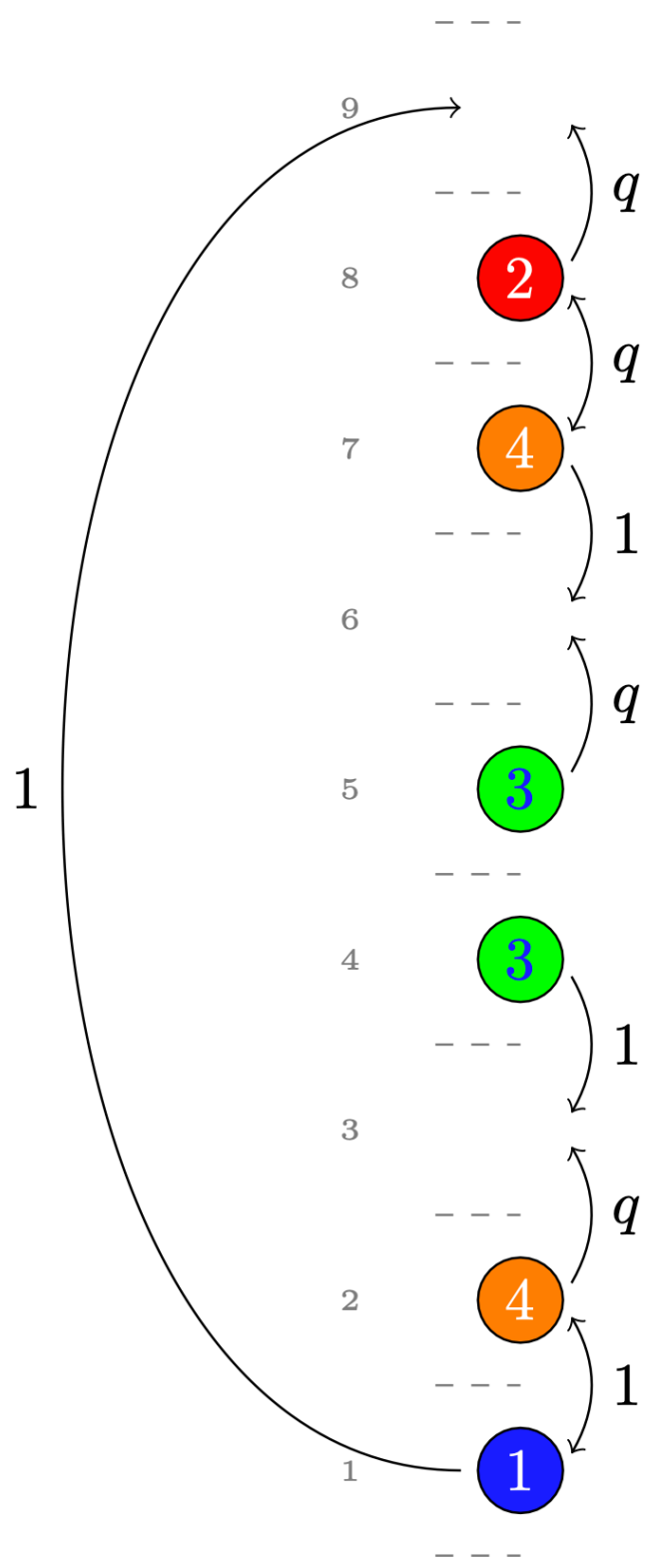
mASEP limit $\delta_1, \delta_2 \rightarrow 0$, $q = \delta_1/\delta_2$

Red > Green

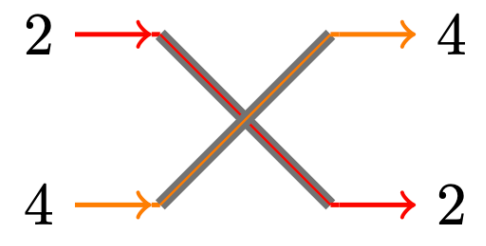


R_u

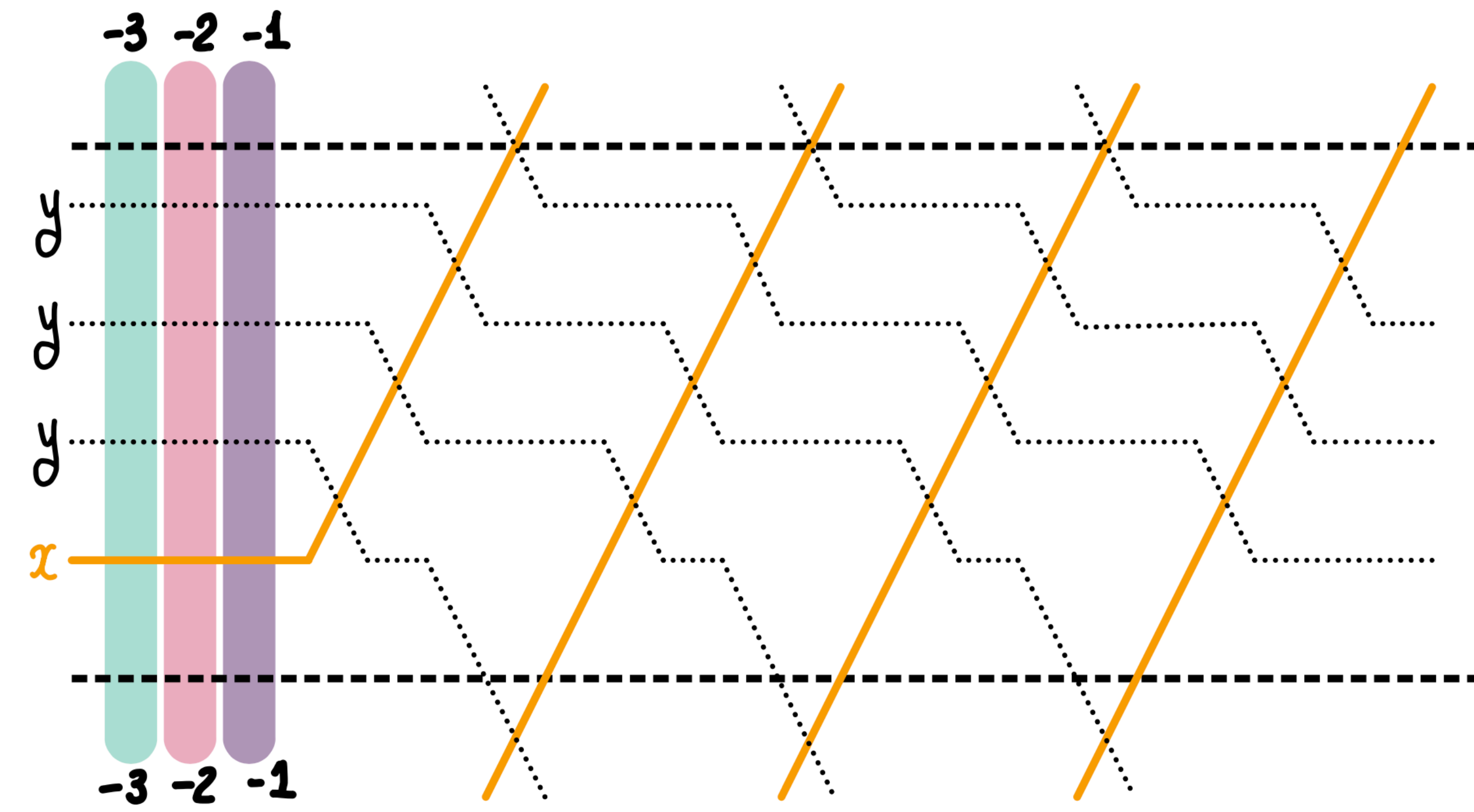
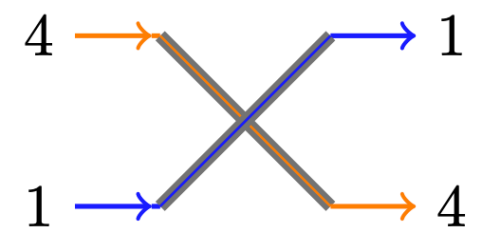
$$u = \frac{1 - \delta_1}{1 - \delta_2}$$



$$\langle 4, 2 | \check{\mathcal{R}}_{1-\epsilon} | 2, 4 \rangle = R_{1-\epsilon}(4, 2, 4, 2) = \frac{q\epsilon}{1-q} + O(\epsilon^2)$$



$$\langle 1, 4 | \check{\mathcal{R}}_{1-\epsilon} | 4, 1 \rangle = R_{1-\epsilon}(1, 4; 1, 4) = \frac{\epsilon}{1-q} + O(\epsilon^2)$$

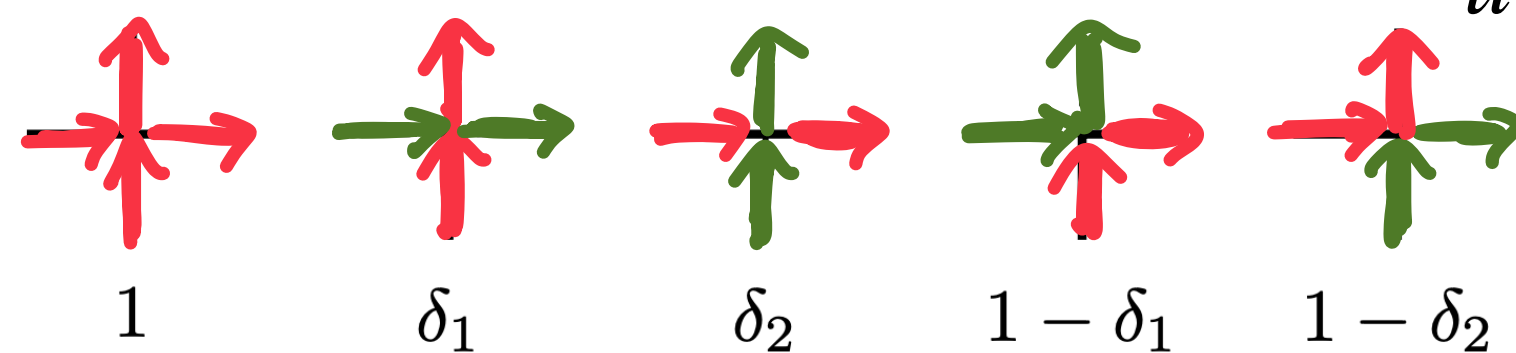


Time $\sim \tau/\epsilon$

Limit to the mASEP, $y/x = 1 - \epsilon$, continuous time

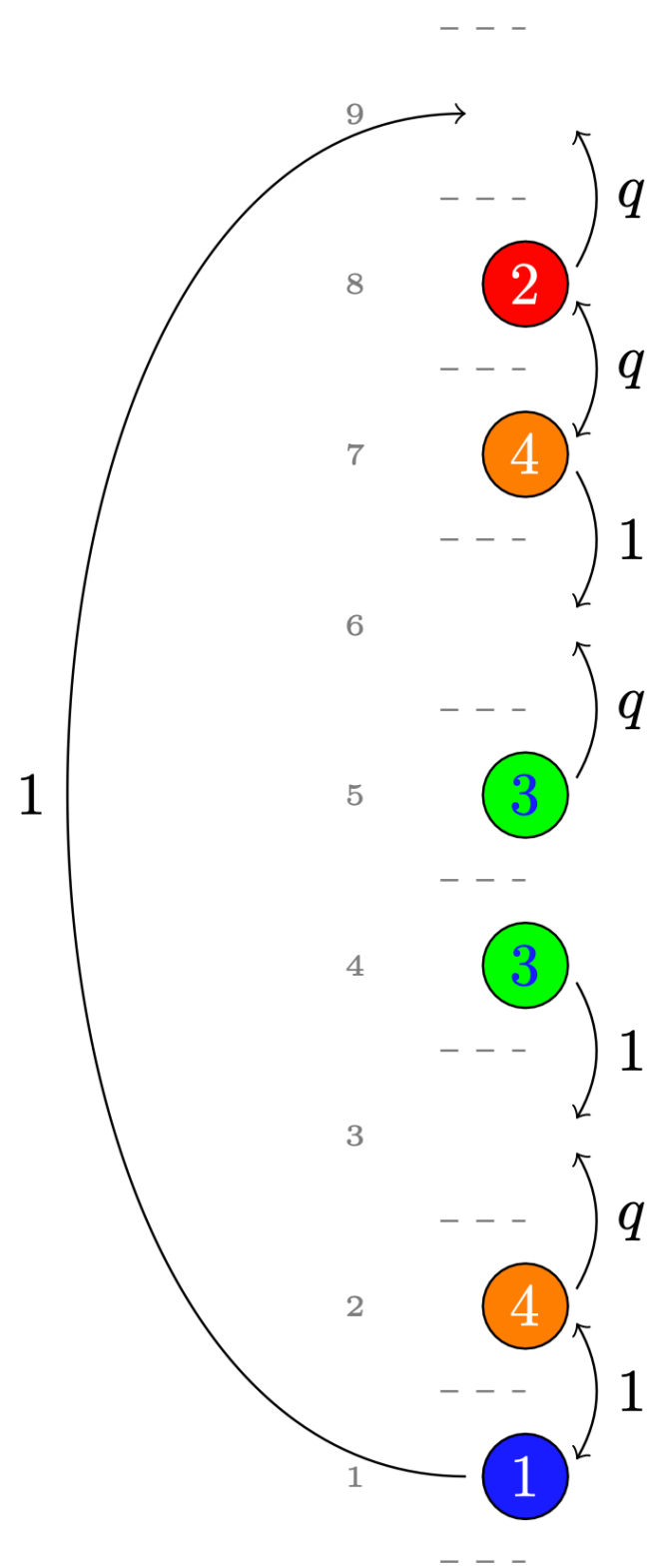
mASEP limit $\delta_1, \delta_2 \rightarrow 0$, $q = \delta_1/\delta_2$

Red > Green

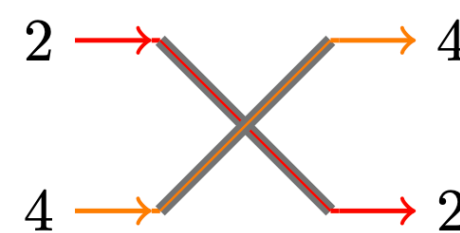


R_u

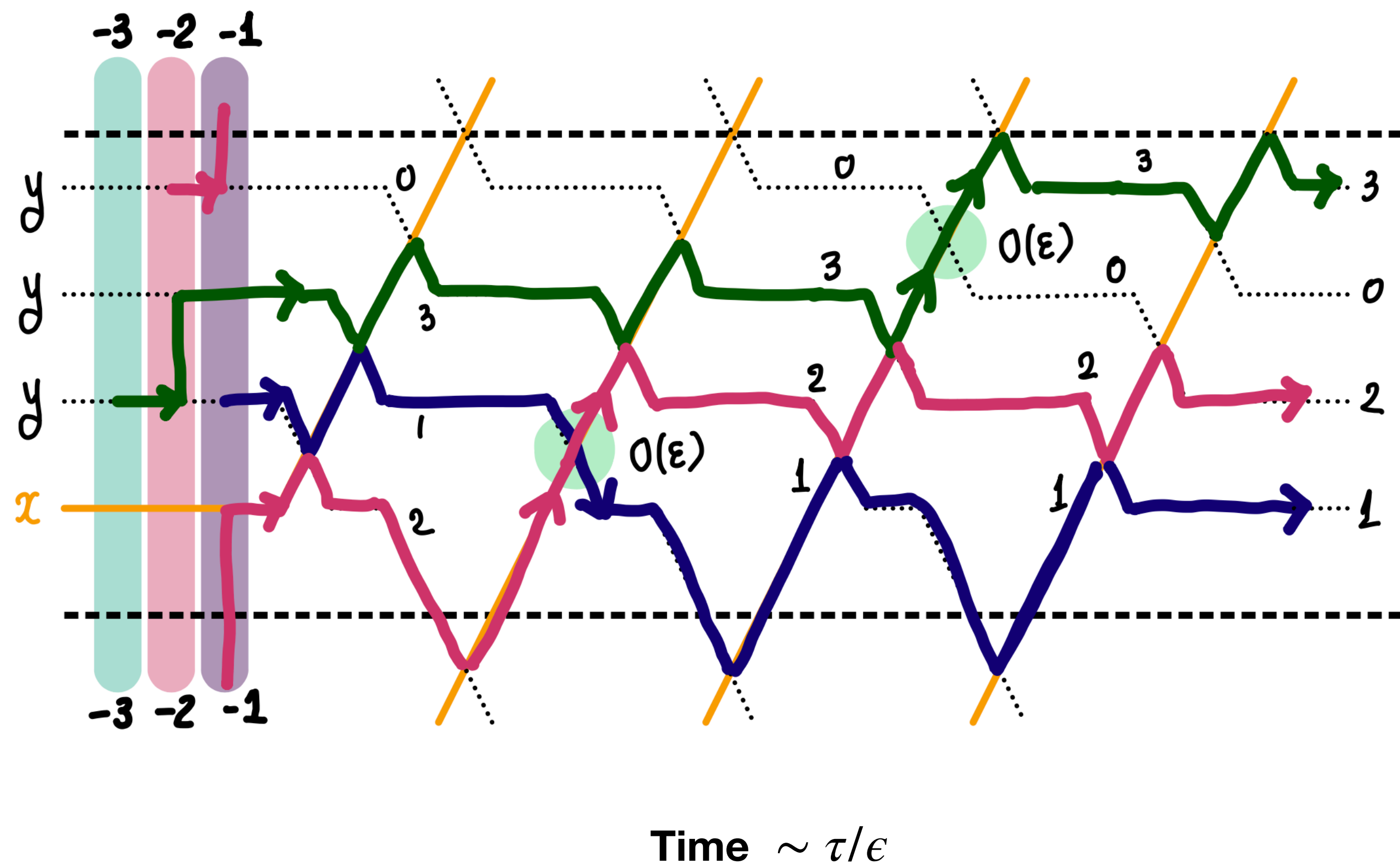
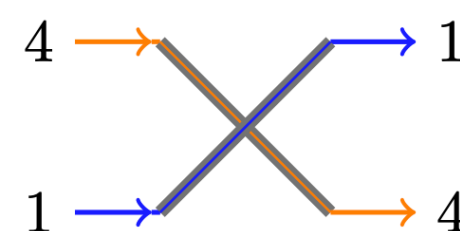
$$u = \frac{1 - \delta_1}{1 - \delta_2}$$



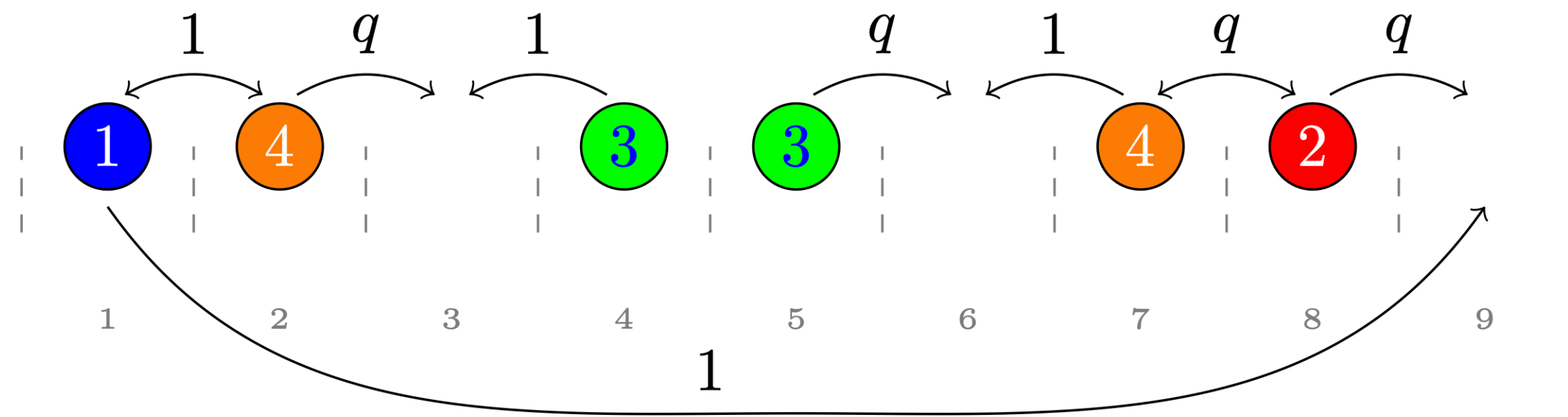
$$\langle 4, 2 | \check{\mathcal{R}}_{1-\epsilon} | 2, 4 \rangle = R_{1-\epsilon}(4, 2, 4, 2) = \frac{q\epsilon}{1-q} + O(\epsilon^2)$$



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Colored ASEP (= multispecies ASEP = mASEP)



- Particles have colors (types) in $\{1, \dots, n\}$.
- Particles of colors (i_k, i_{k+1}) at adjacent sites

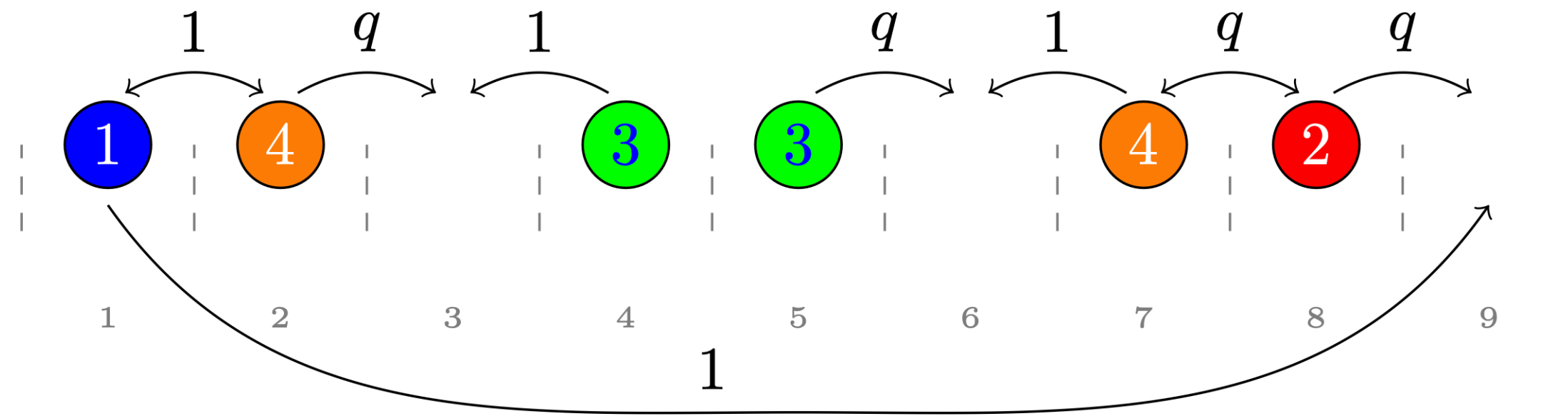
$k, k + 1$ swap at rate:

$$\text{Rate}((i_k, i_{k+1}) \rightarrow (i_{k+1}, i_k)) = \begin{cases} q, & i_k > i_{k+1} \\ 1, & i_k < i_{k+1} \end{cases}$$

(color n :
highest “priority”
to move left)

- $q \in [0, 1)$ is the parameter
- Lives on a ring with N sites; there are N_i particles of color i (conserved quantities)

Colored ASEP (= multispecies ASEP = mASEP)



- There is a unique **stationary distribution**

$\text{Prob}_{N_1, \dots, N_n}(\eta_1, \dots, \eta_N)$ in each “sector”

$\vec{N} = (N_1, \dots, N_n)$, where $\eta_j \in \{0, 1, \dots, n\}$

- Particles have colors (types) in $\{1, \dots, n\}$.
- Particles of colors (i_k, i_{k+1}) at adjacent sites

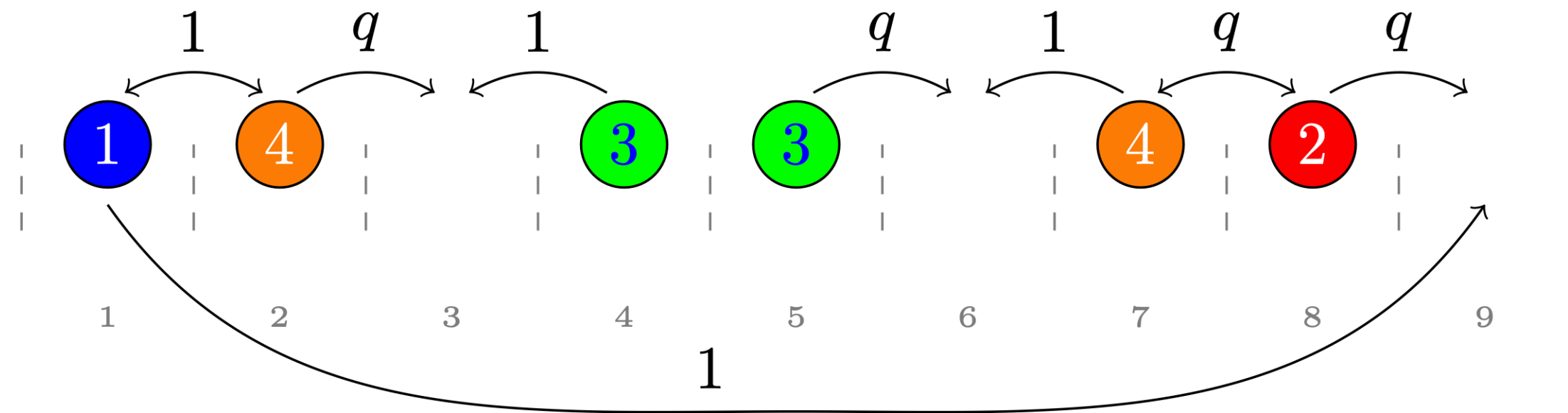
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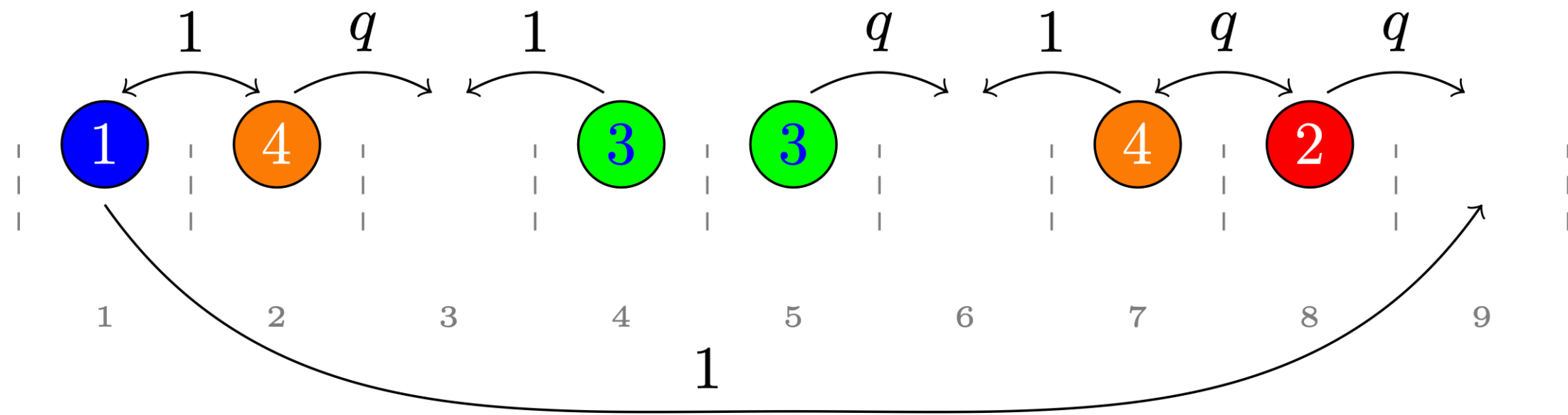
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- For $n = 1$ (single color), it is uniform among all $\binom{N}{N_1}$ configurations

Colored ASEP (= multispecies ASEP = mASEP)



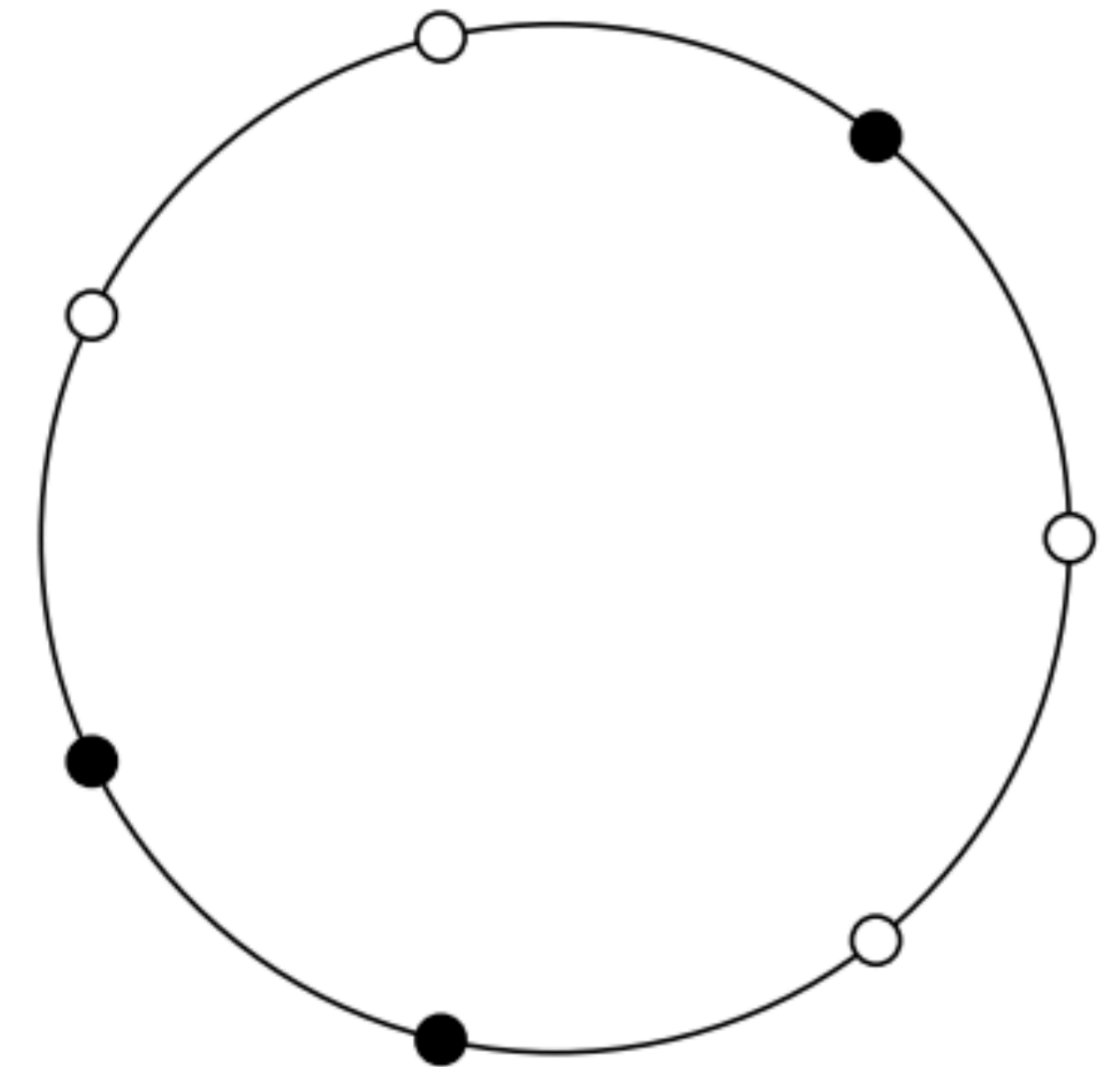
- Particles have colors (types) in $\{1, \dots, n\}$.
- Particles of colors (i_k, i_{k+1}) at adjacent sites $k, k + 1$ swap at rate:

$$\text{Rate}((i_k, i_{k+1}) \rightarrow (i_{k+1}, i_k)) = \begin{cases} q, & i_k > i_{k+1} \\ 1, & i_k < i_{k+1} \end{cases}$$

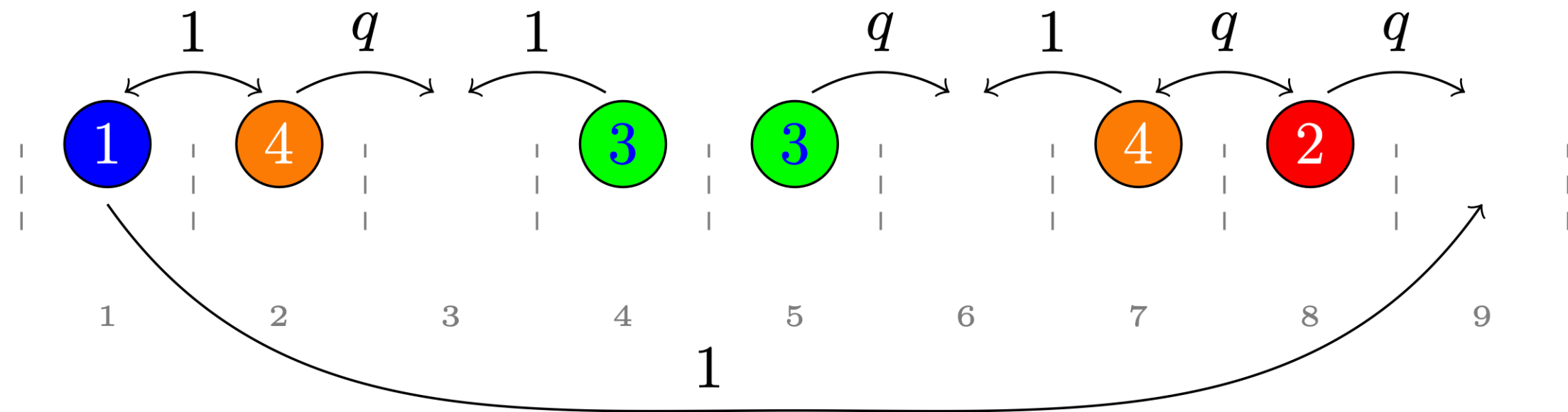
- $q \in [0, 1)$ is the parameter
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- There is a unique **stationary distribution** $\text{Prob}_{N_1, \dots, N_n}(\eta_1, \dots, \eta_N)$ in each “sector” $\vec{N} = (N_1, \dots, N_n)$, where $\eta_j \in \{0, 1, \dots, n\}$
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Colored ASEP (= multispecies ASEP = mASEP)



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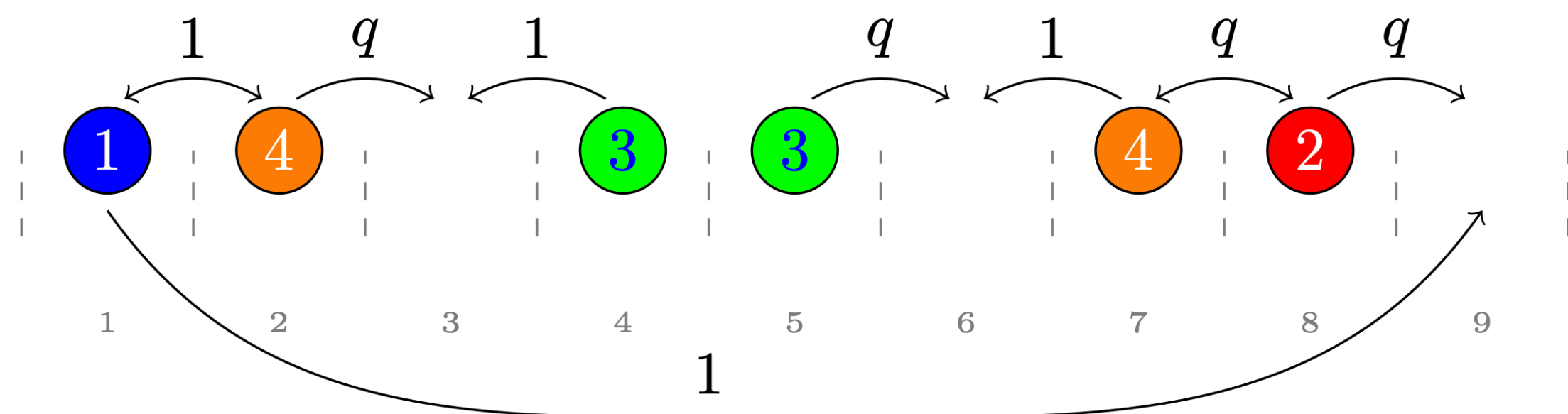
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- For $n = 1$ (single color), it is uniform among all $\binom{N}{N_1}$ configurations
- For many colors, nontrivial correlations

(color n :
highest “priority”
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Example: Stationary probabilities for 4 sites, “rainbow” configuration [Martin 2018]

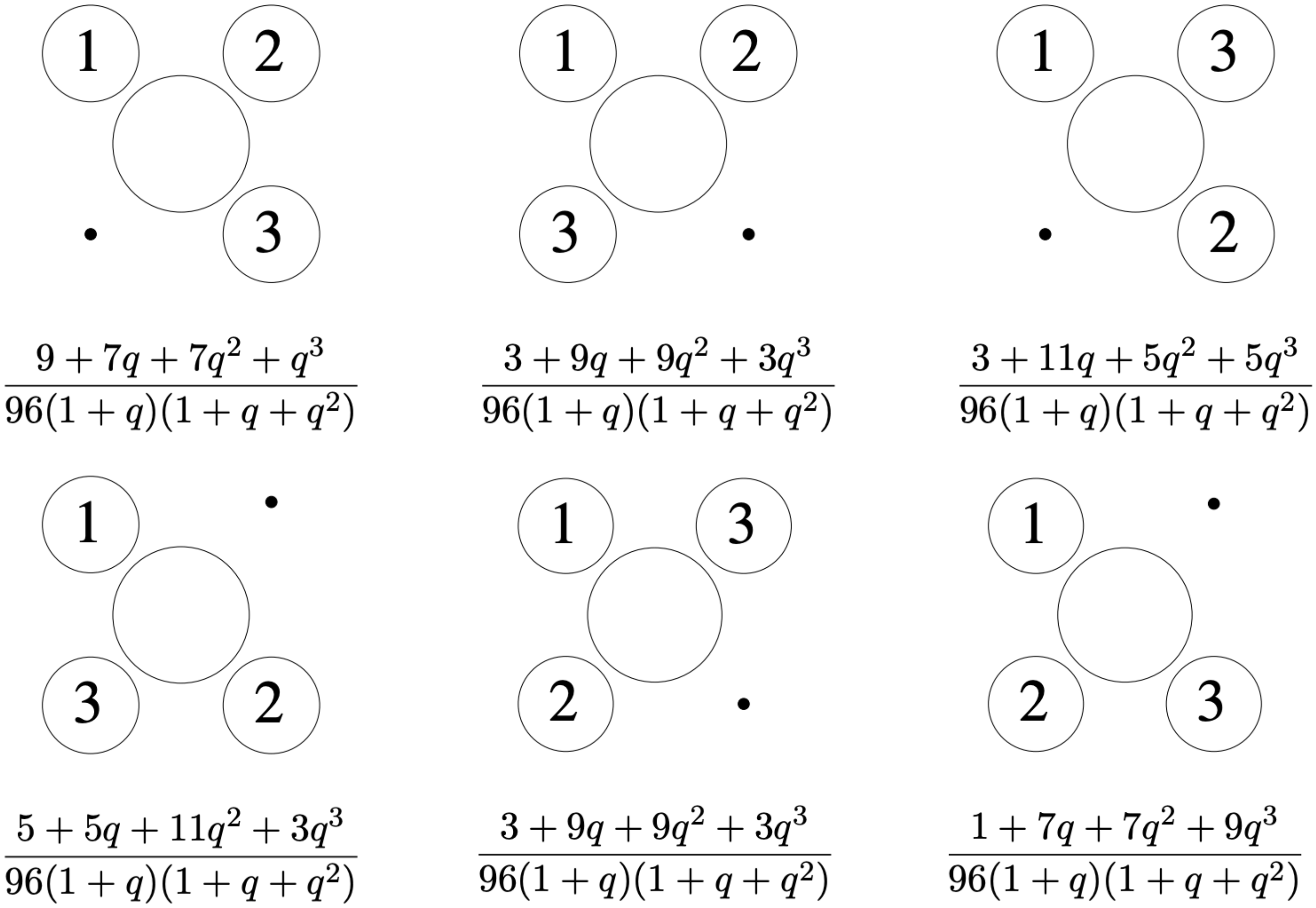
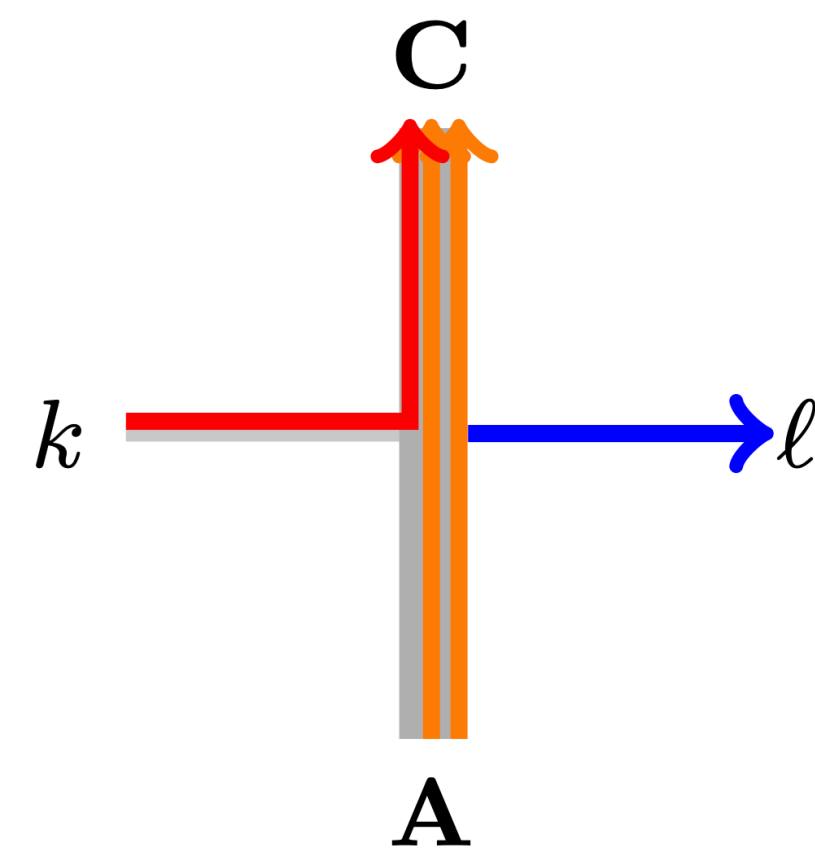


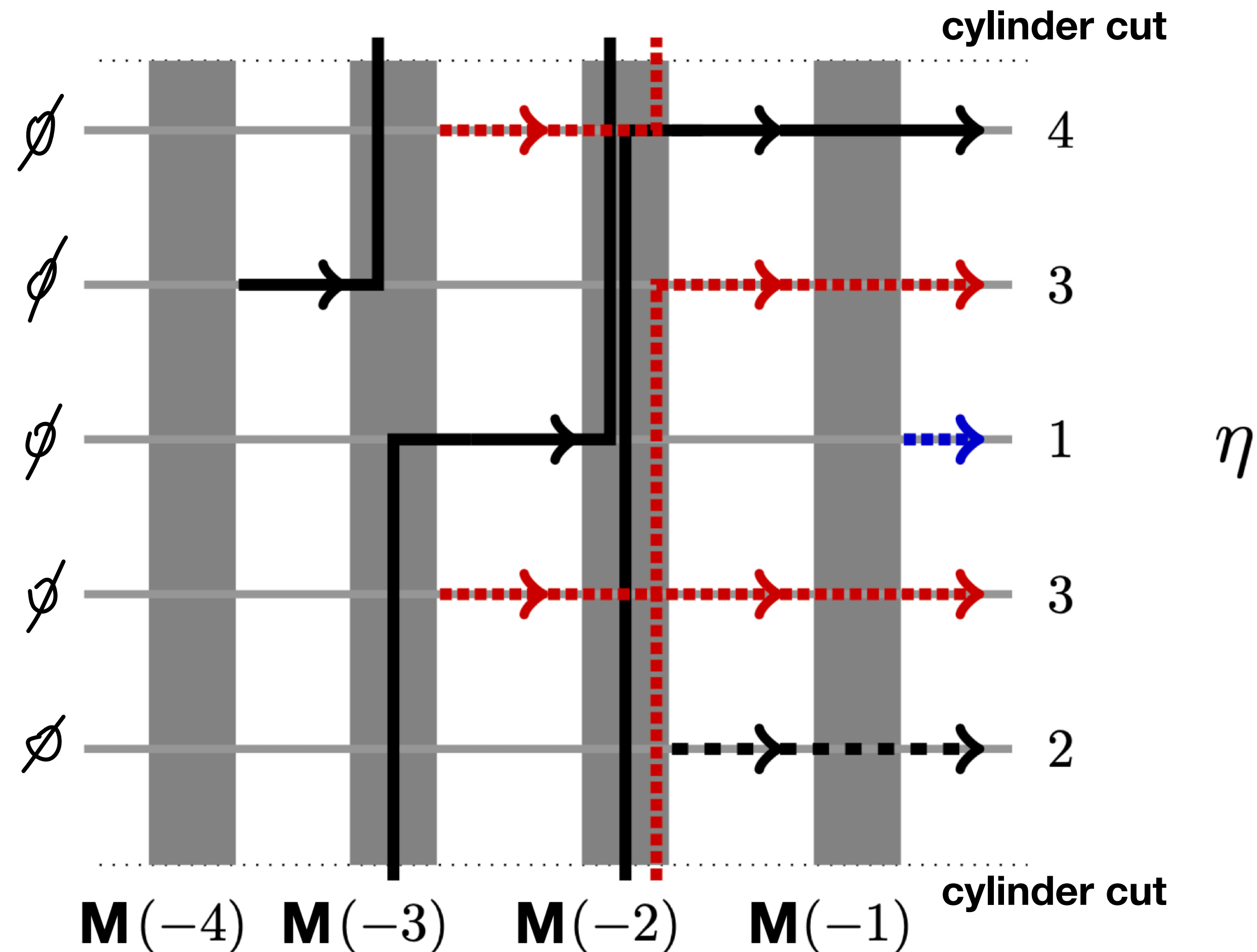
Figure 1.3: Stationary probabilities for a system with 4 sites (numbered clockwise around the ring). The particles are labelled with their type; the single hole may equivalently be seen as a particle of type 4. There are

Stationarity for mASEP on the ring [ANP '23]

- We have a **vertex model** on the cylinder $\{-n, -n+1, \dots, -2, -1\} \times (\mathbb{Z}/N\mathbb{Z})$
- The mASEP configuration $\eta = (\eta_1, \dots, \eta_N)$ encodes the boundary condition.
- $\text{Prob}_{N_1, \dots, N_n}(\eta_1, \dots, \eta_N)$ is proportional to the **partition function** with the boundary η , which involves the summation over the wrappings $\mathbf{M}(-n), \dots, \mathbf{M}(-1)$. There are infinitely many arrows of color m wrapping around column $(-m)$.
- Weights are denoted by $\mathbb{W}_{s,x}^{(-m)}(\mathbf{A}, k; \mathbf{C}, \ell)$, $\mathbf{A}, \mathbf{C} \in \mathbb{Z}_{\geq 0}^n, k, \ell \in \{0, 1, \dots, n\}$.



In column $(-m)$,
use weight $\mathbb{W}_{s_m, x_m}^{(-m)}$

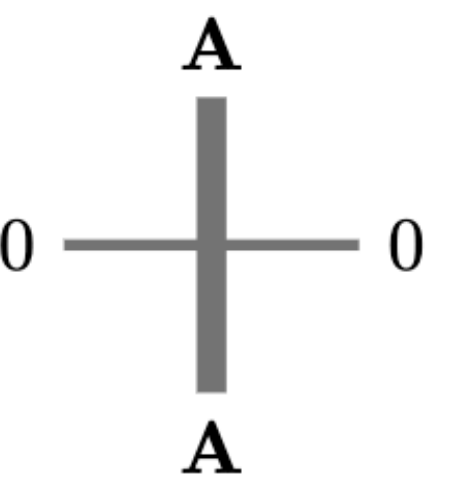
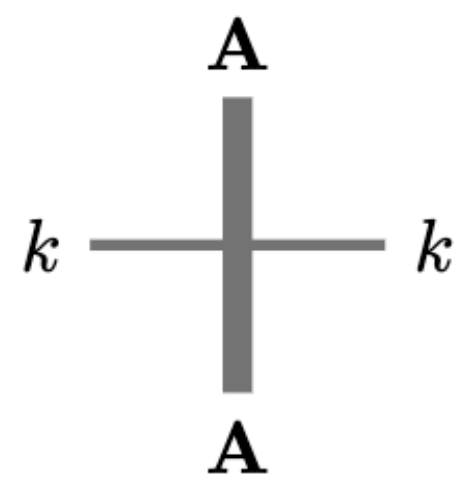
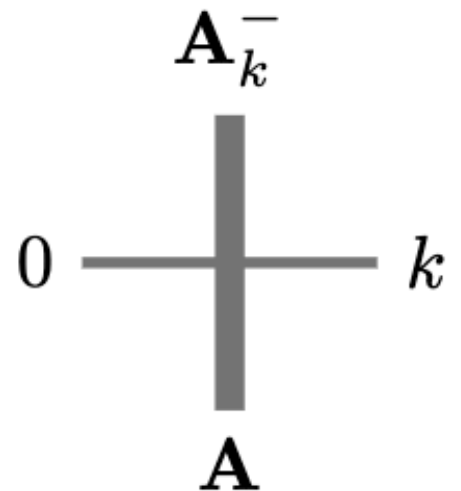
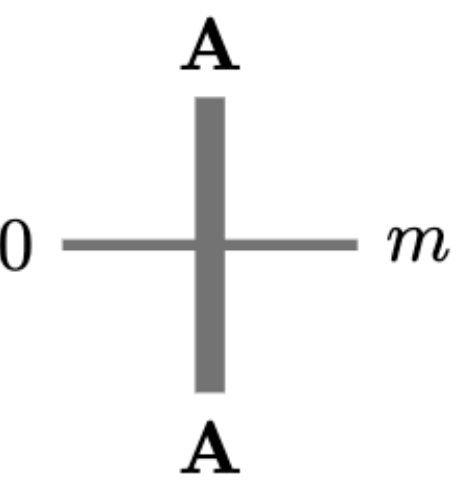
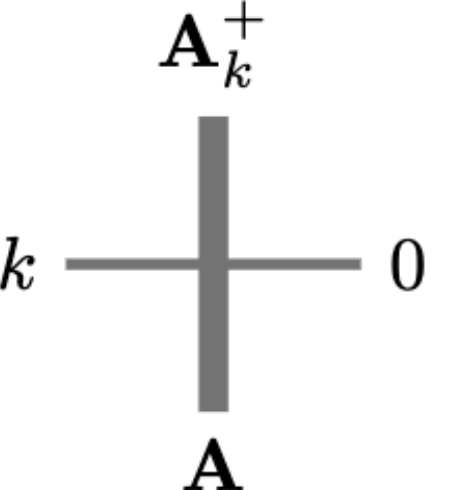
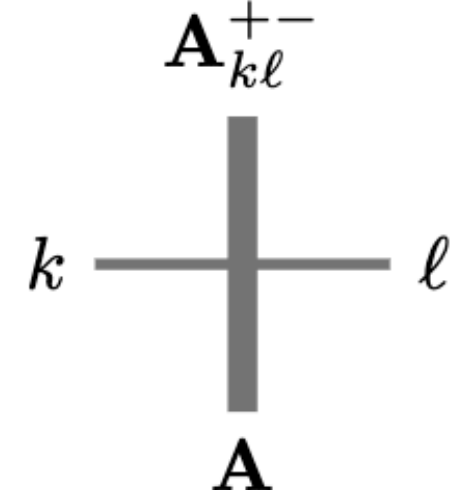
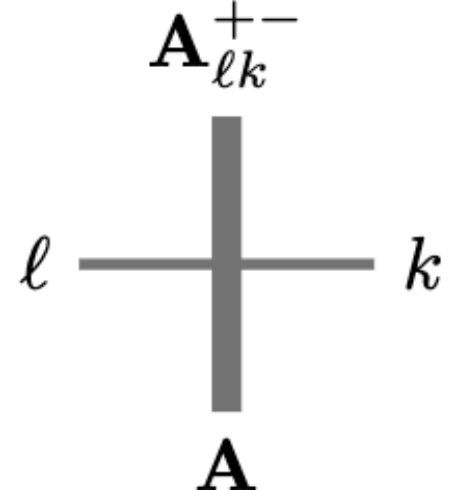
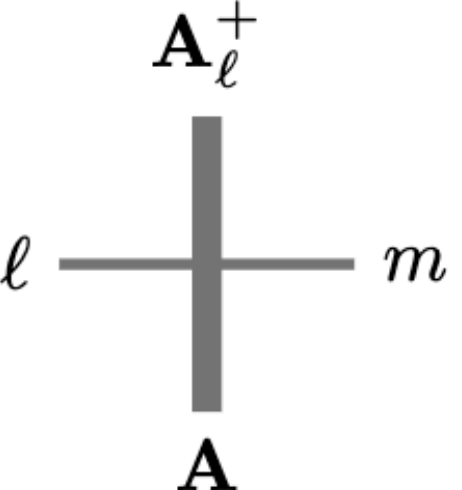


Stationarity for mASEP on the ring [ANP '23]

Theorem. $\text{Prob}_{N_1, \dots, N_n}(\eta_1, \dots, \eta_N)$ is proportional to

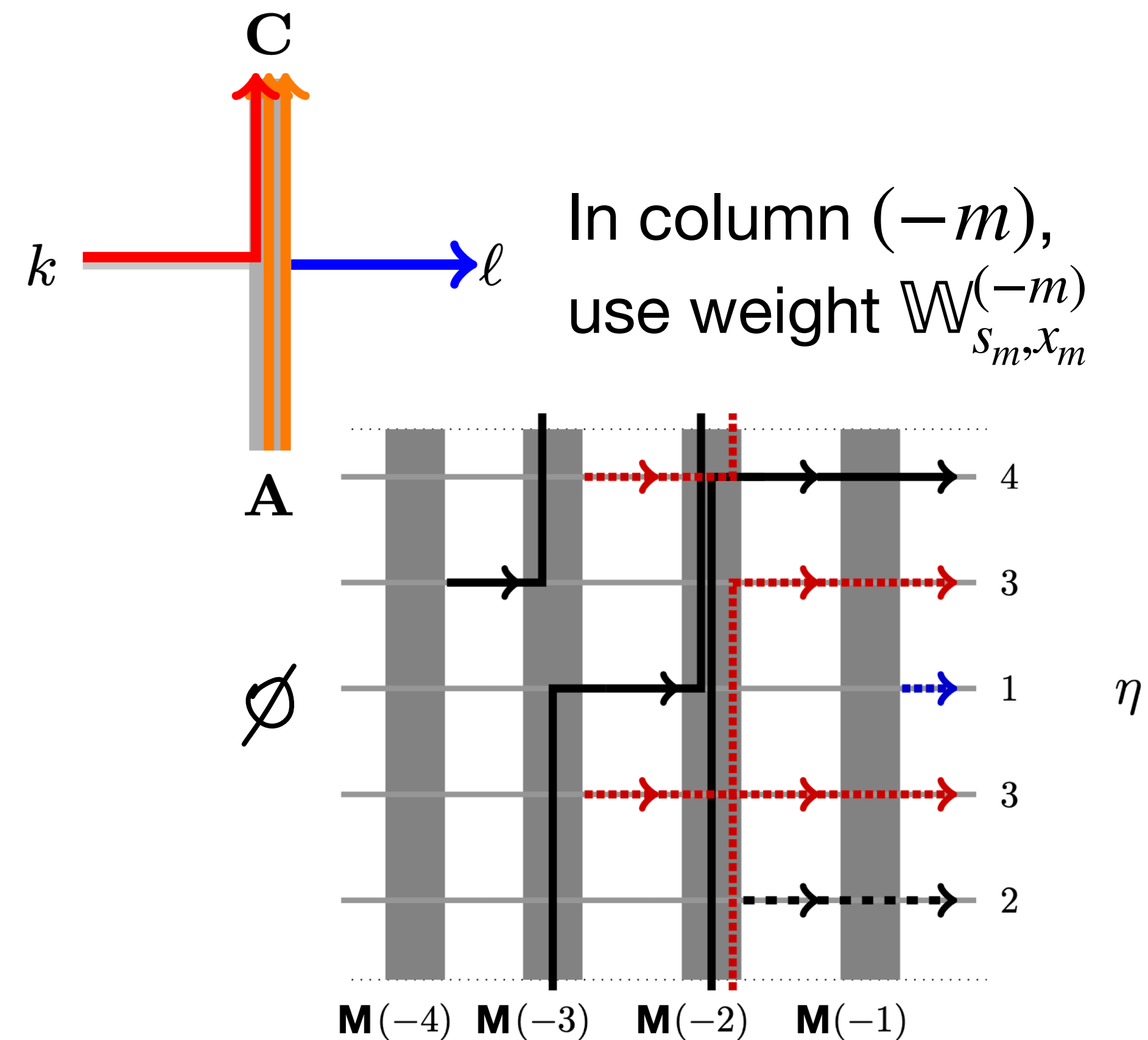
$\sum_{\mathbf{M}(-n), \dots, \mathbf{M}(-1)} \sum_{\text{path conf}}$ of products of the weights

$\mathbb{W}_{S_m, x_m}^{(-m)}$ over all $n \times N$ vertices, with boundaries \emptyset, η .

 <p>1</p>	 <p>$(x - sq^{A_k}) q^{A_{[k+1, n]}}$</p>	 <p>$x(1 - q^{A_k}) q^{A_{[k+1, n]}}$</p>	 <p>$x q^{A_{[m+1, n]}}$</p>
 <p>1</p>	 <p>$x(1 - q^{A_l}) q^{A_{[l+1, n]}}$</p>	 <p>$s(1 - q^{A_k}) q^{A_{[k+1, n]}}$</p>	 <p>$s q^{A_{[m+1, n]}}$</p>

Infinitely many vertical arrows of color m ; $m < k < \ell \leq n$.

These are limits of the fused $U_q(\widehat{\mathfrak{sl}}_n)$ weights to infinitely many arrows.



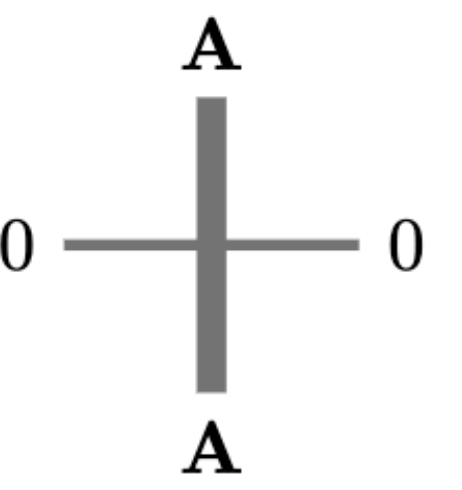
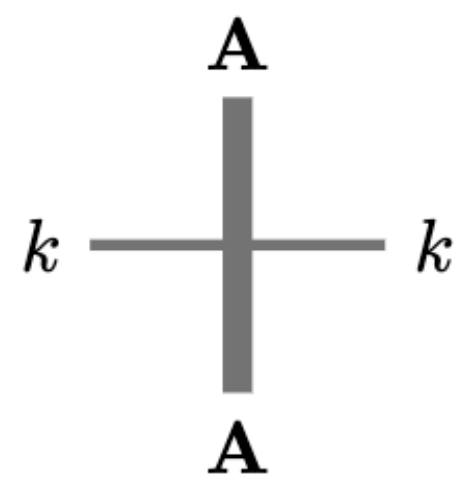
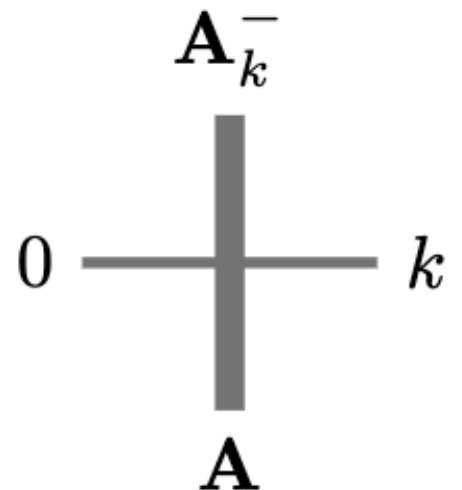
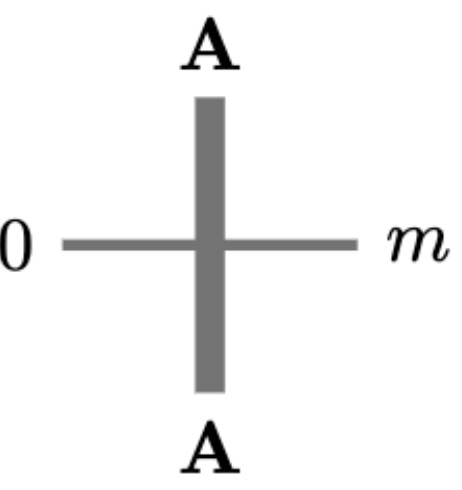
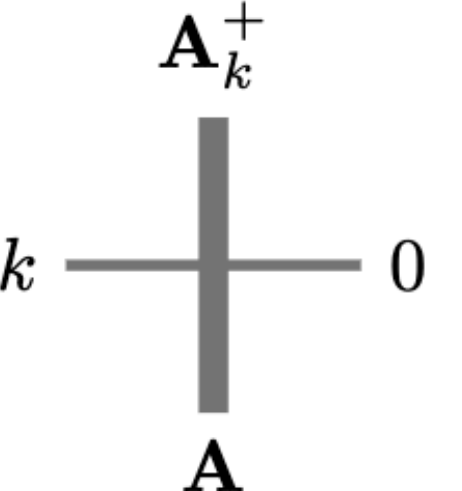
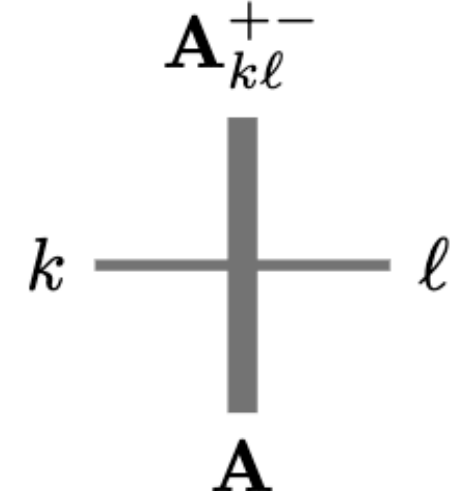
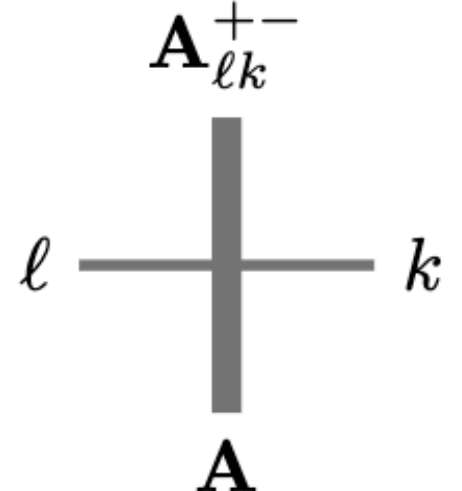
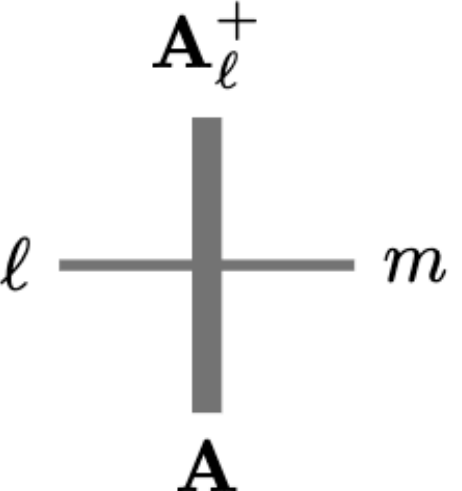
Stationarity for mASEP on the ring [ANP '23]

Theorem. $\text{Prob}_{N_1, \dots, N_n}(\eta_1, \dots, \eta_N)$ is proportional to

$$\sum_{\mathbf{M}(-n), \dots, \mathbf{M}(-1)} \sum_{\text{path conf}}$$

of products of the weights

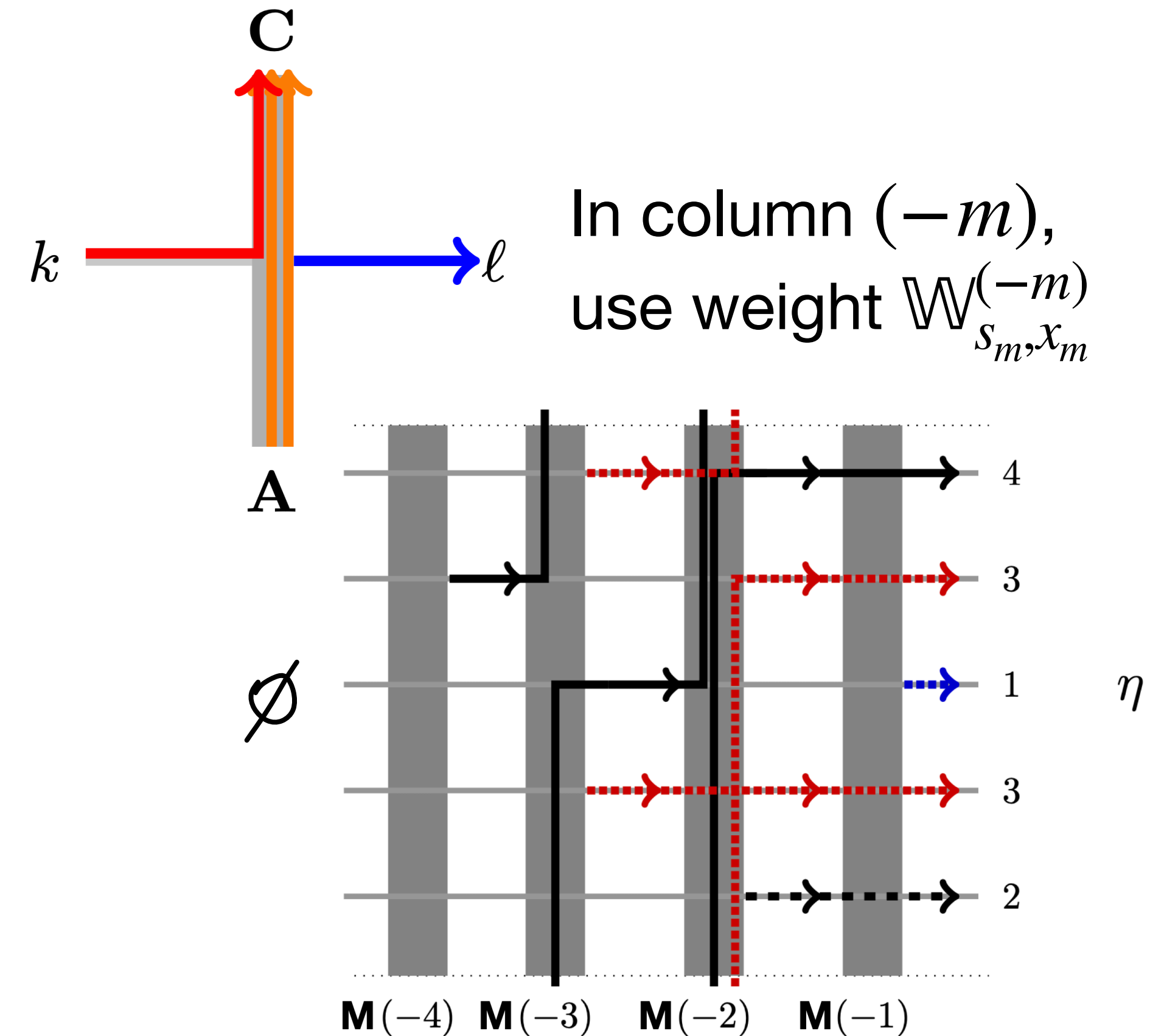
$\mathbb{W}_{S_m, x_m}^{(-m)}$ over all $n \times N$ vertices, with boundaries \emptyset, η .

 <p>1</p>	 <p>$(x - sq^{A_k}) q^{A_{[k+1, n]}}$</p>	 <p>$x(1 - q^{A_k}) q^{A_{[k+1, n]}}$</p>	 <p>$x q^{A_{[m+1, n]}}$</p>
 <p>1</p>	 <p>$x(1 - q^{A_l}) q^{A_{[l+1, n]}}$</p>	 <p>$s(1 - q^{A_k}) q^{A_{[k+1, n]}}$</p>	 <p>$s q^{A_{[m+1, n]}}$</p>

Infinitely many vertical arrows of color m ; $m < k < \ell \leq n$.

These are limits of the fused $U_q(\widehat{\mathfrak{sl}}_n)$ weights to infinitely many arrows.

- The sum *path conf* is over path configurations in the $n \times N$ rectangle with boundaries $\emptyset, \mathbf{M}, \eta, \mathbf{M}$.



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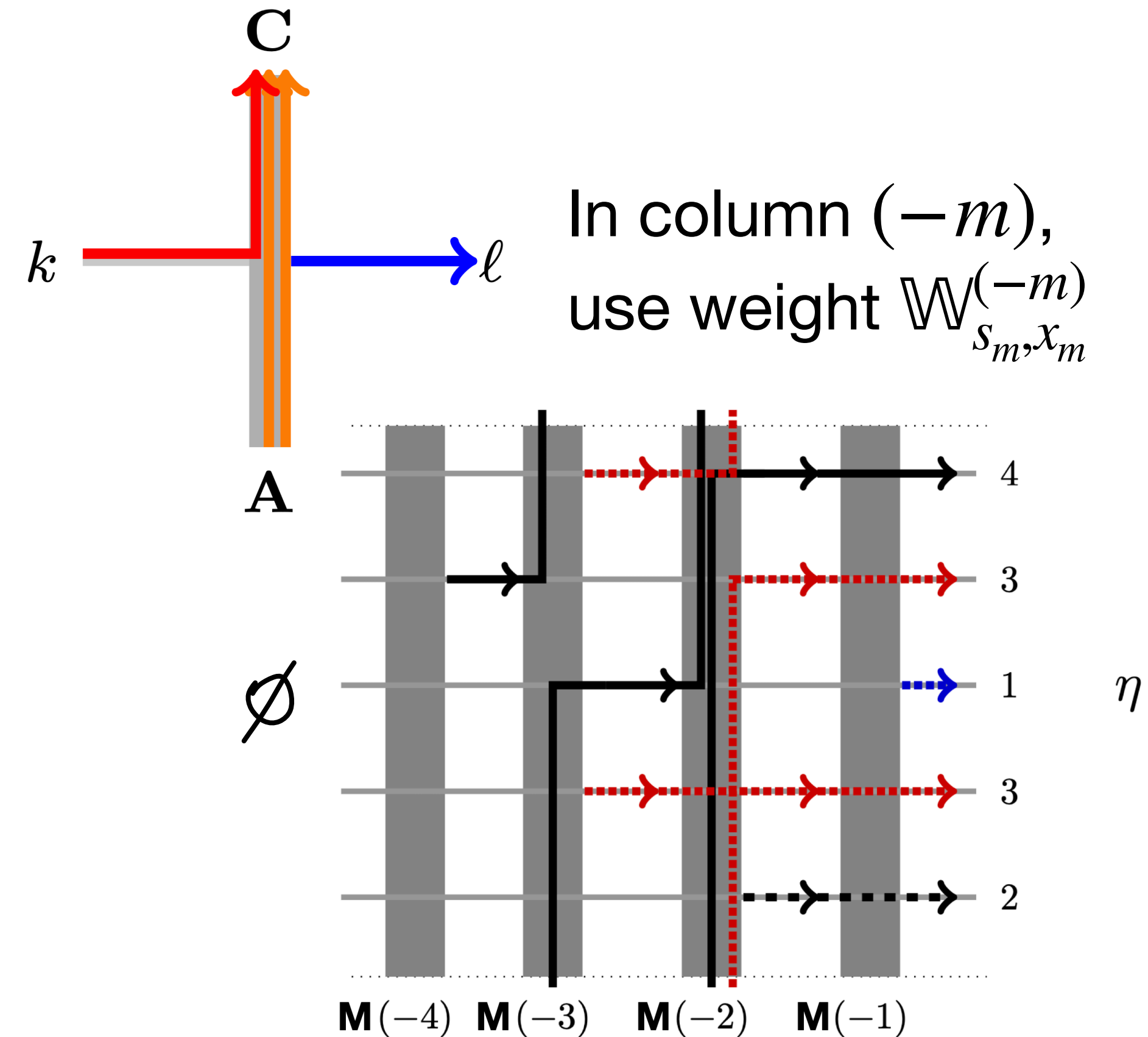
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$\begin{array}{c} \mathbf{A} \\ \\ 0 \text{---} \text{---} 0 \\ \\ \mathbf{A} \end{array}$ <p>1</p>	$\begin{array}{c} \mathbf{A} \\ \\ k \text{---} \text{---} k \\ \\ \mathbf{A} \end{array}$ <p>$(x - sq^{A_k}) q^{A_{[k+1, n]}}$</p>	$\begin{array}{c} \mathbf{A}_k^- \\ \\ 0 \text{---} \text{---} k \\ \\ \mathbf{A} \end{array}$ <p>$x(1 - q^{A_k}) q^{A_{[k+1, n]}}$</p>	$\begin{array}{c} \mathbf{A} \\ \\ 0 \text{---} \text{---} m \\ \\ \mathbf{A} \end{array}$ <p>$xq^{A_{[m+1, n]}}$</p>
$\begin{array}{c} \mathbf{A}_k^+ \\ \\ k \text{---} \text{---} 0 \\ \\ \mathbf{A} \end{array}$ <p>1</p>	$\begin{array}{c} \mathbf{A}_{k\ell}^{+-} \\ \\ k \text{---} \text{---} \ell \\ \\ \mathbf{A} \end{array}$ <p>$x(1 - q^{A_\ell}) q^{A_{[\ell+1, n]}}$</p>	$\begin{array}{c} \mathbf{A}_{\ell k}^{+-} \\ \\ \ell \text{---} \text{---} k \\ \\ \mathbf{A} \end{array}$ <p>$s(1 - q^{A_k}) q^{A_{[k+1, n]}}$</p>	$\begin{array}{c} \mathbf{A}_\ell^+ \\ \\ \ell \text{---} \text{---} m \\ \\ \mathbf{A} \end{array}$ <p>$sq^{A_{[m+1, n]}}$</p>

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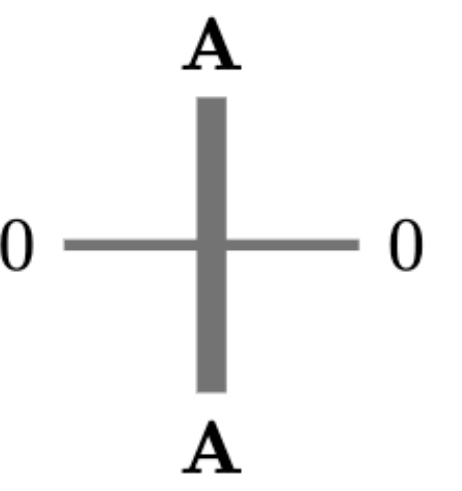
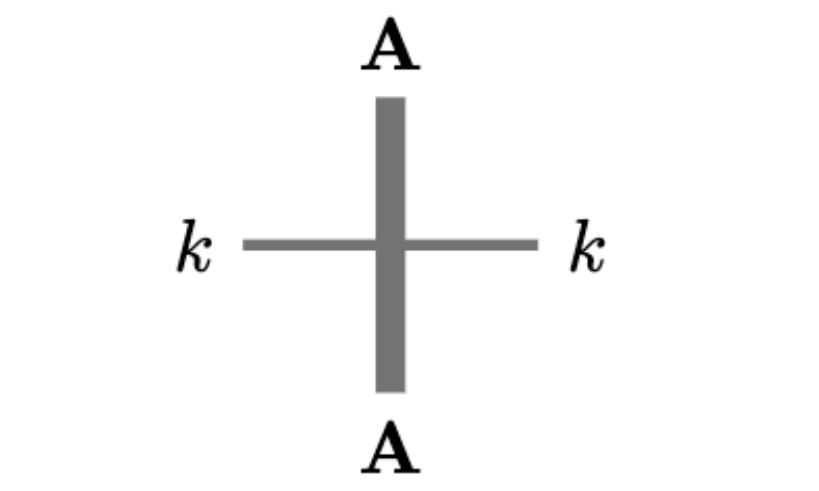
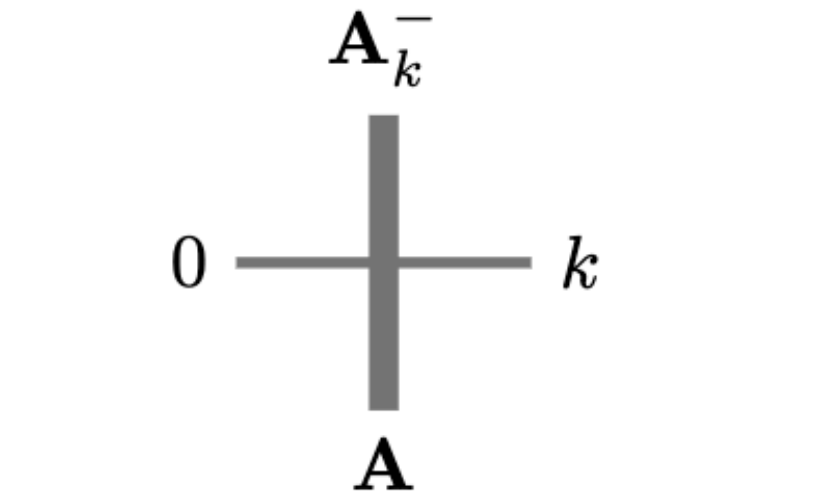
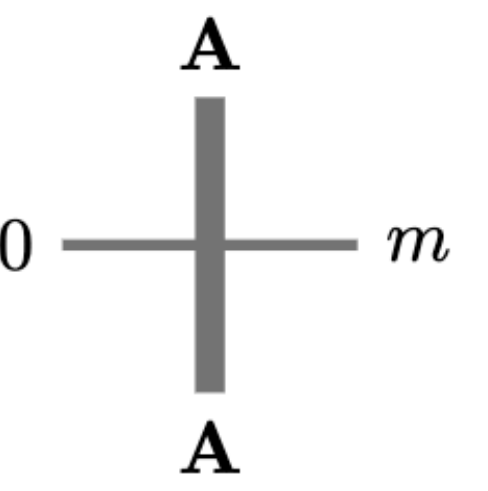
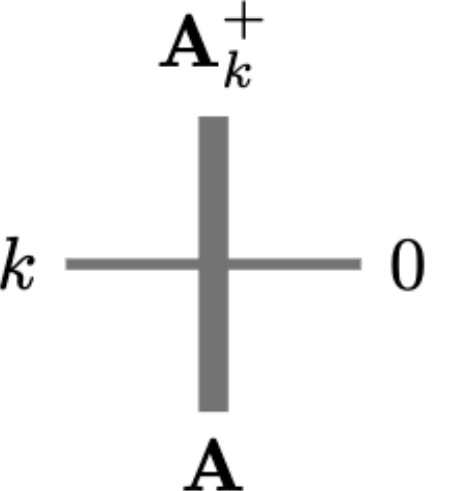
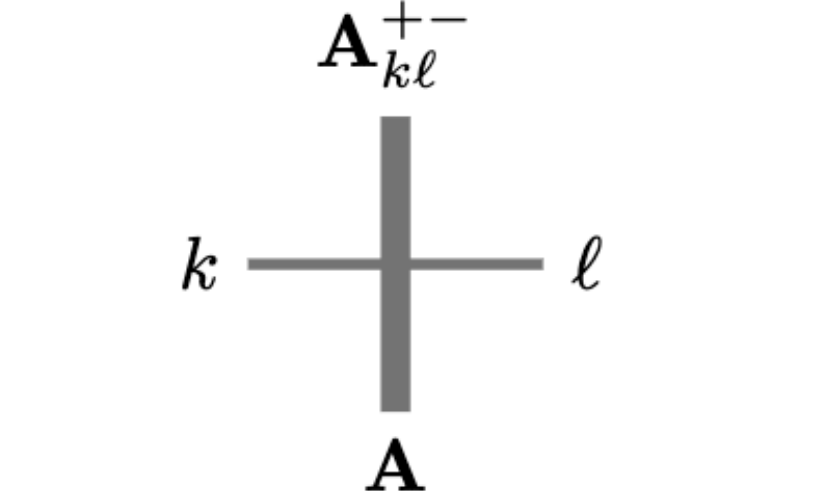
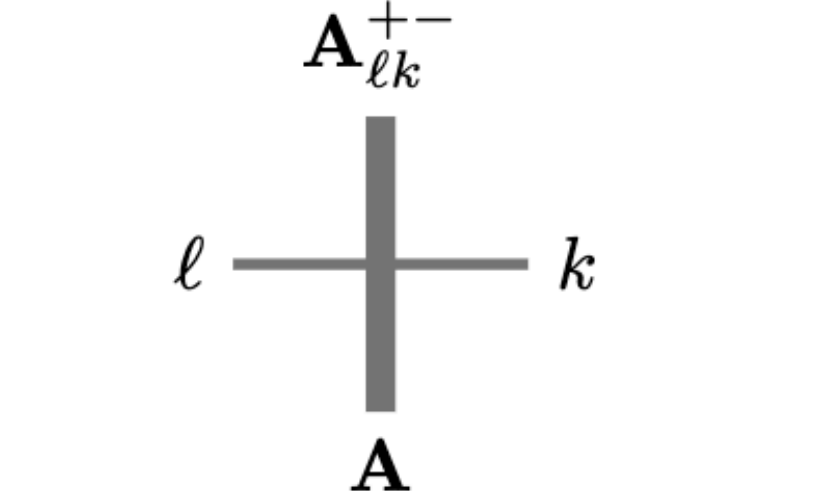
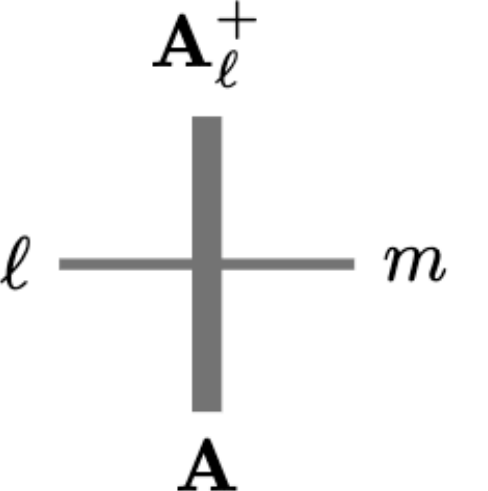


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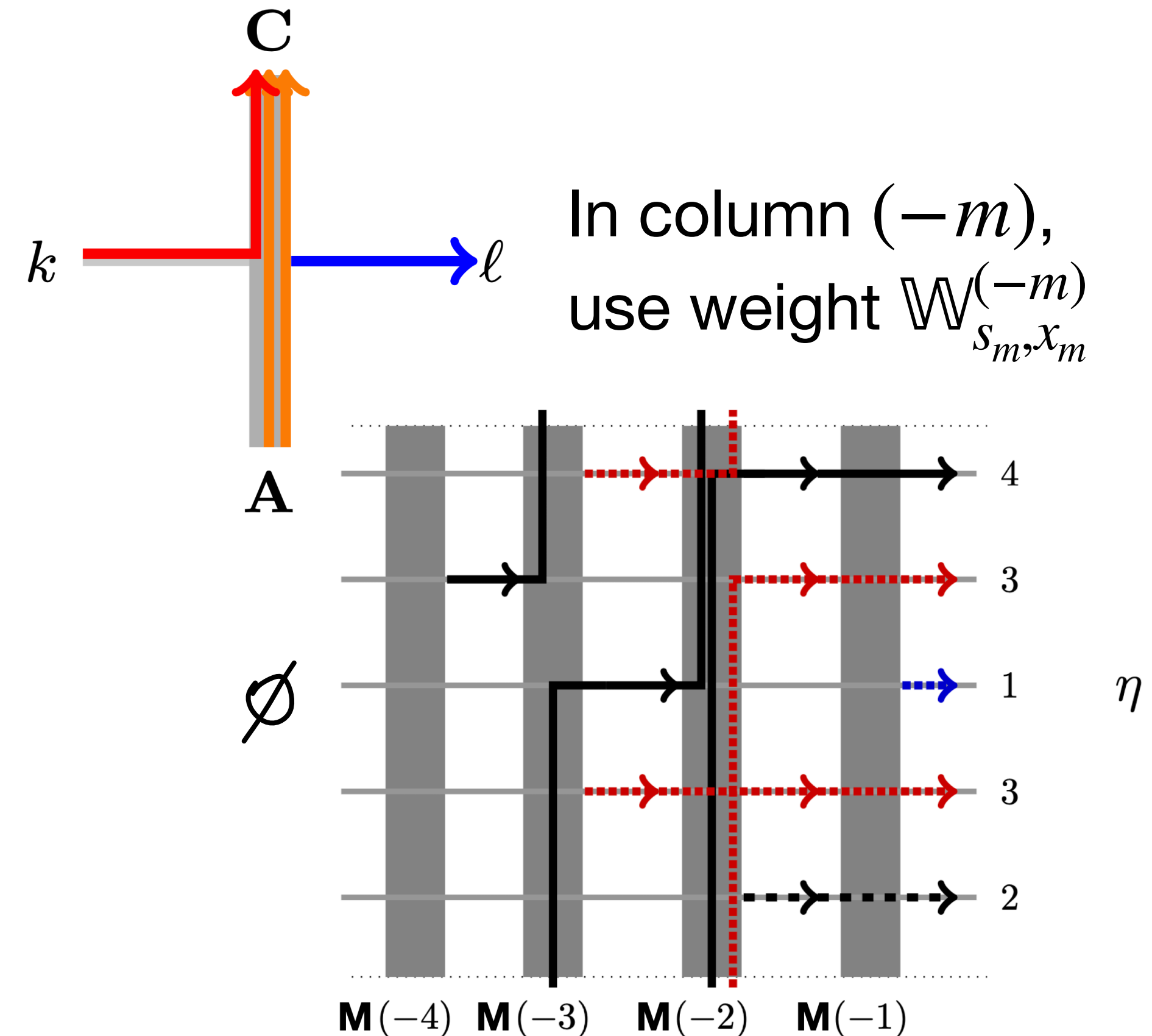
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- Similar result on the line (with fewer parameters for positivity). The remaining parameters are responsible for the color densities.



Conclusions

- Stationary measures for interacting particle systems in different geometries (line, ring, half-space, segment):
 - Motivated by asymptotic phenomena (microscopic characteristics, stationary measures for KPZ equation)
 - Rich algebraic and combinatorial structure (e.g., nonsymmetric Macdonald polynomials)
- We get a Yang-Baxter (vertex) **description of stationarity from first principles**
- Probabilistic consequences follow from **creative placement of Yang-Baxter crosses**, and graphical manipulations.

