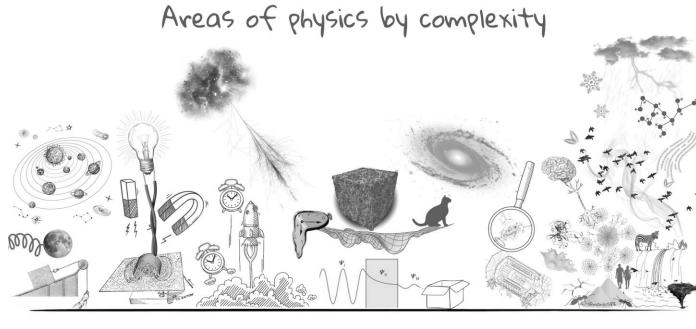
CELLULAR AUTOMATA

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Newton's Mechanics Electro-Magnetism Special Relativity Quantum Mechanics General Relativity Quantum Field Theory Complexity Science

CONTENTS

- 1. Introduction
- 2. CA and PCA
- 3. Focus on DK model
- 4. Generalization of DK
- 5. Analysis
- 6. Results
- 7. Percolation on Complex Network



INTRODUCTION

- First example of DP model
- \triangleright Binary state (0,1) in a lattice configuration
- Can be classified as deterministic (CA) or stocastic (PCA)
- Each one is characterized by LOCAL, MARKOVIAN AND SYNCHRONOUS RULES.



CELLULAR AUTOMATA AND PROBABILISTIC VERSION

CA and PCA, also called Domany-Kinzel Model, are different in the description of the previous rules



In the Domany-Kinzel model that rules are described through **CONDITIONAL PROBABILITY**

$$P(s_i(t+1)|s_{i-1}(t),s_{i+1}(t))$$



CELLULAR AUTOMATA AND PROBABILISTIC VERSION

➤ CA and PCA, also called Domany-Kinzel Model, are different in the description of the previous rules



➤ In the Domany-Kinzel model that rules are described through **CONDITIONAL PROBABILITY**



Only one absorbing state, the inactive one!



FOCUS ON DK MODEL

p, probability of open bond, is the Control Parameter

Order Parameters

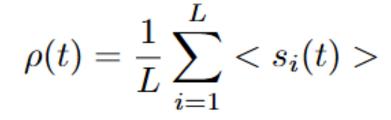
Density of Active

States **p**, Probability, **P**, of not yet reached the absorbing state



FOCUS ON DK MODEL

Order Parameters
Density of Active
States **p**, Probability, **P**, of
not yet reached the
absorbing state



$$P(t) = <1 - \prod_{i=1}^{L} (1 - s_i(t)) >$$



FOCUS ON DK MODEL

Once establish the critical exponents, we can prove if the model belongs to the **DP** universality class

$$\xi_{\parallel} = (p - p_c)^{-\nu_{\parallel}}$$

$$\xi_{\perp} = (p - p_c)^{-\nu_{\perp}}$$

$$z = \frac{\nu_{\parallel}}{\nu_{\perp}}$$

$$\xi_{\parallel} = (p-p_c)^{-
u_{\parallel}} \qquad P(p) = (p-p_c)^{eta'} \qquad N(t) \sim t^{ heta}$$

$$\xi_{\perp}=(p-p_c)^{-
u_{\perp}} \qquad
ho(p)=(p-p_c)^{eta} \qquad heta=rac{d
u_{\perp}-eta-eta'}{u_{\perp}}$$

$$N(t) \sim t^{\theta}$$

$$heta = rac{d
u_{\perp} - eta - eta'}{
u_{\parallel}}$$

- \triangleright Introduction of correlation, ξ , lengths for expansion in space and survival time of the cluster
- > Z, dynamical exponent
- > N(t) number of active sites at time t
- \triangleright Hyperscaling relation, θ



GENERALIZATION OF DK

- Mendonça and de Oliveira perform a combination of simple interactional rules
- \rightarrow p182-q200 with p+q=1
- ➤ New absorbing states: the fully inactive one and the fully active
- > They prove that the model belongs to the DP universality class



GENERALIZATION OF DK

Finite Lattice configuration with PBC and size L

MODEL STRUCTURE
Binary model with 0
(extinction) or
1(survival) states.

Table 1. Rule table for PCA p182-q200, p+q=1. The first row gives the initial neighbourhood, and the other two rows give the final state reached by the central bit of the initial neighbourhood with the probability given at the leftmost column. Clearly, the configurations $00 \cdot \cdot \cdot 0$ and $11 \cdot \cdot \cdot 1$ are absorbing configurations of the PCA.

	111	110	101	100	011	010	001	000
p^{-}	1	0	1	1	0	1	1	0
q	1	1	0	0	1	0	0	0

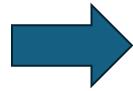


- First description through Mean Field approximation
- ➤ Computational one through Monte Carlo simulation
- Final goals: establish the critical exponent of the model



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Mean Field

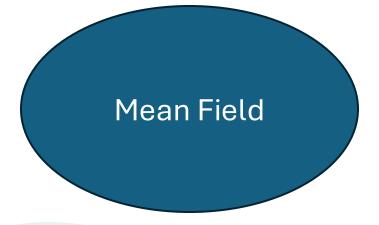


$$P_{t+1}(\boldsymbol{\eta}') = \sum_{\boldsymbol{\eta}} W(\boldsymbol{\eta}'|\boldsymbol{\eta}) P_t(\boldsymbol{\eta})$$

- > Probability evolution of the system state
- Depending on the conditional probability **W** and actual probability



- First description through Mean Field approximation
- ➤ Computational one through Monte Carlo simulation
- Final goals: establish the critical exponent of the model



$$P_t(\eta_{\ell-1}, \eta_{\ell}, \eta_{\ell+1}) \approx P_t(\eta_{\ell-1}) P_t(\eta_{\ell}) P_t(\eta_{\ell+1})$$

- Solution strictly depend on the approximation of consecutive sites **n**
- > By that we can extract density of active states



- First description through Mean Field approximation
- ➤ Computational one through Monte Carlo simulation
- Final goals: establish the critical exponent of the model

Mean Field

$$\rho^{(1)} = (\rho^{(1)})^3 + (2 - p)(\rho^{(1)})^2 (1 - \rho^{(1)}) + 3p\rho^{(1)} (1 - \rho^{(1)})^2$$

- >Solution of density active sites at stationary state
- This combination depends on the rules described in table 1



- First description through Mean Field approximation
- ➤ Computational one through Monte Carlo simulation
- Final goals: establish the critical exponent of the model

Mean Field

$$\rho^* = 1 \quad \rho^* = 0 \quad \rho^* = \frac{3p-1}{4p-1}$$

The firsts indicate the absorbing states, the latter one the active region.



The main result of Mean Field Approximation is in the furher table

Table 2. Critical parameter $p_c^{(n)}$ and value of the density of active sites $\rho^{(n)}(p)$ at p=1 obtained by mean-field approximations or order n and Monte Carlo simulation (cf section 4). The numbers between parentheses (in this table and elsewhere in this paper) indicate the uncertainty in the last digit(s) of the data. For p=1, PCA p182-q200 reduces to CA 182, for which the exact stationary density $\rho_{182}^{\text{exact}} = 3/4$.

\overline{n}	$p_c^{(n)}$	$\rho^{(n)}(p=1)$
1	1/3	2/3
2	1/3	2/3
3	0.4015	0.7135
4	0.4203	0.7166
MC	0.488 10(5)	0.7500(5)
Exact	NA	3/4



➤ Slowly convergence of the density active sites when we increase the number of consecutive sites **n**

- First description through Mean Field approximation
- ➤ Computational one through Monte Carlo simulation
- Final goals: establish the critical exponent of the model

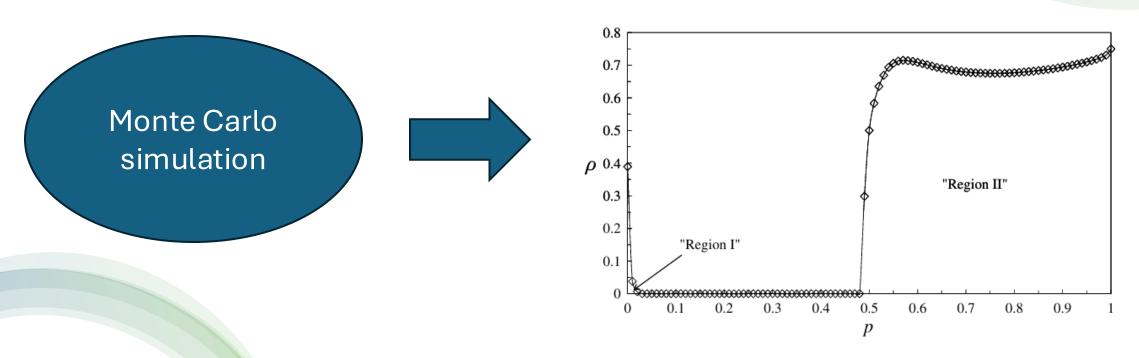




Figure 2. Density $\rho_L(p)$ of active sites for a lattice of L=8000 sites initialized randomly with density 1/2. Each value of $\rho_L(p)$ is an average over 10^6 samples after relaxation through $\sim L^2$ MCS. Errors in the Monte Carlo data are similar to the ones reported in figure 1.

The main result of Monte Carlo simulation is

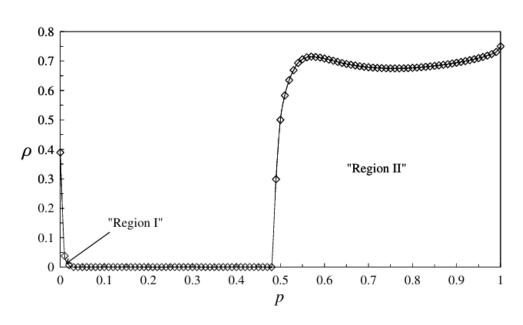


Figure 2. Density $\rho_L(p)$ of active sites for a lattice of L=8000 sites initialized randomly with density 1/2. Each value of $\rho_L(p)$ is an average over 10^6 samples after relaxation through $\sim L^2$ MCS. Errors in the Monte Carlo data are similar to the ones reported in figure 1.

- 2 active regions, region I is an artifact due the initial configuration
- "bump" effect for p = 0.57 due the competion of 111 cluster and annihilation effect from boundaries in region II
- NONMONOTONIC behaviour of the density profile
- \triangleright Extintion-survival phase transition for p = 0.48



First determination of the critical point through Linear Regression is done in further picture

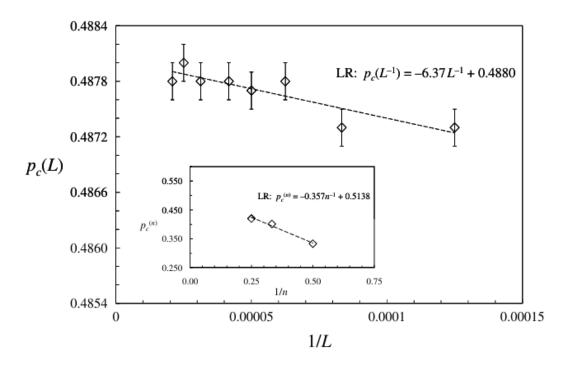


Figure 4. Critical points $p_c(L)$ for several lattice lengths $8000 \le L \le 48\,000$. A linear fit gives $p_c(L^{-1}) = (-6.37 \pm 1.40)L^{-1} + (0.4880 \pm 0.0001)$ with an $R^2 = 0.776$. The inset exhibits data from the mean-field approximations of orders n = 2, 3, and 4.



- > Another determination of the critical point Pc = 0.48810(5) through the plot in figure (a)
- Then they extract the best δ =0.17(1) critical exponent from figure (b) at Pc = 0.4881

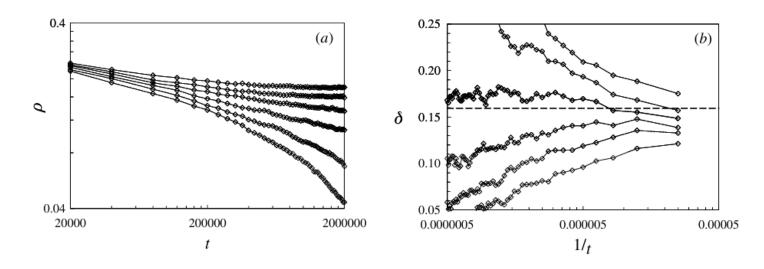


Figure 5. (a) Logarithmic plot of $\rho_L(t)$ at fixed ε with $L=16\,000$ averaged over 1000 samples. From the lowermost curve upwards, $p=0.4879,\,0.4880,\,0.4881,\,0.4882,\,0.4883,\,$ and 0.4884. From this dataset we estimated $p_c=0.488\,10(5)$. (b) Instantaneous values of δ obtained from the data depicted in figure 5(a). In panel (b) the uppermost curve corresponds to p=0.4879. From the curve with p=0.4881, we estimated $\delta=0.17(1)$. The dashed line corresponds to the best value available for $\delta_{\rm DP}$.



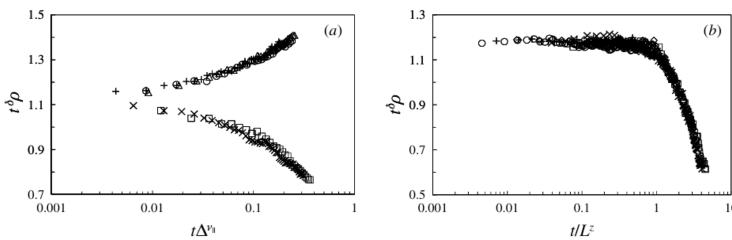


Figure 6. (a) Data collapse of the scaled time-dependent density profiles for $\varepsilon=\pm 0.0001$, ± 0.0002 , and 0.0003. The upper (lower) branches correspond to $p>p_c$ ($p< p_c$). The best data collapse was obtained with $p_c=0.48812$, $\delta=0.16$, and $\nu_{\parallel}=1.70$. (b) Finite-size data collapse of the scaled time-dependent density profiles on the critical point $p_c=0.4881$ for $2000\leqslant L\leqslant 16\,000$. Best data collapse was obtained with $\delta=0.165$ and z=1.55.

- In figure (a) they obtain the best determination of $\delta = 0.16(5)$ and v|| = 1.70(5) for Pc = 0.48812, by them extract $\beta = \delta v|| = 0.29(2)$
- In (b) the best determination is got for Pc = 0.4881 where δ = 0.165 and z = 1.55(5)

In order to establish the other critical exponents, they study critical behaviour for ρ and extract data collapsing for different ε, they tune respectively v|| and z.

Finally we can compare their results with respect the theoretical ones for DP critical exponents

δ^{DP}	0.159464(6)
$\mid u_{\parallel}^{DP} \mid$	1.733847(6)
β^{DP}	0.276486(8)
\mathbf{z}^{DP}	1.580745(10)

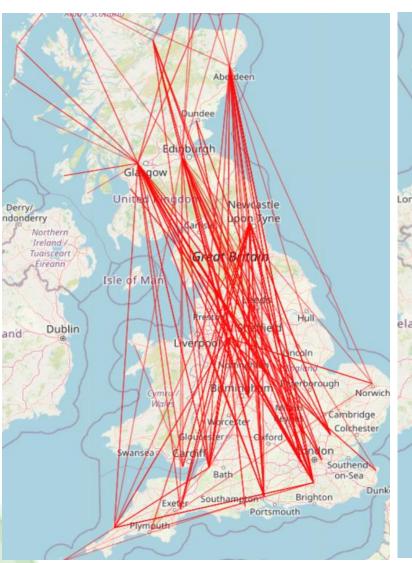
DP critical exponents expected critical exponents

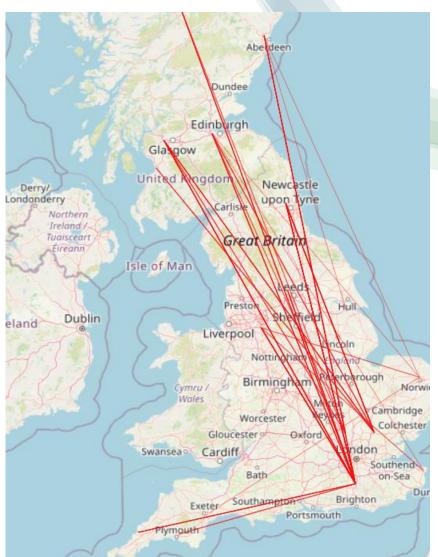
We can conclude that the model proposed belongs to the DP universality class



PERCOLATION ON COMPLEX NETWORK

Fundamental application for the P is found in the Resilience and Robustness behaviour of Complex Network





Simulation
UK air
transport
system before
and after
attacking the
London one.
(degree
removal
approach)

Result:
diminuishing
of the Greatest
Connected
Component



Data from: The multilayer temporal network of public transport in Great Britain

Gallotti, Riccardo¹; Barthelemy, Marc¹

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THANKS FOR THE ATTENTION

