Arturo L. Zamorategui. Modélisation Stochastique

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Outline

1 Introduction

- 2 Part 1. Statistics
- 3 Results
- 4 Part 2. Towards an effective model
- 5 Partial Results
- 6 Perspectives

Goals

- Understand the phase coexistence of active-inactive regions at the point where the dynamical phase transition observed in glassy systems occurs. Very well captured by KCMs.
- **2** Determine an *effective model* of the dynamics in the phase transition from the simplest possible model. Is there something simpler that a KCM ?

Anomalous scaling in a kinetically constrained model in 1+1 dimensions

- Introduction



2D binary mixture of hard disks with different radius (*Keys et al* Phys. Rev. X 1, 021013, 2011).

Start movie

Inactive particles vs Active particles

- Dynamic heterogeneity: inactive regions with *slow* dynamics and active regions with *fast dynamics*.
- Facilitated dynamics: mobility in a region *leads* to motion of neighbouring particles. An *adjacent* excitation is required for both the birth or death of an excitation.

- Introduction

Activity vs Inactivity

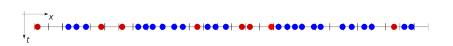
Inactive regions surrounded by active particles.

- The *persistent time* (t_p): time a particle remains inactive before the first move.
- The exchange time (t_x) : time between two consecutive moves. (Jung et al 2004).

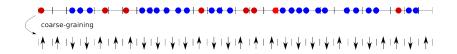
	Not a glass	A glass
Dynamic heterogeneity	$\langle t_p \rangle = \langle t_x \rangle = \tau$	$\langle t_x \rangle \ll \langle t_p \rangle$
Facilitation	-	Particles close to excitation lines diffuse more quickly
Stokes-Einstein relations:		
$D\eta/T = \text{constant}$	Satisfied	Broken,
		since $ au_{lpha} pprox \langle t_p angle$
$D\tau_{\alpha} = \text{constant}$		and $D \approx \delta x^2 / \langle t_x \rangle$:
τ_{α} (relaxation time)		$(D au_{lpha} pprox \delta x^2 \langle t_p angle / \langle t_x angle)$
D (diffusion coefficient)		

Dynamic heterogeneity (bubbles of inactivity) and facilitation (excitation lines) are captured by **kinetically constrained models** (KCMs).

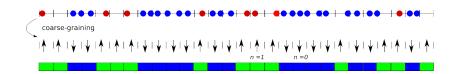
• One spatial dimension (discrete) + one temporal dimension (continuous)



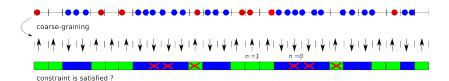
- One spatial dimension (discrete) + one temporal dimension (continuous)
- It is a coarse-grained model with $n_i = 1$ if active and $n_i = 0$ if inactive.



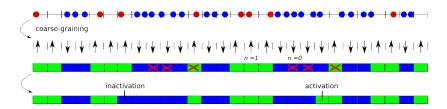
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- Dynamic is controlled by a local **constraint**.



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Statics vs Dynamics

- Non-conservative system
- Site *i* changes state with rate $f_i[(1-c)n_i + c(1-n_i)]$, where *c* is the density of active sites and f_i is the **kinetic constraint**.
- $f_i = 1$ if constraint is satisfied and $f_i = 0$ otherwise.
- f_i depends on the neighbourhood but not on n_i .
- Detailed balanced holds w.r.t Boltzmann distribution (Bernoulli product measure) with energy $\sum_{i} n_i$ and inverse temperature β ($c = 1/(1 + e^{\beta})$).
- Since *statics* is trivial, we need a *dynamical description*.

A dynamic observable: the Activity

Let C(t) be a configuration of the system at time t. We define a (discrete) **observable** as

$$A[\text{trajectory}] = \sum_{k=1}^{K} \alpha(\mathcal{C}(t_{k-1}) \to \mathcal{C}(t_k)),$$

over K changes of configurations between times 0 and T.

Activity

The activity is K[trajectory] = #events, i.e. $\alpha(\mathcal{C}(t_{k-1}) \rightarrow \mathcal{C}(t_k)) = 1$ when configuration changes.

Evolution of a KCM

The master equation for the evolution of the probability P(C, A, t) is

$$\frac{\partial P(\mathcal{C}, A, t)}{\partial t} = \sum_{\mathcal{C}'} W(\mathcal{C}' \to \mathcal{C}) P(\mathcal{C}', A - \alpha(\mathcal{C}' \to \mathcal{C}), t) - r(\mathcal{C}) P(\mathcal{C}, A, t)$$

having measured a value A of the observable between 0 and t. $r(\mathcal{C}) = \sum_{\mathcal{C}'} W(\mathcal{C} \to \mathcal{C}')$ is the escape rate.

Continuous time: at each site there is a clock that changes the state n_i after a time Δt given by $p(\Delta t) = W(n_i \rightarrow 1 - n_i)e^{-W(n_i \rightarrow 1 - n_i)\Delta t}$.

Large deviation

To have certain dynamics one can *bias* a trajectory according to a parameter s, with trajectory with *lower than normal activity* (s > 0) or *higher than normal activity* (s < 0):

$$P[\text{trajectory}] \rightarrow P_s[\text{trajectory}] = \frac{P[\text{trajectory}]e^{-sK[\text{trajectory}]}}{Z_s},$$

where $Z_s = \langle e^{-sK[\text{trajectory}]} \rangle$. For large observation times:

$$\lim_{t \to \infty} \frac{\ln Z_s}{t} \to \psi_K(s).$$

 $\psi_K(s)$ is a large deviation function, also known as dynamical free energy.

First order phase transition

 $\psi_K(s)$ presents a singularity at s = 0:

- s < 0: trajectory where $\langle K_t \rangle$ is larger.
- s = 0: trajectory with coexistence of active and inactive regions.
- s > 0: trajectory where $\langle K_t \rangle$ is smaller.

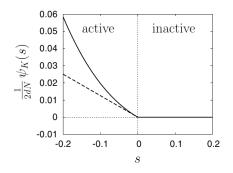


Figure: Active-Inactive transition (Garrahan et al (2007)).

FA model

Fredrickson-Andersen Model (FA-1f)

The transition rates in the FA model are

$$W(n_i \to 1 - n_i) = f_i(n_j) \frac{e^{\beta(n_i - 1)}}{1 + e^{-\beta}},$$

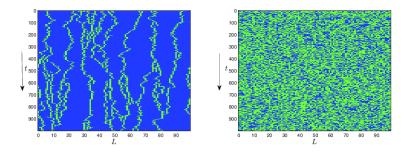
where $f_i = 1$ if $\sum_{j \sim i} n_j > 0$, i.e if there is *at least one* active site in the neighbourhood, otherwise $f_i = 0$.

- For an activation: $W(0 \rightarrow 1) = f_i \frac{1}{1+e^{\beta}}$. the term $c = 1/(1+e^{\beta})$ is the density of active sites.
- Mean distance between excitations: l = 1/c

- Examples FA-1f

Typical histories (with s = 0) for different densities

Histories of length L = 100 and t = 1000 for c = 0.1 and 0.6.



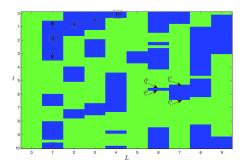
Anomalous scaling in a	kinetically constrained	model in 1+1	dimensions
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Part 1

Describe bubbles of inactivity

There is not an effective model to understand the **phase coexistence of** activity and inactivity which is generic in glasses.

Such a model must describe how bubbles of inactivity evolve in space-time .

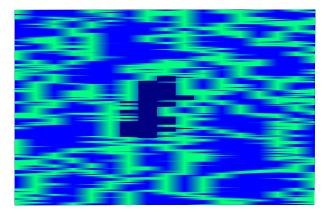


- 1 Order columns of inactivity
- 2 Columns \rightarrow Nodes
- Build adjacency matrix (from overlap of nodes)
- 4 Find bubbles by identifying one node, its neighbours,...

- Statistics

Statistics on bubbles

Focus on one bubble...

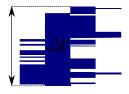


Geometrical Properties

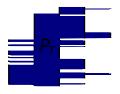
Area



Temporal extension



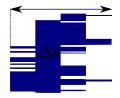
Temporal perimeter



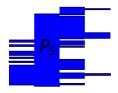
Number of Nodes



Spatial extension

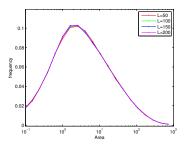


Spatial perimeter



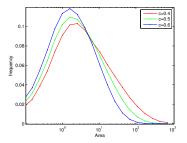
Histograms for the Area

Varying L:



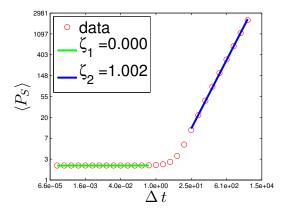
Curves superimpose for different \boldsymbol{L}

Varying c:



As \boldsymbol{c} decreases, bigger bubbles appear

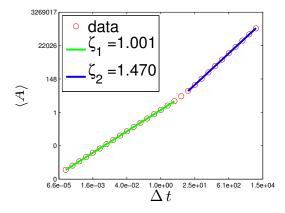
Spatial Perimeter



 $P_S \sim \Delta t^{1.002}$ for large bubbles

- Statistics

Area

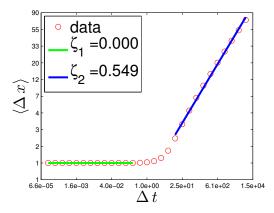


 $A \sim \Delta t^{1.470}$ for large bubbles, close to Brownian with $\zeta = 3/2.^*$

*S. Majumdar et al. 2005

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Spatial extension

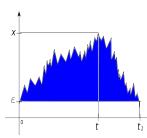


 $\Delta x \sim \Delta t^{0.549}$ for large bubbles, bigger than Brownian where $\zeta = 1/2$

Mean shape of bubbles

The probability that r.w. arrives to x_1 at time t_1 given that started at x_0 at time t_0 is:

$$P_{\varepsilon}(x_1, t_1 | x_0, t_0) = \frac{1}{\sqrt{2\pi D(t_1 - t_0)}} \left[e^{\frac{-(x_1 - x_0 - \varepsilon)^2}{2D(t_1 - t_0)}} - e^{\frac{-(x_1 - x_0 + \varepsilon)^2}{2D(t_1 - t_0)}} \right]$$



The mean value of $x(t, t_1)$ is:

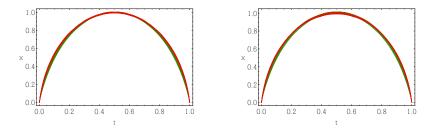
$$x(t,t_1)\rangle_{[t_0,t_1]} = \frac{\int_0^\infty dx \, x \, P_\varepsilon(x_1,t_1|x,t) P_\varepsilon(x,t|x_0,t_0)}{\int_0^\infty dx P_\varepsilon(x_1,t_1|x,t) P_\varepsilon(x,t|x_0,t_0)}$$

- Scaling

Numerical mean shape

By scaling average curves of bubbles with duration $\Delta t - \varepsilon < \Delta t < \Delta t + \varepsilon$ as $F(\tau) \sim \Delta t^{-\zeta} f(\tau \Delta t)$.

$$\zeta = 0.5: \qquad \qquad \zeta = 0.6$$



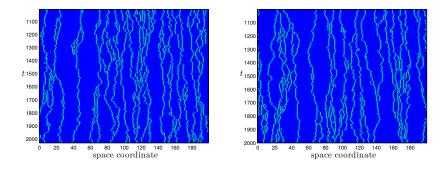
(Towards an) Effective model

Part 2

- (Towards an) Effective model

FA model for small c

At low temperature (small c) the borders of the bubbles of inactivity in the FA model have some few active sites (left). The dynamics in the FA can be reproduced by a model of branching-coalescence (right) (Whitelan,Berthier,Garrahan 2005).



Borders of activity look like random walkers that branch, diffuse and coalesce.

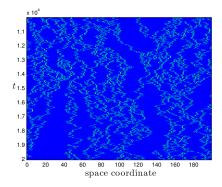
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- (Towards an) Effective model

Branching-Coalescing process

We can simulate the system as a branching-coalescing process if

- it captures the same dynamics that the FA model
- Is valid at finite time scales
- Is analytically tractable



- (Towards an) Effective model

Model of branching coalescence

 \blacksquare Initial condition with density c of active sites.

Model of branching coalescence

- Initial condition with density c of active sites.
- A configuration C changes after a time Δt as $p(\Delta t) = r(C)e^{-r(C)\Delta t}$ where
- the escape rate is

$$r(\mathcal{C}) = \sum_{i} f_i(\mathcal{C})[\underbrace{(1-n_i)c}_{\text{activation}} + \underbrace{n_i(1-c)}_{\text{inactivation}}] = r_{\text{act}}(\mathcal{C}) + r_{\text{inact}}(\mathcal{C})$$

Model of branching coalescence

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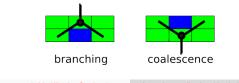
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- A border of activity constrained to have maximum 3 active sites.



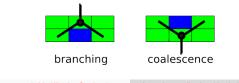
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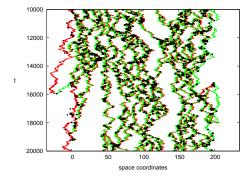


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Strategy

In continuous space: two random walkers will cross an infinite number of times.

In discrete space: is reflected in small bubbles. Focus on branching/coalescing points of large bubbles (of duration T > 10)



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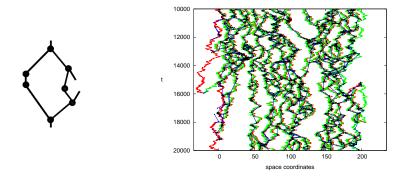
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- (Towards an) Effective model

Analysis

The rates are the same by time reversal *symmetry*. How often do we have a branching/coalescing event?

To have just branching and coalescing points we use a **contraction** algorithm until there's no isolated point...

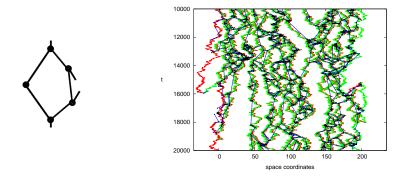


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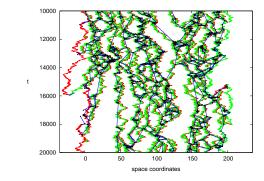


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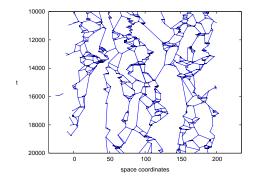


- (Towards an) Effective model

Analysis

We end up with a brownian net with just branching and coalescing points.

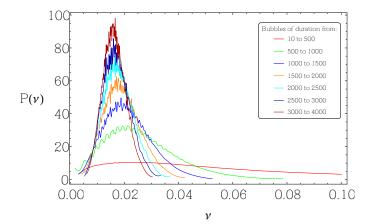
How many events occur along the borders of a bubble? The frequency of branching/coalescing sould not depend on size of bubbles.



- (Towards an) Effective model

Probability distribution of frequency ν

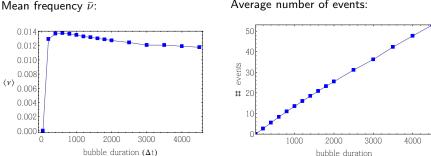
We can study the PDF of the frequency ν of branching and coalescing events for different bubbles' sizes.



- (Towards an) Effective model

Average frequency

Are branching/coalescencing rates independent of bubble size?



Average number of events:

- (Towards an) Effective model

Perspectives

- **I** Check that the effective model from "brownian net" is realistic.
- **2** Convergence of the distribution of the event rates as statistics is increased
- 3 Determine average frequency $\bar{\nu}$?
- 4 How ν and D are related to c? Scaling limits?
- 5 What information do we have about the phase coexistence?
- 6 Low temperature limits for other KCM?
- For a biased dynamics (s < 0 or s > 0), what can be relevant from this simple model?

- (Towards an) Effective model

Thank you for listening!

- Bibliography

Bibliography

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- Appendix

Order parameter

Activity

$$K = \Delta t \sum_{t=0}^{t_{obs}} \sum_{i=1}^{L} (r_i(t + \Delta t) - r_i(t))^2$$

where L is the total number of particles considered and $t_{\rm obs}$ is the amount of time the systems is observed. The mean activity is

$$\langle K \rangle = Lt_{\rm obs} \langle (r_1(t + \Delta t) - r_1(t))^2 \rangle = 2dLt_{\rm obs} D\Delta t$$

Anomalous scaling in a kinetically constrained model in 1+1 dimensions

- Appendix

Tests

For an **unconstrained model**, the probability of a configuration $\vec{n} = (n_1, n_2, \ldots, n_L)$ is $P_{eq}^{unc}(\vec{n}) = c^n (1-c)^{L-n}$, therefore the average value of a site is

$$\frac{1}{L} \left\langle \sum_{i} n_{i} \right\rangle_{eq}^{unc} = c$$

For a **constrained model** where $\sum_{i}^{L} n_i > 0$, the probability has a normalization factor $Z \ P_{eq}(\vec{n}) = \frac{c^n (1-c)^{L-n}}{Z}$ which is found to be $Z = 1 - (1-c)^L$. The average value of a site is

$$\langle n_j \rangle_{eq} = \frac{c}{1 - (1 - c)^L}$$

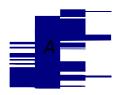
We compare this value with the one obtained numerically. The bigger the lattice, the more accurate the numerical value is.

- Appendix

└─ Other statistics

Temporal Perimeter

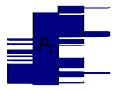
Area



Temporal extension



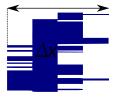
Temporal perimeter



Number of Nodes



Spatial extension



- Appendix

└─ Other statistics

Spatial Perimeter

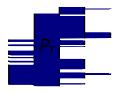
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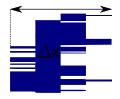
Temporal perimeter



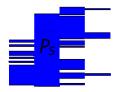
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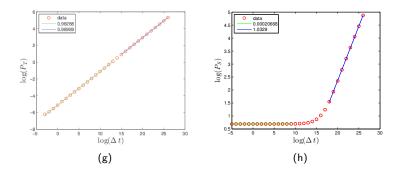
Spatial perimeter



- Appendix

└─ Other statistics

Perimeter geometry



 $P_T \sim \Delta t$ for all of the bubbles and $P_S \sim \Delta t$ for large bubbles.