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A NON-ERGODIC PROBABILISTIC CELLULAR AUTOMATON WITH A UNIQUE INVARIANT MEASURE

PHILIPPE CHASSAING AND JEAN MAIRESSE

ABSTRACT. We exhibit a Probabilistic Cellular Automaton (PCA) on $\{0, 1\}^{\mathbb{Z}^d}$ with a neighborhood of size 2 which is non-ergodic although it has a unique invariant measure. This answers by the negative an old open question on whether uniqueness of the invariant measure implies ergodicity for a PCA.

1. INTRODUCTION

Consider a random process on $\Sigma^{\mathbb{Z}^d}$, where Σ is a finite set, with local interactions and a translation invariant dynamic. There are two natural instantiations, one with asynchronous updates of the sites of \mathbb{Z}^d , and one with synchronous updates. In the first case, the model is a continuous time Markov process, known as a (finite range) *Interacting Particle System (IPS)*. In the second case, the model is a discrete time Markov chain known as a *Probabilistic Cellular Automaton (PCA)*.

The relevance of IPS in statistical mechanics, as well as in many other contexts, is well established. Let us mention a couple of motivations for studying PCA. First, the investigation of fault-tolerant computational models was the motivation for the Russian school [12, 5]. Second, PCA appear in combinatorial problems related to the enumeration of directed animals [3, 2, 6]. Third, in the context of the classification of (deterministic) cellular automata (Wolfram's program), robustness to random errors can be used as a discriminating criterion [4].

For IPS and PCA, the first question is to study the equilibrium behavior. An equilibrium is characterized by an *invariant measure*, that is a probability measure on the state space which is left invariant by the dynamic. An invariant measure μ is *attractive* if, for any initial condition, the state of the system converges (weakly) to μ as time goes on.

By a compactness argument, there always exists at least one invariant measure. Therefore, there are, a priori, three possible situations:

- (1) several invariant measures;
- (2) a unique invariant measure which is not attractive;
- (3) a unique invariant measure which is attractive.

In the last case, which corresponds to the nicest possible situation, the model is said to be *ergodic*. Roughly, an ergodic system completely forgets about its initial condition, while a non-ergodic one remembers something forever.

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A classical foundational question is whether the intermediate case exists. In other words, does uniqueness of the invariant measure imply convergence to it? For monotone systems, the intermediate case does not exist. But in general, the question is open.

For IPS, this question is *Open Problem 4* in Chapter 1 of the classical textbook by Liggett [7]. In [9], Mountford proves that the intermediate case does not exist for 1-dimensional IPS (that is $d = 1$). Quoting [9], “it seems more than plausible that the conclusion (...) is true in higher dimensions”. However, the question remains unsettled. For PCA, the same question is *Unsolved problem 3.4.3* in Toom [10], or *Unsolved problem 5.7* in Toom [11].

In the present paper, we answer the question for PCA by exhibiting a 1-dimensional model F_A corresponding to the intermediate case (Theorem 3.1). There is a unique invariant measure of the form $(\mu_0 + \mu_1)/2$ and $\mu_0 F_A = \mu_1$, $\mu_1 F_A = \mu_0$. Starting from an initial measure μ_0 , the probability measure of the state of the system is μ_0 at even times and μ_1 at odd times. Therefore there is no convergence.

Observe that the situations for IPS and PCA are different: in 1-d, the intermediate case exists for PCA, and not for IPS. This is consistent with the situation for Markov processes on a finite state space: in discrete time, periodic phenomena may occur which result in the existence of the intermediate case; in continuous time, the intermediate case does not exist.

To prove the result, we introduce two auxiliary PCA which are interesting in themselves. The first one, model B , corresponds to independently moving particles annihilating when they meet ($p+p \rightarrow \emptyset$). The second one, model C , corresponds to independently moving particles merging when they meet ($p+p \rightarrow p$). Both models are shown to be ergodic, the unique invariant measure being the Dirac measure on the “all empty” configuration. We prove that the speed of convergence to the invariant measure is of order $1/\sqrt{n}$ (Theorem 5.2 and Prop. 6.1). This disproves a conjecture appearing in Toom [10, §3.5.1] and stating that ergodicity implies an exponentially fast convergence.

Continuous-time versions of models B and C with a finite set of sites have been studied in the literature, see for instance [1] for B , [8] for C , and the references therein.

2. PROBABILISTIC CELLULAR AUTOMATON

Let Σ be a finite set. Denote by $\mathcal{M}(\Sigma)$ the set of probability measures on Σ . Let us equip $X = \Sigma^{\mathbb{Z}}$ with the product topology. Denote by $\mathcal{M}(X)$ the set of probability measures on X for the Borelian σ -algebra. Weak convergence of $(\mu_n)_n$ to μ is denoted by $\mu_n \xrightarrow{w} \mu$. Let K be a finite subset of \mathbb{Z} and consider $x \in \Sigma^K$. The *cylinder* defined by x is the set

$$*x* = \left\{ u \in \Sigma^{\mathbb{Z}}, \forall k \in K, u_k = x_k \right\}.$$

Given $k \in \mathbb{Z}$ and $V = (v_1, \dots, v_n) \in \mathbb{Z}^n$, we use the notation $k+V$ for $(k+v_1, \dots, k+v_n)$, and the notation $V(K)$ for $\{i \mid \exists k \in K, \exists v \in V, i = k+v\}$.

Let us introduce probabilistic cellular automata, restricting ourselves to 1-dimensional models.

Definition 2.1. *The alphabet is a finite set Σ ; the set of sites is \mathbb{Z} . The set of configurations is $X = \Sigma^{\mathbb{Z}}$. Given $V \in \mathbb{Z}^n$, a transition function of neighborhood V is a function $f : \Sigma^V \rightarrow \mathcal{M}(\Sigma)$. The probabilistic cellular automaton (PCA) F of transition function f is the application $\mathcal{M}(X) \rightarrow \mathcal{M}(X)$, $\mu \mapsto \mu F$ defined on cylinders by: $\forall K, \forall y \in \Sigma^K$,*

$$\mu F(*y*) = \sum_{x \in \Sigma^{V(K)}} \mu(*x*) \prod_{k \in K} f((x_i)_{i \in k+V})(y_k).$$

Let us look at how F acts on a Dirac measure δ_x . The value of all the sites are updated. The value x_k of the k -th site is changed into the letter $a \in \Sigma$ with probability $f((x_i)_{i \in k+V})(a)$, *independently* of the evolution of the other sites.

By specializing Definition 2.1, we recover two famous models:

- Assume that $V = \{0\}$, then all the sites behave independently. The restriction of the PCA to one site is a Markov chain evolving on Σ . Conversely, any Markov chain on a finite state space E can be realized as (a restriction of) a PCA on the alphabet E with neighborhood $V = \{0\}$.
- Assume that the transition function f is such that: $\forall u \in \Sigma^V, f(u)$ is a Dirac probability measure. Then we may view f as a function $\Sigma^V \rightarrow \Sigma$. We obtain a (deterministic) *cellular automaton*.

A PCA F may be viewed as a Markov chain on the state space $\Sigma^{\mathbb{Z}}$. Thus we borrow the classical terminology of Markov chains.

Definition 2.2. *An invariant (probability) measure of F is a probability measure $\mu \in \mathcal{M}(X)$ such that $\mu F = \mu$. The PCA F is ergodic if it has a unique invariant measure which is attractive, i.e. if*

$$(1) \quad (i) [\exists! \mu \in \mathcal{M}(X), \mu F = \mu], \quad (ii) [\forall \nu \in \mathcal{M}(X), \nu F^n \xrightarrow{w} \mu].$$

Consider for a moment a Markov chain on a finite state space with transition matrix P . Let $\mathcal{G}(P)$ be the graph of the matrix P . Classically, we have

$$(2) \quad (i) \iff \mathcal{G}(P) \text{ has a unique terminal component} \\ (i)+(ii) \iff \mathcal{G}(P) \text{ has a unique terminal component which is aperiodic.}$$

In particular, uniqueness of the invariant measure does not imply ergodicity. The simplest example of a non-ergodic Markov chain with a unique invariant measure is the following: the state space is $X = \{0, 1\}$ and the transition matrix is

$$(3) \quad P = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}.$$

The unique invariant measure is $\mu = (\delta_0 + \delta_1)/2$ and for $\nu = \delta_0$, we do not have $\nu P^n \xrightarrow{w} \mu$.

For PCA, it was an open question to know if (i) implies (ii) in (1). The purpose of the present paper is to settle the question by proposing a non-ergodic PCA with a unique invariant measure.

To get a hint of the difficulty, consider for instance a PCA F with neighborhood $V = \{0\}$. Recall that each site behaves independently and as a finite Markov chain P . As recalled in (2), P may satisfy either $[\neg(i)]$, $[(i), \neg(ii)]$, or $[(i), (ii)]$. We show in Table 1 how this gets reflected on the PCA F .

Markov chain P	PCA F
$\neg(i)$	$\neg(i)$
$(i), \neg(ii)$	$\neg(i)$
$(i), (ii)$	$(i), (ii)$

TABLE 1. Finite Markov chain versus “neighborhood 0 PCA”.

Let us justify the Table. If μ is an invariant measure of P , then the product measure $\mu^{\otimes \mathbb{Z}}$ is an invariant measure of F . Therefore, if P has several invariant measures, the same holds for F . Assume now that P is ergodic with unique invariant measure μ . One proves easily that $\mu^{\otimes \mathbb{Z}}$ is attractive, so F is ergodic. Let us concentrate now on the intermediate case for P . If P satisfies $[(i), \neg(ii)]$ then $\mathcal{G}(P)$ has a unique terminal component which is periodic, say of period 2. Let $(\mu_0 + \mu_1)/2$ be the unique invariant measure of P . Then F has an infinite number of invariant measures. Indeed, consider any $(u_i)_{i \in \mathbb{Z}} \in \{0, 1\}^{\mathbb{Z}}$, and let $(v_i)_{i \in \mathbb{Z}}$ be defined by $v_i = 1 - u_i$ for all i . Then the probability measure $(\otimes_{i \in \mathbb{Z}} \mu_{u_i} + \otimes_{i \in \mathbb{Z}} \mu_{v_i})/2$ is clearly an invariant measure of F .

3. STATEMENT OF THE MAIN RESULT

3.1. Model A. Consider the PCA F_A on the alphabet $\Sigma = \{0, 1\}$, with neighborhood $V = \{-1, 0\}$, and transition function a defined by:

$$a(00)(1) = 1/2, \quad a(01)(1) = 0, \quad a(10)(1) = 1, \quad a(11)(1) = 1/2.$$

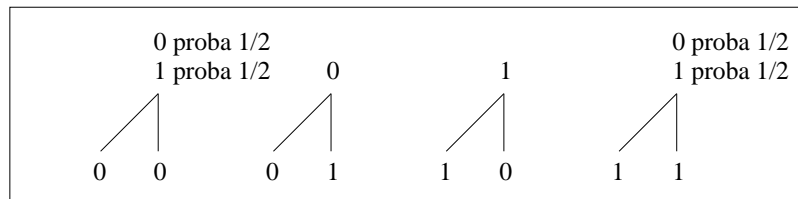


FIGURE 1. The transition function of the PCA F_A .

A realization of the Markov chain is obtained as follows. Consider the function

$$(4) \quad \mathcal{A}: \quad \{0, 1\}^{\mathbb{Z}} \times \mathcal{U}^{\mathbb{Z}} \rightarrow \{0, 1\}^{\mathbb{Z}}$$

$$(x_i)_{i \in \mathbb{Z}}, (u_i)_{i \in \mathbb{Z}} \mapsto (\tilde{x}_i)_{i \in \mathbb{Z}},$$

with $\mathcal{U} = \{\uparrow, \rightarrow\}$, and

$$\tilde{x}_i = \begin{cases} 0 & \text{if } x_{i-1}x_i = 01 \text{ or } (x_{i-1}x_i, u_i) \in \{(00, \rightarrow), (11, \uparrow)\} \\ 1 & \text{if } x_{i-1}x_i = 10 \text{ or } (x_{i-1}x_i, u_i) \in \{(00, \uparrow), (11, \rightarrow)\}. \end{cases}$$

Let $U = (U_{i,j})_{(i,j) \in \mathbb{Z} \times \mathbb{N}}$ be a doubly-indexed sequence of i.i.d. r.v.'s with common law

$$\mathbb{P}(U_{i,j} = \uparrow) = \mathbb{P}(U_{i,j} = \rightarrow) = 1/2,$$

called the *update process*. Set $U_n = (U_{i,n})_{i \in \mathbb{Z}}$. Given a $\{0, 1\}^{\mathbb{Z}}$ -valued r.v. $X_0 = (X_{i,0})_{i \in \mathbb{Z}}$, such that $U \perp X_0$, define the sequence of $\{0, 1\}^{\mathbb{Z}}$ -valued r.v.'s $(X_n)_{n \in \mathbb{N}}$ as follows:

$$(5) \quad X_{n+1} = \mathcal{A}(X_n, U_n).$$

Then $(X_n)_{n \in \mathbb{N}}$ is a realization of model A . The process U is used to randomly update the value of a site, when needed, with \rightarrow being interpreted as “keep” and \uparrow as “switch”, and $X_{i,n}$ is the state of site i at time n , so that $X_n = (X_{i,n})_{i \in \mathbb{Z}}$ denotes the state of the system at time n .

3.2. Invariant measure. Let $x = (01)^{\mathbb{Z}}$ be the configuration defined by: $\forall n \in \mathbb{Z}$, $x_{2n} = 0$, $x_{2n+1} = 1$. The configuration $(10)^{\mathbb{Z}}$ is defined similarly.

Theorem 3.1. *The PCA F_A has a unique invariant measure which is $\mu = (\delta_{(01)^{\mathbb{Z}}} + \delta_{(10)^{\mathbb{Z}}})/2$. The PCA is non-ergodic.*

On configurations without 00 and 11, the PCA acts as the translation shift. Therefore $\mu = (\delta_{(01)^{\mathbb{Z}}} + \delta_{(10)^{\mathbb{Z}}})/2$ is an invariant measure. Assume that it is the unique one. Then the non-ergodicity is straightforward, the situation being the same as for (3): consider $\nu = \delta_{(01)^{\mathbb{Z}}}$, then $\nu F_A^n = \delta_{(01)^{\mathbb{Z}}}$ if n is even, and $\nu F_A^n = \delta_{(10)^{\mathbb{Z}}}$ if n is odd.

The purpose of Sections 4 and 5 is to prove Theorem 3.1.

4. TWO AUXILIARY MODELS

We now define two new PCA, that we call respectively *model B* and *model C*. For both models, the alphabet is $\Sigma = \{\circ, \bullet\}$ and the set of sites is \mathbb{Z} . Given a configuration $u \in \{\circ, \bullet\}^{\mathbb{Z}}$, the following interpretation holds: if $u_i = \circ$, the site i is “empty”; if $u_i = \bullet$, the site i contains a “particle”. At a given time step, a particle decides (independently of the others and independently of the past) to remain at its site with probability 1/2, or to jump to the site on the right with probability 1/2. In model B , if two particles collide, then they annihilate. In model C , if two particles collide, they are merged into one particle. Let us define the models more formally.

4.1. Model B. It is the Markov chain on $\{\circ, \bullet\}^{\mathbb{Z}}$ defined as follows. Consider the function

$$(6) \quad \mathcal{B}: \quad \{\circ, \bullet\}^{\mathbb{Z}} \times \mathcal{U}^{\mathbb{Z}} \rightarrow \{\circ, \bullet\}^{\mathbb{Z}} \\ (y_i)_{i \in \mathbb{Z}}, (u_i)_{i \in \mathbb{Z}} \mapsto (\tilde{y}_i)_{i \in \mathbb{Z}},$$

with $\mathcal{U} = \{\uparrow, \rightarrow\}$, and

$$\tilde{y}_i = \begin{cases} \bullet & \text{if } (y_{i-1}y_i, u_{i-1}u_i) \in \{(\bullet\circ, \rightarrow \mathcal{U}), (\circ\bullet, \mathcal{U} \uparrow), (\bullet\bullet, \uparrow\uparrow), (\bullet\bullet, \rightarrow\rightarrow)\} \\ \circ & \text{otherwise.} \end{cases}$$

Let U be an update process, defined as in Section 3.1. Given a $\{\circ, \bullet\}^{\mathbb{Z}}$ -valued r.v. Y_0 , such that $U \perp Y_0$, define the sequence of $\{\circ, \bullet\}^{\mathbb{Z}}$ -valued r.v.'s $(Y_n)_{n \in \mathbb{N}}$ as follows:

$$(7) \quad Y_{n+1} = \mathcal{B}(Y_n, U_n).$$

Then $(Y_n)_{n \in \mathbb{N}}$ is a realization of model B .

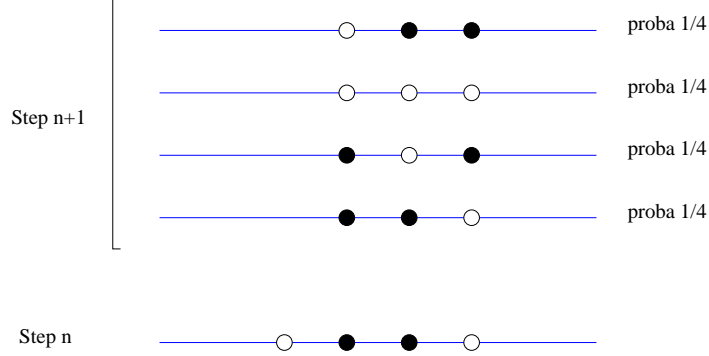


FIGURE 2. The transition function of model B .

Remark. In the above presentation, model B is a Markov chain with synchronous updates and local interactions, but not *stricto sensu* a PCA. Indeed, if Y_0 is deterministic, then the r.v.'s $Y_{i,1}$ and $Y_{i+1,1}$ are not independent, since they are updated using the non-disjoint r.v.'s $\{U_{i-1,0}, U_{i,0}\}$ and $\{U_{i,0}, U_{i+1,0}\}$. However, it is possible to give a PCA presentation of model B on a larger alphabet. Define the sequence of $(\{\circ, \bullet\} \times \mathcal{U})^{\mathbb{Z}}$ -valued r.v.'s $(\tilde{Y}_n)_{n \in \mathbb{N}}$ by $\tilde{Y}_n = (Y_n, U_n)$. We have:

$$(\tilde{Y}_{n+1})_i = (\mathcal{B}(\tilde{Y}_n)_i, U_{i,n+1}).$$

Thus $(\tilde{Y}_n)_n$ is a realization of a PCA on the alphabet $\{\circ, \bullet\} \times \mathcal{U}$, with neighborhood $V = \{-1, 0\}$. The same remark holds for model C below.

4.2. Model C . It is the Markov chain on $\{\circ, \bullet\}^{\mathbb{Z}}$ defined as follows. Consider the function

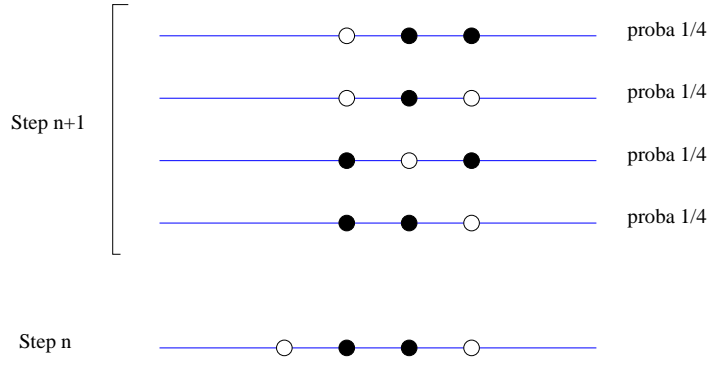
$$\begin{aligned} \mathcal{C} : \quad \{\circ, \bullet\}^{\mathbb{Z}} \times \mathcal{U}^{\mathbb{Z}} &\rightarrow \{\circ, \bullet\}^{\mathbb{Z}} \\ (z_i)_{i \in \mathbb{Z}}, (u_i)_{i \in \mathbb{Z}} &\mapsto (\tilde{z}_i)_{i \in \mathbb{Z}}, \end{aligned}$$

with

$$\tilde{z}_i = \begin{cases} \bullet & \text{if } (z_{i-1}z_i, u_{i-1}u_i) \in \{(\bullet\circ, \rightarrow \mathcal{U}), (\circ\bullet, \mathcal{U} \uparrow), (\bullet\bullet, \uparrow\uparrow), (\bullet\bullet, \rightarrow \mathcal{U})\} \\ \circ & \text{otherwise} . \end{cases}$$

Let U be an update process. Given a $\{\circ, \bullet\}^{\mathbb{Z}}$ -valued r.v. Z_0 , such that $U \perp Z_0$, define the sequence of $\{\circ, \bullet\}^{\mathbb{Z}}$ -valued r.v.'s $(Z_n)_{n \in \mathbb{N}}$ as follows:

$$Z_{n+1} = \mathcal{C}(Z_n, U_n).$$


 FIGURE 3. The transition function of model C .

Then $(Z_n)_{n \in \mathbb{N}}$ is a realization of model C .

4.3. **Links between models A , B , and C .** One-step transition of the model B , resp. C , defines the mapping

$$F_B : \mathcal{M}(\{\circ, \bullet\}^{\mathbb{Z}}) \longrightarrow \mathcal{M}(\{\circ, \bullet\}^{\mathbb{Z}})$$

$$\mu \longmapsto \mu F_B,$$

respectively,

$$F_C : \mathcal{M}(\{\circ, \bullet\}^{\mathbb{Z}}) \longrightarrow \mathcal{M}(\{\circ, \bullet\}^{\mathbb{Z}})$$

$$\mu \longmapsto \mu F_C.$$

Define

$$\varphi : \{0, 1\}^{\mathbb{Z}} \longrightarrow \{\circ, \bullet\}^{\mathbb{Z}}$$

$$(x_i)_{i \in \mathbb{Z}} \longmapsto (y_i)_{i \in \mathbb{Z}},$$

with

$$y_i = \begin{cases} \bullet & \text{if } x_i x_{i+1} \in \{00, 11\} \\ \circ & \text{if } x_i x_{i+1} \in \{01, 10\} \end{cases}$$

By extension, define $\varphi : \mathcal{M}(\{0, 1\}^{\mathbb{Z}}) \rightarrow \mathcal{M}(\{\circ, \bullet\}^{\mathbb{Z}})$.

Lemma 4.1. *The diagram below is commutative:*

$$\begin{array}{ccc} \mathcal{M}(\{0, 1\}^{\mathbb{Z}}) & \xrightarrow{F_A} & \mathcal{M}(\{0, 1\}^{\mathbb{Z}}) \\ \downarrow \varphi & & \downarrow \varphi \\ \mathcal{M}(\{\circ, \bullet\}^{\mathbb{Z}}) & \xrightarrow{F_B} & \mathcal{M}(\{\circ, \bullet\}^{\mathbb{Z}}) \end{array}$$

If $(X_n)_{n \in \mathbb{N}}$ is a realization of the Markov chain A , then $(\varphi(X_n))_{n \in \mathbb{N}}$ is a realization of the Markov chain B .

Proof. Recall that \mathcal{A} and \mathcal{B} are defined in (4) and (6) respectively. We are going to prove that:

$$(8) \quad \varphi \circ \mathcal{A} = \mathcal{B} \circ (\varphi, \text{Id}).$$

The statement of the lemma follows. Set

$$(x_i)_i, (u_i)_i \xrightarrow{\mathcal{A}} (\tilde{x}_i)_i \xrightarrow{\varphi} (\tilde{y}_i)_i, \quad (x_i)_i, (u_i)_i \xrightarrow{\varphi, \text{Id}} (y_i)_i, (u_i)_i \xrightarrow{\mathcal{B}} (\hat{y}_i)_i.$$

To obtain (8), it is enough to check that $\tilde{y}_0 = \hat{y}_0$. This is done by systematic inspection in the table below. Each one of the 16 boxes mimicks the commutative diagram: in the first line, from left to right, (x_{-2}, x_{-1}, x_0) , (u_{-1}, u_0) , and $(\tilde{x}_{-1}, \tilde{x}_0)$; in the second line, from left to right, (y_{-1}, y_0) , (u_{-1}, u_0) , and $\tilde{y}_0 = \hat{y}_0$.

111 or 000	$\rightarrow\rightarrow$	11 or 00	101 or 010	$\rightarrow\rightarrow$	10 or 01
••	$\rightarrow\rightarrow$	•	◦◦	$\rightarrow\rightarrow$	◦
111 or 000	$\rightarrow\uparrow$	10 or 01	101 or 010	$\rightarrow\uparrow$	10 or 01
••	$\rightarrow\uparrow$	◦	◦◦	$\rightarrow\uparrow$	◦
111 or 000	$\uparrow\rightarrow$	01 or 10	101 or 010	$\uparrow\rightarrow$	10 or 01
••	$\uparrow\rightarrow$	◦	◦◦	$\uparrow\rightarrow$	◦
111 or 000	$\uparrow\uparrow$	00 or 11	101 or 010	$\uparrow\uparrow$	10 or 01
••	$\uparrow\uparrow$	•	◦◦	$\uparrow\uparrow$	◦
110 or 001	$\rightarrow\rightarrow$	11 or 00	100 or 011	$\rightarrow\rightarrow$	10 or 01
•◦	$\rightarrow\rightarrow$	•	◦•	$\rightarrow\rightarrow$	◦
110 or 001	$\rightarrow\uparrow$	11 or 00	100 or 011	$\rightarrow\uparrow$	11 or 00
•◦	$\rightarrow\uparrow$	•	◦•	$\rightarrow\uparrow$	•
110 or 001	$\uparrow\rightarrow$	01 or 10	100 or 011	$\uparrow\rightarrow$	10 or 01
•◦	$\uparrow\rightarrow$	◦	◦•	$\uparrow\rightarrow$	◦
110 or 001	$\uparrow\uparrow$	01 or 10	100 or 011	$\uparrow\uparrow$	11 or 00
•◦	$\uparrow\uparrow$	◦	◦•	$\uparrow\uparrow$	•

TABLE 2. The 32 possible cases.

If the process X is defined by (5), relation (8) entails that the process Y , defined by $Y_n = \varphi(X_n)$, satisfies relation (7). \square

Lemma 4.2. *Model B is dominated by model C : for $x, u \in \{\circ, \bullet\}^{\mathbb{Z}} \times \mathcal{U}^{\mathbb{Z}}$,*

$$\mathcal{B}(x, u) \leq \mathcal{C}(x, u),$$

where \leq is the coordinate-wise product ordering on $\{\circ, \bullet\}^{\mathbb{Z}}$, with $\circ \leq \bullet$.

Proof. This can be checked directly on the definitions of \mathcal{B} and \mathcal{C} . Intuitively, particles are merged in model C , and annihilate in model B . \square

Lemma 4.3. *The following implications hold:*

$$\begin{aligned} & [C \text{ is ergodic with invariant measure } \delta_{\circ^{\mathbb{Z}}}] \\ \implies & [B \text{ is ergodic with invariant measure } \delta_{\circ^{\mathbb{Z}}}] \\ \iff & [A \text{ is non-ergodic with invariant measure } (\delta_{(01)^{\mathbb{Z}}} + \delta_{(10)^{\mathbb{Z}}})/2]. \end{aligned}$$

Proof. This is a direct consequence of Lemmas 4.1 and 4.2. \square

Therefore, in order to prove Theorem 3.1, it is sufficient to prove that model C is ergodic with invariant measure $\delta_{\circ z}$. This is the purpose of next section.

5. MODEL C IS ERGODIC

Lemma 5.1. *Model C is monotone, that is: for $z \in \{\circ, \bullet\}^{\mathbb{Z}}$, $\tilde{z} \in \{\circ, \bullet\}^{\mathbb{Z}}$, $u \in \mathcal{U}^{\mathbb{Z}}$,*

$$z \leq \tilde{z} \implies \mathcal{C}(z, u) \leq \mathcal{C}(\tilde{z}, u),$$

where \leq is the coordinate-wise product ordering.

Proof. This can be checked directly on the definition of \mathcal{C} . □

With this monotonicity, to get the ergodicity, it is enough to prove that $\delta_{\bullet z} F_C^n \rightarrow \delta_{\circ z}$. Indeed, consider two realizations of model C , one, say $Z = (Z_n)_n$, that starts with all sites occupied, the other, say $\tilde{Z} = (\tilde{Z}_n)_n$, that starts with an arbitrary initial condition, their evolution using the same update process U . According to Lemma 5.1, at any time $n \in \mathbb{N}$, $\tilde{Z}_n \leq Z_n$.

From now on, we focus on the process Z . Recall that for each n , $Z_n = (Z_{k,n})_{k \in \mathbb{Z}}$ is the state of the system at time n . The process Z_n is stationary, i.e. invariant by translation, since Z_0 , U , and \mathcal{C} are invariant too. Define

$$(9) \quad d_n = \mathbb{P}(Z_{k,n} = \bullet) = \mathbb{P}(Z_{0,n} = \bullet).$$

This is the density of particles at time n . The density d_n can also be viewed as an evaluation of the distance between Z_n and $\delta_{\circ z}$. Indeed, for any finite subset E of \mathbb{Z} , consider the Hamming distance on $\{\circ, \bullet\}^E$, and denote by \mathcal{W}_H the corresponding Wasserstein distance on $\mathcal{M}(\{\circ, \bullet\}^E)$. Setting $Z_{E,n} = (Z_{k,n})_{k \in E}$, we have

$$\mathcal{W}_H(Z_{E,n}, \delta_{\circ^E}) = |E| d_n.$$

Theorem 5.2. *Let T be the time that a simple symmetric random walk on \mathbb{Z} needs to reach 2, starting from 0. We have*

$$(10) \quad d_n = \mathbb{P}(T > 2n)$$

$$(11) \quad = 4^{-n} \binom{2n+1}{n}.$$

In particular, $d_n \sim 2/\sqrt{\pi n}$, hence converges to 0 as n grows.

Corollary 5.3. *Model C is ergodic with unique invariant measure $\delta_{\circ z}$.*

The remainder of the section is devoted to the proof of Theorem 5.2. We first prove (11), assuming (10).

Let $S = (S_k)_{k \in \mathbb{N}}$ be a realization of the simple symmetric random walk on \mathbb{Z} , starting from 0. Define $M_k = \max\{S_i, 0 \leq i \leq k\}$, the maximum of the random walk at time k .

Recall that $T = \inf\{i \geq 0 \mid S_i = 2\}$. We have

$$\begin{aligned} \mathbb{P}(T > 2n) &= \mathbb{P}(M_{2n} \leq 1) = 1 - \mathbb{P}(M_{2n} \geq 2) \\ &= 1 - \sum_{\ell \in \mathbb{Z}} \mathbb{P}(M_{2n} \geq 2, S_{2n} = \ell) \\ &= 1 - \mathbb{P}(S_{2n} \geq 2) - \sum_{\ell \leq 1} \mathbb{P}(M_{2n} \geq 2, S_{2n} = \ell) \end{aligned}$$

According to the reflection principle, $\mathbb{P}(M_{2n} \geq 2, S_{2n} = \ell) = \mathbb{P}(S_{2n} = 4 - \ell)$. Therefore,

$$\begin{aligned} \mathbb{P}(T > 2n) &= 1 - \mathbb{P}(S_{2n} \geq 2) - \mathbb{P}(S_{2n} \geq 3) \\ &= 1 - \mathbb{P}(S_{2n} \leq -2) - \mathbb{P}(S_{2n} \geq 3) \\ &= \mathbb{P}(S_{2n} \in \{0, 2\}) \\ &= 4^{-n} \left(\binom{2n}{n} + \binom{2n}{n+1} \right) = 4^{-n} \binom{2n+1}{n}. \end{aligned}$$

Using Stirling's formula, we get

$$4^{-n} \binom{2n+1}{n} \sim \frac{2}{\sqrt{\pi n}}.$$

A first proof of (10). Recall that $Z = (Z_n)_{n \in \mathbb{N}}$ is a realization of model C with $Z_0 = \bullet_{\mathbb{Z}}$. Assume that in case of collision, the moving particle survives, and the motionless particle dies. This convention enables to track down particles until they disappear. For $k \in \mathbb{Z}$, let p_k denote the particle whose initial position is k . Let $S_{k,n}$ be the event of survival of p_k at time n . Let $\Delta_{k,n}$ be the displacement of p_k at time n , i.e. the difference between its position at time n and k , defined only on the event $S_{k,n}$. Let \tilde{d}_n be the probability of survival of a tagged particle at time n , that is,

$$\tilde{d}_n = \mathbb{P}(S_{k,n}) = \mathbb{P}(S_{0,n}).$$

In contrast, recall that d_n is the probability of presence of a particle at a given site, say 0, at time n , see (9). We have

$$\begin{aligned} d_n &= \sum_{k \geq 0} \mathbb{P}(S_{-k,n} \cap \{\Delta_{-k,n} = k\}) \\ &= \sum_{k \geq 0} \mathbb{P}(S_{0,n} \cap \{\Delta_{0,n} = k\}) \\ &= \mathbb{P}(S_{0,n}) = \tilde{d}_n. \end{aligned}$$

Now, let us associate with particle p_k an evolving set of indices $(I_{k,n})_n$ as follows: $I_{k,0} = \{k\}$; at time n , if the particle p_k kills the particle $p_{k'}$ then $I_{k,n} = I_{k,n-1} \cup I_{k',n-1}$, otherwise $I_{k,n} = I_{k,n-1}$. On the event $S_{k,n}$, the set $I_{k,n}$ is an interval starting with k . And, the intervals associated with the surviving particles form a partition of \mathbb{Z} .

Now, at time n , let p^- be the particle whose interval contains -1, and let p^+ be the particle whose interval contains 0. On the event $S_{0,n}$, the particle p_0 is alive which implies that $p^- \neq (p^+ = p_0)$. On the other hand, on the event $S_{0,n}^c$, we have $p^- = p^+$.

Let W_n^- , resp. W_n^+ , be the position of p^- , resp. p^+ , at time n . In particular, $W_0^- = -1$ and $W_0^+ = 0$. Set

$$R = \inf \{n \geq 0 \mid W_n^- = W_n^+\} .$$

So R is the instant at which particle p_0 disappears. Therefore

$$d_n = \tilde{d}_n = \mathbb{P}(S_{0,n}) = \mathbb{P}(R > n) .$$

From the definition of the process Z , using updating r.v.'s $(U_{k,n})_{(k,n) \in \mathbb{Z} \times \mathbb{N}}$, as described in Section 4.2, $(W_n^-, W_n^+)_{n \in \mathbb{N}}$ has the same distribution as two independent random walks coalescing when they meet, one starting at -1 , the other starting at 0 , with the same distribution of the increments, that is, $(\delta_0 + \delta_1)/2$. As a consequence,

$$\Delta_n = W_n^+ - W_n^-$$

is a random walk with increments distributed according to

$$\nu = \frac{1}{4}\delta_{-1} + \frac{1}{2}\delta_0 + \frac{1}{4}\delta_1 ,$$

starting at 1 and killed when it reaches 0 . Observe that $(\delta_{-2}/4 + \delta_0/2 + \delta_2/4)$ is the two-steps increment of a simple symmetric random walk on \mathbb{Z} . Thus, $(2\Delta_n)_{n \in \mathbb{N}}$ has the same distribution as the sequence of positions of a simple symmetric random walk on \mathbb{Z} , observed at even times. This ends the first proof of (10).

A second proof of (10). One can extend the definition of Z via coupling from the past. Consider the i.i.d. r.v.'s $(U_{k,n})_{(k,n) \in \mathbb{Z} \times \mathbb{Z}}$ with $\mathbb{P}(U_{i,j} = \uparrow) = \mathbb{P}(U_{i,j} = \rightarrow) = 1/2$. For each $s \in \mathbb{Z}$, define $Z^{(s)} = (Z_n^{(s)})_{n \geq s}$ by

$$Z_s^{(s)} = \bullet_{\mathbb{Z}}, \quad \forall n \geq s, \quad Z_{n+1}^{(s)} = \mathcal{C}(Z_n^{(s)}, (U_{k,n})_{k \in \mathbb{Z}}) .$$

The starting time of $Z^{(s)}$ is s , but, besides that, the dynamic is the same as that of process Z . Observe that $Z^{(0)} = Z$. More generally, $Z^{(s)}$ has the same distribution as Z . Thus, we have

$$d_n = \mathbb{P}\left(Z_{0,0}^{(-n)} = \bullet\right) .$$

Furthermore, according to Lemma 5.1, we have

$$\forall s \leq s', \quad Z_n^{(s)} \leq Z_n^{(s')} .$$

In Figure 4, we have represented space-time diagrams for the model. The point of coordinate (k, n) corresponds to site k at step n . We have also represented the updating variables with the following convention: at the point (k, n) , there is an arrow pointing north if $U_{k,n} = \uparrow$ and an arrow pointing north-east if $U_{k,n} = \rightarrow$. This allows to visualize the evolution of particles in the processes $Z^{(s)}$. In Figures 4.b and 4.c, the processes $Z^{(-3)}$ and $Z^{(-5)}$ are represented; the grey nodes are the ones whose color depend on updating variables outside of the represented window. In Figure 4.d, the particles painted in orange (gray) are those that merged into the particle present at time 0 and site 0 .

Let I_n , $n \geq 0$, be the set of indices of particles present at time $-n$ in $Z^{(-n)}$ that merge into particle 0 at time 0 . Either $I_n = \llbracket a_n, b_n \rrbracket$, $a_n \leq b_n$, in which case $Z_{0,0}^{(-n)} = \bullet$, or

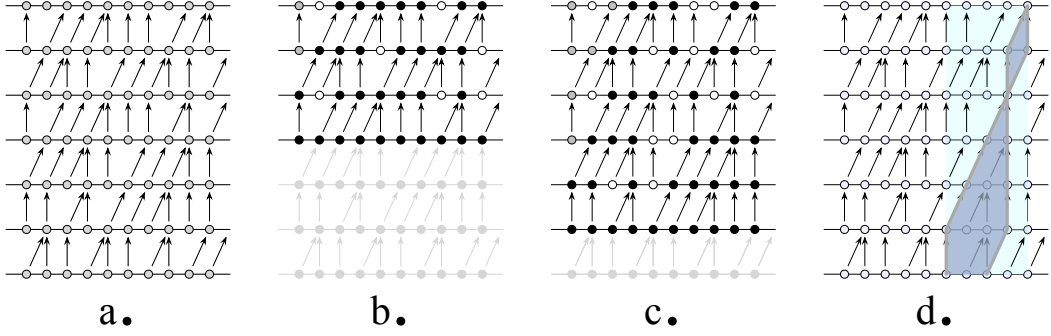


FIGURE 4. **a.** The updating $(U_{k,n})_{(k,n) \in [-9,0] \times [-6,0]}$. **b.** The process $Z^{(-3)}$ during the span $[-3, 0]$. **c.** The process $Z^{(-5)}$ during the span $[-5, 0]$. **d.** The merging of particles.

$I_n = \emptyset$, in which case $Z_{0,0}^{(-n)} = \circ$. We set

$$\tilde{\Delta}_n = \#I_n.$$

For instance, in Figure 4.d, we have $(\tilde{\Delta}_n)_{n \in [0,6]} = (1, 2, 1, 2, 3, 4, 3)$. Observe that

$$(12) \quad d_n = \mathbb{P}\left(Z_{0,0}^{(-n)} = \bullet\right) = \mathbb{P}\left(\tilde{\Delta}_n \geq 1\right).$$

We check the following:

- $a_0 = b_0 = 0$, and $\tilde{\Delta}_0 = 1$;
- Assume that $a_n < b_n$. Then,

$$a_{n+1} = \begin{cases} a_n - 1 & \text{if } U_{a_n-1, -n-1} = \rightarrow \\ a_n & \text{if } U_{a_n-1, -n-1} = \uparrow \end{cases}, \quad b_{n+1} = \begin{cases} b_n - 1 & \text{if } U_{b_n, -n-1} = \rightarrow \\ b_n & \text{if } U_{b_n, -n-1} = \uparrow \end{cases}.$$

Thus, $\tilde{\Delta}_{n+1} - \tilde{\Delta}_n \in \{0, \pm 1\}$, and the conditional distribution of $\tilde{\Delta}_{n+1} - \tilde{\Delta}_n$ is ν .

- Assume that $a_n = b_n$. Then

$$I_{n+1} = \begin{cases} \emptyset & \text{if } (U_{a_n-1, -n-1}, U_{a_n, -n-1}) = (\uparrow, \rightarrow) \\ [a_n - 1, a_n - 1] & \text{if } (U_{a_n-1, -n-1}, U_{a_n, -n-1}) = (\rightarrow, \rightarrow) \\ [a_n - 1, a_n] & \text{if } (U_{a_n-1, -n-1}, U_{a_n, -n-1}) = (\rightarrow, \uparrow) \\ [a_n, a_n] & \text{if } (U_{a_n-1, -n-1}, U_{a_n, -n-1}) = (\uparrow, \uparrow). \end{cases}$$

For instance, the third case appears between lines -3 and -2 in Figure 4.d. Here again, the conditional distribution of $\tilde{\Delta}_{n+1} - \tilde{\Delta}_n$ is ν .

- If $I_n = \emptyset$, then $I_{n+1} = \emptyset$.

Consequently $\tilde{\Delta} = (\tilde{\Delta}_n)_{n \in \mathbb{N}}$ is a random walk with step ν , starting from 1, and killed when it reaches 0. Using (12), we obtain (10).

6. SPEED OF CONVERGENCE FOR MODELS A AND B

Let $(A_n)_{n \in \mathbb{N}}$ be a realization of model A , with $A_0 \sim \mu$, $\mu \in \mathcal{M}(\{0, 1\}^{\mathbb{Z}})$. The subsequences $(A_{2n})_{n \in \mathbb{N}}$ and $(A_{2n+1})_{n \in \mathbb{N}}$ converge respectively to the limits $p\delta_{(01)^{\mathbb{Z}}} + (1-p)\delta_{(10)^{\mathbb{Z}}}$ and $(1-p)\delta_{(01)^{\mathbb{Z}}} + p\delta_{(10)^{\mathbb{Z}}}$ for some $p \in [0, 1]$. In general, we have $p \neq 1/2$ and the two limits are different. An evaluation of the distance to the limits is given by

$$\mathbb{P}(A_{0,n}A_{1,n} \in \{00, 11\}) .$$

Since model A is not monotone, we do not know for which initial measure μ this distance will be maximized. Hence we evaluate the speed of convergence for model A by the quantity:

$$d_n^A = \max_{\mu \in \mathcal{M}(\{0,1\}^{\mathbb{Z}})} \mathbb{P}(A_{0,n}A_{1,n} \in \{00, 11\}) .$$

The quantity d_n^A is also the speed of convergence to $\delta_{\circ^{\mathbb{Z}}}$ for model B . Indeed we have $\mathbb{P}(A_{0,n}A_{1,n} \in \{00, 11\}) = \mathbb{P}(\varphi(A_n)_0 = \bullet)$, which implies that

$$d_n^A = \max_{\nu \in \mathcal{M}(\{\circ, \bullet\}^{\mathbb{Z}})} \mathbb{P}(B_{0,n} = \bullet) ,$$

where $(B_n)_n$ is a realization of model B with $B_0 \sim \nu$.

Recall that $d_n = 4^{-n} \binom{2n+1}{n}$ is the speed of convergence for model C , see (9) and Theorem 5.2.

Proposition 6.1. *Let $(A_n)_n$ be a realization of model A , with $A_0 \sim \mu$. If μ is the uniform distribution on $\{0, 1\}^{\mathbb{Z}}$, i.e. the r.v.'s $A_{i,0}$ are i.i.d. with $\mathbb{P}(A_{0,0} = 0) = \mathbb{P}(A_{0,0} = 1) = 1/2$, then we have $\mathbb{P}(A_{0,n}A_{1,n} \in \{00, 11\}) = d_n/2$. If $\mu = \delta_{1^{\mathbb{Z}}}$, then we have $\mathbb{P}(A_{0,n}A_{1,n} \in \{00, 11\}) = d_{n-1}/2$. In particular, we have*

$$\frac{1}{2}d_{n-1} \leq d_n^A \leq d_n .$$

The results can be translated to model B : the density of particles at step n is $d_n/2$ if the initial distribution is uniform, and it is $d_{n-1}/2$ if the initial distribution is $\delta_{\bullet^{\mathbb{Z}}}$.

The end of the section is devoted to the proof of Prop. 6.1.

We define a new PCA, called model D , which is a coupling of models B and C . The alphabet is $\{\circ, b, g\}$ and the set of sites is \mathbb{Z} . Given a configuration $u \in \{\circ, b, g\}^{\mathbb{Z}}$, the interpretation is as follows: if $u_i = \circ$ then site i is empty; if $u_i = b$ then site i contains a *blue* particle; if $u_i = g$ then site i contains a *green* particle. Particles move as in models B and C . When two particles collide, they get merged into one particle as in model C . In absence of collision, particles keep their color. In case of a collision, the merged particle is colored according to the rules:

$$(13) \quad b + b \rightarrow g, \quad g + g \rightarrow g, \quad b + g \rightarrow b, \quad g + b \rightarrow b .$$

We have represented a realization of model D on Figure 5. The ‘‘question mark’’ nodes are the ones whose color depend on updating variables outside of the represented window. Define

$$\begin{aligned} \pi_B : \{\circ, b, g\} &\longrightarrow \{\circ, \bullet\}, & \pi_B(\circ) &= \circ, \pi_B(b) = \bullet, \pi_B(g) = \circ, \\ \pi_C : \{\circ, b, g\} &\longrightarrow \{\circ, \bullet\}, & \pi_C(\circ) &= \circ, \pi_C(b) = \bullet, \pi_C(g) = \bullet. \end{aligned}$$

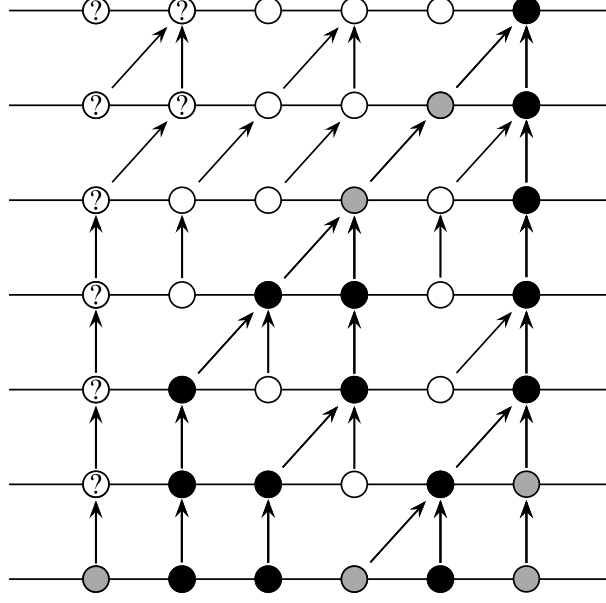


FIGURE 5. A realization of process D (gray for g(reen), black for b(lue)).

We keep the same notations for the product applications: $\pi_B : \{\circ, b, g\}^{\mathbb{Z}} \rightarrow \{\circ, \bullet\}^{\mathbb{Z}}$, $(u_i)_i \mapsto (\pi_B(u_i))_i$, and $\pi_C : \{\circ, b, g\}^{\mathbb{Z}} \rightarrow \{\circ, \bullet\}^{\mathbb{Z}}$, $(u_i)_i \mapsto (\pi_C(u_i))_i$.

Lemma 6.2. *If $(D_n)_n$ is a realization of model D , then $(\pi_B(D_n))_n$ is a realization of model B , and $(\pi_C(D_n))_n$ is a realization of model C . In particular, model D is ergodic with unique invariant measure $\delta_{\circ^{\mathbb{Z}}}$.*

Let $(D_n)_n$ be a realization of model D with D_0 being defined as follows: the r.v.'s $D_{i,0}$ are i.i.d. with $\mathbb{P}(D_{0,0} = b) = \mathbb{P}(D_{0,0} = g) = 1/2$.

Consider two particles whose colors are independent and uniform (blue with probability 1/2, green with probability 1/2). If they merge, according to (13), the resulting color will still be uniformly distributed. Next property follows from this observation. At step n , conditionally on the position of the particles, their colors are i.i.d. and uniform. Therefore we have

(14)

$$\mathbb{P}(\pi_B(D_{0,n}) = \bullet) = \mathbb{P}(D_{0,n} = b) = \frac{1}{2}\mathbb{P}(D_{0,n} \in \{b, g\}) = \frac{1}{2}\mathbb{P}(\pi_C(D_{0,n}) = \bullet) = \frac{1}{2}d_n,$$

where the last equality follows from Theorem 5.2.

Now let $(\tilde{D}_n)_n$ be a realization of model D with $\tilde{D}_0 = b^{\mathbb{Z}}$. Define $E = (E_i)_i$ by

$$E_i = \begin{cases} b & \text{if } \tilde{D}_{i,1} = b \\ g & \text{if } \tilde{D}_{i,1} = \circ \text{ or } g \end{cases}.$$

The r.v.'s $(E_i)_i$ are i.i.d. with $\mathbb{P}(E_0 = b) = \mathbb{P}(E_0 = g) = 1/2$. Let us justify this point. The state at time 1 of a realization of model A that starts from $0^{\mathbb{Z}}$ is uniformly

distributed by definition. Hence, the state at time 1 of a realization of model B that starts from $\bullet^{\mathbb{Z}}$ is uniformly distributed. And E has the same law as the latter up to the transformation $b \leftrightarrow \bullet$, $g \leftrightarrow \circ$.

So we have $E \sim D_0$. Observe also that $\pi_B(\tilde{D}_1) = \pi_B(E)$. We deduce that, for all $n \geq 1$, we have $\pi_B(\tilde{D}_n) \sim \pi_B(D_{n-1})$. In particular, using (14),

$$\mathbb{P}\left(\pi_B(\tilde{D}_{0,n}) = \bullet\right) = \mathbb{P}\left(\tilde{D}_{0,n} = b\right) = \mathbb{P}(D_{0,n-1} = b) = d_{n-1}/2.$$

This completes the proof of Prop. 6.1.

Conclusion. In Theorem 5.2 and Prop. 6.1, we have obtained exact results for the one-dimensional marginals of the processes at step n for models A , B , and C (with natural initial conditions). Studying the full distribution of these processes at step n is more intricate and is a work in progress: coalescence phenomena show up, and random trees appear.

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INSTITUT ÉLIE CARTAN, UNIV. HENRI POINCARÉ, BP 239, 54506 VANDOEUVRE-LES-NANCY CEDEX, FRANCE

E-mail address: chassain@iecn.u-nancy.fr

LIAFA, CNRS ET UNIV. PARIS 7, CASE 7014, 75205 PARIS CEDEX 13, FRANCE

E-mail address: mairese@liafa.jussieu.fr.