

Interacting Particle Systems

Diploma Thesis Presentation

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Outline

- 1 Introduction and Some Background
- 2 Independent Random Walks
- 3 Simple Exclusion Process
- 4 Zero Range Process



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Interacting Particle Systems?

- Large-scale systems of components interacting with each other governed by stochastic dynamics
- Several applications on
 - natural sciences: reaction diffusion, gas particles systems...
 - social sciences: traffic flow, opinion dynamics, spread of epidemics...

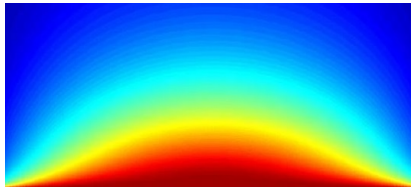


Goal?



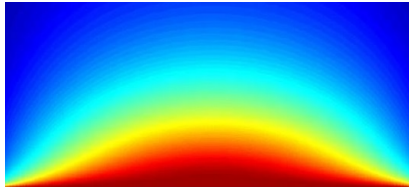
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Deduce macroscopic behavior

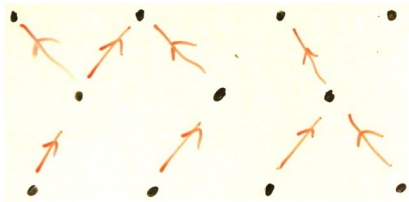


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Deduce macroscopic behavior



from microscopic interactions.



Markov Chains



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- Markov Process: collection $(\mathbb{P}^\eta : \eta \in X)$ of probability measures **with**
- Markov Property: $\mathbb{P}^\eta(\eta_{t+s} \in A | \mathcal{F}_t) = \mathbb{P}^{\eta_t}(\eta_s \in A)$
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"Memorylessness"
- Markov Chain: Markov Process on countable now X
characterized by *transition rates* $c(\eta, \eta')$



Invariant Measures

Main question: What about invariant measures in Interacting Particle Systems?



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- Phase transitions, i.e. existence of more than one invariant measures, occur only in infinite systems.



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Space

- \mathbb{Z}^d the d -dimensional integer lattice
- $\mathbb{T}_L = \mathbb{Z}_L = \{0, 1, \dots, L-1\}$ the torus with L points and
 $\mathbb{T}_L^d = (\mathbb{T}_L)^d$
- L represents the inverse of the distance between the points of \mathbb{T}_L^d , namely the particle sites



Space and Stochastics

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- L represents the inverse of the distance between the points of \mathbb{T}_L^d , namely the particle sites
- Transition probability $p(x, y) = p(0, y - x) =: p(y - x)$ for some $p(\cdot)$ on \mathbb{Z}^d (*elementary transition probability*)



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- the state space is finite,
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Thus, there is only one invariant measure.



Poisson Measures

Poisson distribution of parameter $\alpha > 0$ is the probability measure

$$p_{\alpha,k} = p_k = e^{-\alpha} \frac{\alpha^k}{k!}, \quad k \in \mathbb{N}.$$



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Call a *Poisson measure* $\nu_{\rho(\cdot)}^L$ on \mathbb{T}_L^d associated to a fixed positive function $\rho : \mathbb{T}_L^d \rightarrow \mathbb{R}_+$, a probability on $\mathbb{N}^{\mathbb{T}_L^d}$, denoted by $\nu_{\rho(\cdot)}^L$, satisfying that:



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- under $\nu_{\rho(\cdot)}^L$ the random variables $(\eta(x) : x \in \mathbb{T}_L^d)$ must be independent,
- for every fixed site $x \in \mathbb{T}_L^d$,

$$\nu_{\rho(\cdot)}^L(\eta(x) = k) = p_{\rho(x),k}.$$



Poisson Measures

Theorem

If particles are initially distributed according to a Poisson measure associated to a constant function equal to α then the distribution at time t is exactly the same Poisson measure ν_{α}^L .



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Note that

$$E_{\nu_\alpha^L}(\eta(x)) = \sum_{k \geq 0} e^{-\alpha} \frac{\alpha^k}{k!} k = \alpha.$$

The Poisson measures are in this way naturally parametrized by the density of particles.



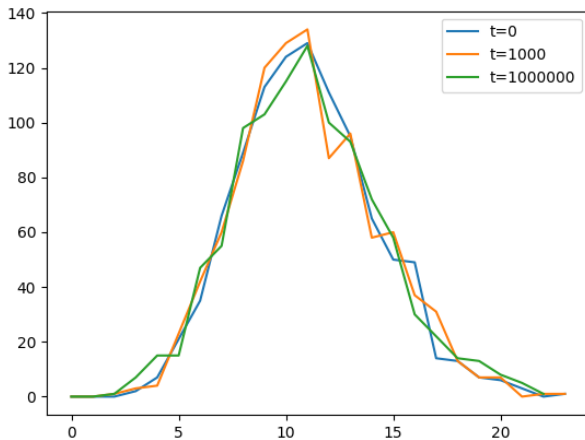


Figure: Distribution at time t of IRW on \mathbb{T}_{1000}^1 with $\alpha = 10$



Macroscopic Profile



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- Is that the same profile?



Macroscopic Profile

- We have different space scales, \mathbb{T}^d and $L^{-1}\mathbb{T}_L^d$.
- Why not distinguish between two different time scales?
- A microscopic time t and a macroscopic time infinitely large with respect to t .



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- Why not distinguish between two different time scales?
- A microscopic time t and a macroscopic time infinitely large with respect to t .
- Let $m := \sum x p(x) \in \mathbb{R}^d$, the expectation of $p(\cdot)$.
- Introducing time scale tL :

$$\lim_{L \rightarrow \infty} p_{tL}^L([uL]) = \rho_0(u - mt) =: \rho(t, u)$$

- Now the profile did change. We observe a new macroscopic profile: the original one translated by mt .



Macroscopic Profile

- Scaling limits \rightarrow Hydrodynamic description

$$\partial_t \rho + m \cdot \nabla \rho = 0.$$



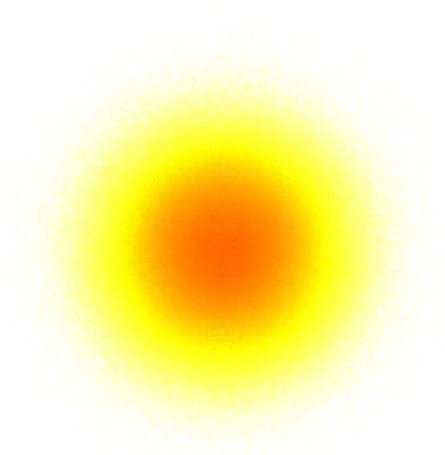
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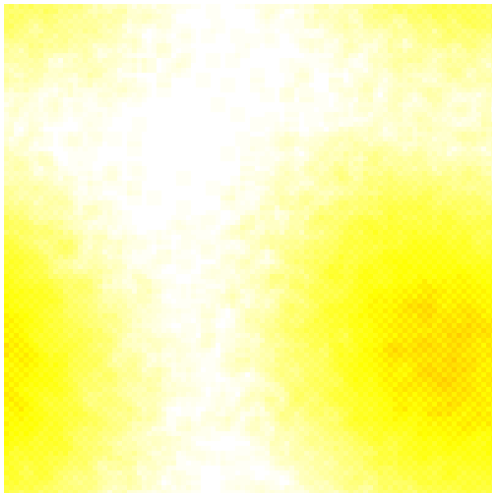
- Scaling limits \rightarrow Hydrodynamic description

$$\partial_t \rho + m \cdot \nabla \rho = 0.$$

- However, if the random walk is not asymmetric, then again the profile remains the same.
- Still, if we consider a larger time scale, times of order L^2 , even when $m = 0$, we can observe an interesting time evolution.







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Model

- First of all, SEP allows at most one particle per site.
- State space: $\{0, 1\}^{\mathbb{T}_L^d}$
- $\eta^{x,y}$: configuration from η letting a particle jump from x to y

$$\eta^{x,y}(z) = \begin{cases} \eta(z) & \text{if } z \neq x, y, \\ \eta(x) - 1 & \text{if } z = x, \\ \eta(y) + 1 & \text{if } z = y \end{cases}$$



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- Each particle in x jumps to y at rate

$$\eta(x)(1 - \eta(y))p(y - x)$$



Bernoulli Measures

Again, there is a unique invariant measure for the process.



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Let $(\nu_\alpha : 0 \leq \alpha \leq 1)$, the *Bernoulli measure* on $\{0, 1\}^{\mathbb{T}_L^d}$ of parameter α , satisfying that:

- under ν_α , the variables $(\eta(x) : x \in \mathbb{T}_L^d)$ are independent,
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Again, the hydrodynamic description given by the heat equation

$$\partial_t p = (1/2)\Delta \rho$$



ASEP with step initial condition

- Consider the integer lattice \mathbb{Z} .
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ASEP with step initial condition

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- Let $\gamma = q - p$.

Main quantity of interest: the position of the m th particle from the left at time t

$$x_m(t), \text{ with } x_m(0) = m.$$



Marginal particle

Behavior of $|x_1|$, i.e. the distance that the marginal particle has covered on a given time t ?



Marginal particle

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Assume that

$$E(|x_1(t)|) \sim ct^a,$$

which transforms to

$$\log E(|x_1(t)|) \sim a \log t + \log c.$$



Expected value

Performing experiments for $\gamma = 0.5$:

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It is true that, in general,

$$E(|x_1(t/\gamma)|) \sim t$$

for every $\gamma \in (0, 1]$.



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Also, the order of the variance of $|x_1(t)|$, provides the suitable normalization, in order to get its distribution for every t .



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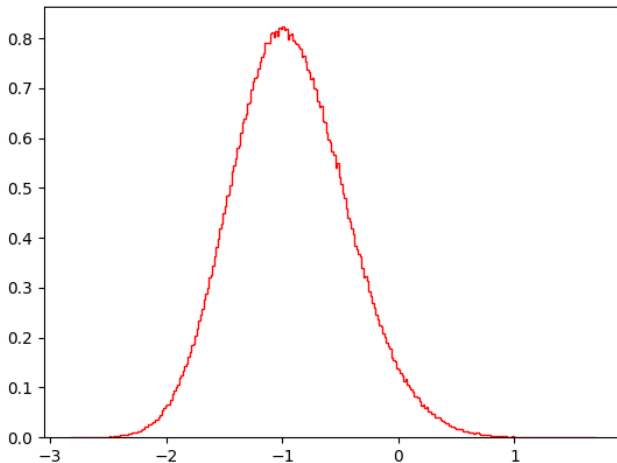
Therefore, what about

$$\frac{|x_1(t)| - \gamma t}{t^{0.6}}$$

?



Tracy-Widom distribution!



From Ecosystems to RMT



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So, distribution of the largest eigenvalue λ_{max} ?



Appearance of the distribution

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- But... in 1999, the same distribution was found in the length of the longest increasing subsequence of random permutations.
- It started to appear in models all over physics and mathematics.
- Especially in systems with interacting components.



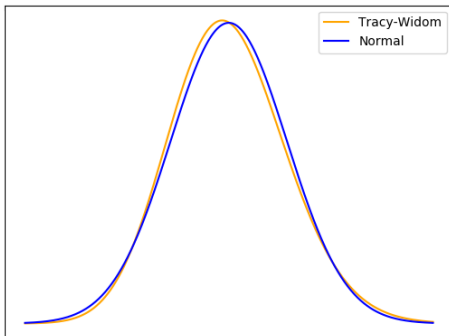
Universality

- Universality: diverse microscopic effects \rightarrow same collective behavior



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- Tracy-Widom complex cousin of the familiar bell curve...



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Universality

- Central Limit Theorem: natural observations and other uncorrelated variables form a Normal distribution. (rigorous about a century ago)
- Tracy-Widom from strongly correlated variables, such as interacting species, stock prices, matrix eigenvalues...
- Tracy-Widom universally proved to hold for certain classes of random matrices.
- Looser handle in counting problems, random walk problems, growth models...



Maybe an explanation?

- Asymmetric character of the distribution \rightarrow some kind of universal phase transition



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In general,

- left tail: all components act in concert, (unstable)
- right tail: the components act alone. (stable)



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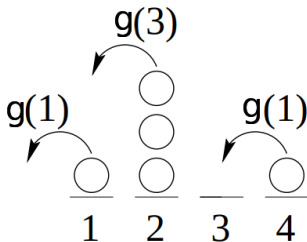
- Non-linear (parabolic) hydrodynamic description

$$\partial_t \rho = (1/2)\Delta(\Phi(\rho))$$

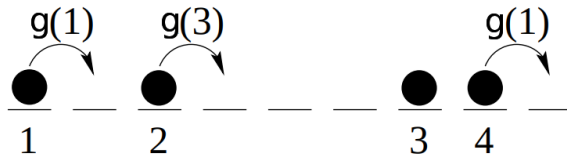
where $\Phi(\cdot)$ is the inverse of $\rho(\cdot)$ until a critical density ρ_c .



Duality



Zero Range



Simple Exclusion



Supercritical Configuration



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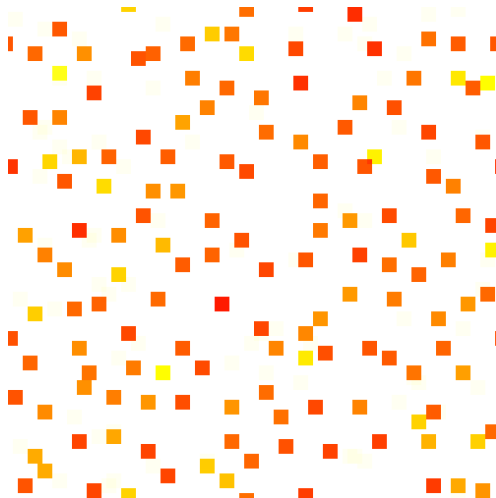
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- For $b > 2$, there is a critical density

$$\rho_c = \frac{1}{b-2}$$





Order of time needed to reach equilibrium?



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Performing experiments, for 3 initial states,

- totally asymmetric zero range process:

$$T_{eq} = \mathcal{O}(L^2)$$

- symmetric zero range process:

$$T_{eq} = \mathcal{O}(L^3)$$

(diffusion without a drift)



Tagged Particles

Three classes \rightarrow a jump occurs from the tagged particle's site x ,

- First class: the tagged will jump,
- Random: the tagged will jump with probability $1/\eta(x)$,
- Second class: the tagged will jump last.



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Distance covered by the tagged particle in a given time:
(space scale L , time scale L^2)

- First class: $X_{tag}(tL^{-2})/L = \mathcal{O}(1)$,
- Random: $X_{tag}(tL^{-2})/L = \mathcal{O}(\sqrt{t})$,
- Second class: $X_{tag}(tL^{-2})/L = \mathcal{O}(\sqrt{t})$.



Thank you very much!

