# Cluster Growth using the DLA Model

By Tahoe, Ksenia, and Xinmeng

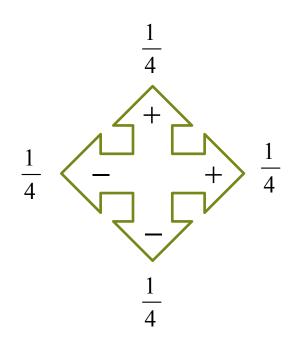
#### In this presentation:

- 2D Random Walks
- The 1D Diffusion Equation
- Diffusion Limited Aggregation Model for Cluster Growth

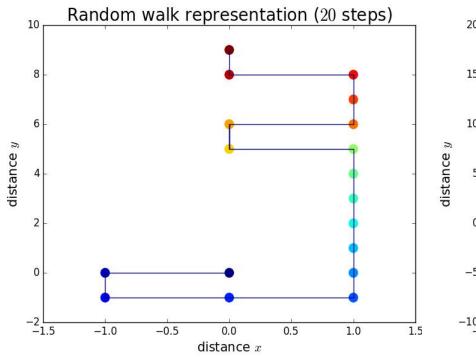
### 2D Random Walks

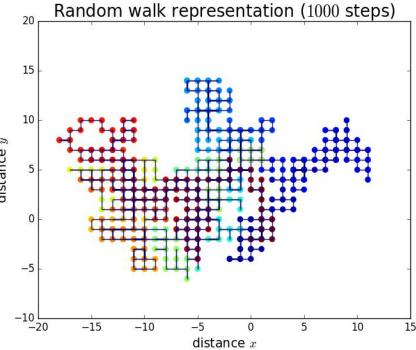
#### Analytical parameters for a 2D random walk

$$< x >= \sum_{i=1}^{N} < x_i >= \sum_{i=1}^{N} [0.25 \times (-1) + 0.25 \times 1] = 0$$
 $< x^2 >= < \sum_{i=1}^{N} x_i^2 > + < \sum_{i \neq j}^{N} x_i x_j >= N < x_i^2 >$ 
 $= N (0.25 \times 1^2 + 0.25 \times (-1)^2) = 0.5 N$ 
 $< d^2 >= < x^2 + y^2 >= < x^2 > + < y^2 >= 0.5 N + 0.5 N = N$ 



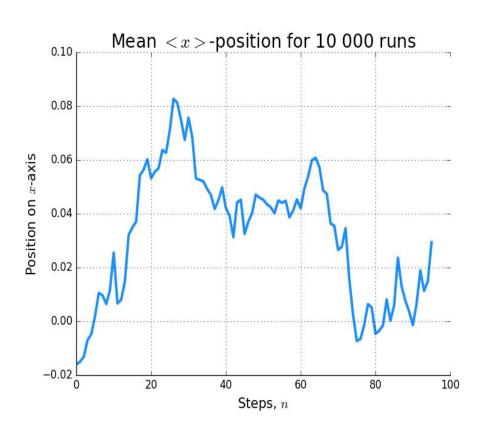
#### Simulation of 2D Random Walk

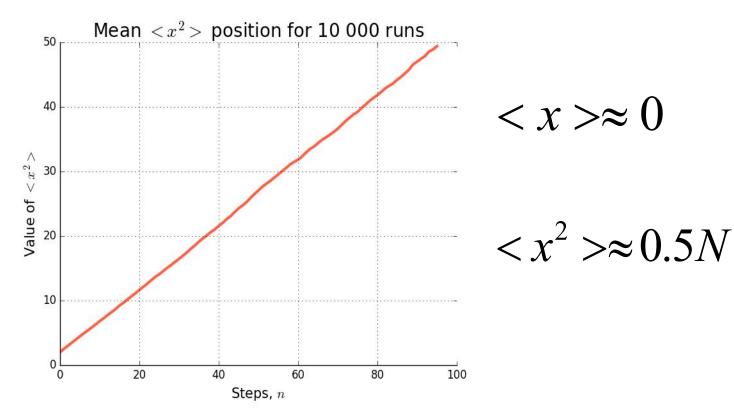


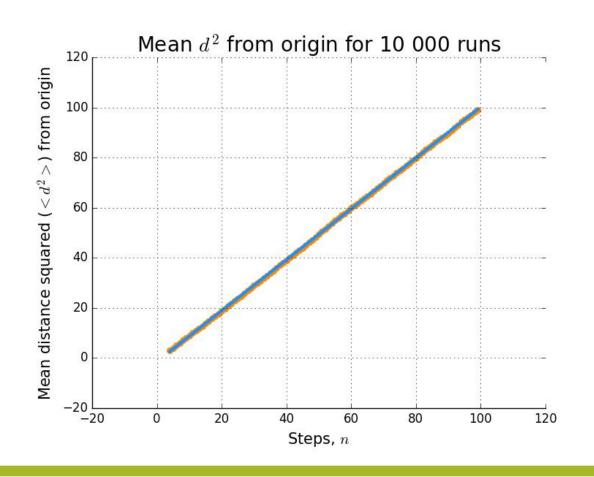


- Define random-walk function using 4 thresholds in random numbers among (0,1)
- Record position and displacement information for each step
- Average over 10,000 different walkers

#### Simulation of 2D Random Walk







### 2D Random Walk is diffusive

Diffusive motion has

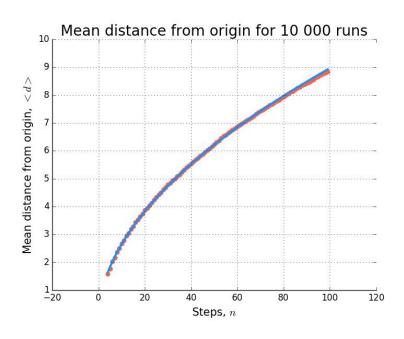
$$< x^2 > \propto t (= 2Dt)$$

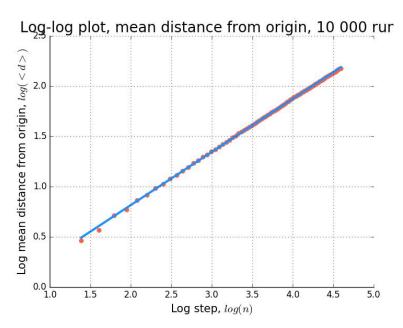
• For 2D R.W. our simulation gives the relation

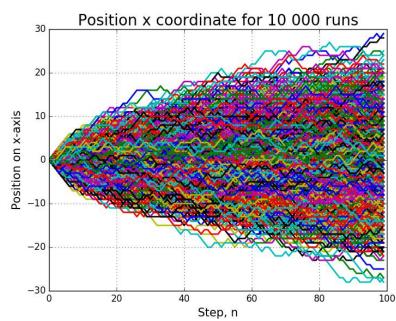
$$\langle d^2 \rangle = n \quad t \sim n$$

• Thus, the diffusion coefficient is given by D=0.25.

#### Simulation of 2D Random Walk - Plots of interest







### 1D Diffusion Equation Solver

#### Modelling the Equation

#### **Differential Form**

• Time dependent diff. eq.

$$\frac{\partial \rho(x,t)}{\partial t} = D\nabla^2 \rho(x,t)$$

 For a box density, later solutions should be Gaussian

$$\rho(x,t) = \frac{1}{\sqrt{2\pi\sigma(t)^2}} \exp\left(-\frac{x^2}{2\sigma(t)^2}\right)$$
$$\sigma(t) = \sqrt{2Dt}.$$

#### Finite Difference Form

Convert to an iterable form

$$\rho(x,t) = \rho(i\Delta x, n\Delta t)$$

 Algebraically manipulate formal derivatives

$$\rho(i, n+1) = \rho(i, n) + \frac{D\Delta t}{\Delta x^2} \left( \rho(i+1, n) + \rho(i-1, n) - 2\rho(i, n) \right)$$

 For our purposes, D=2 and stability is guaranteed by

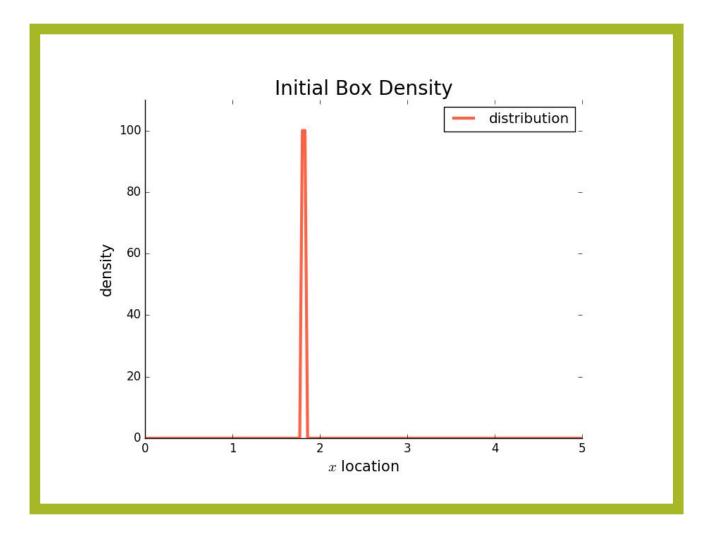
$$\Delta t \le \frac{(\Delta x)^2}{2D}$$

#### Variance of a Gaussian - Quick Proof

- **Expectation** values are of the form:  $\langle x \rangle = \int_{-\infty}^{\infty} f(x)x dx$
- Thus, after using the fact that we are dealing with an even function

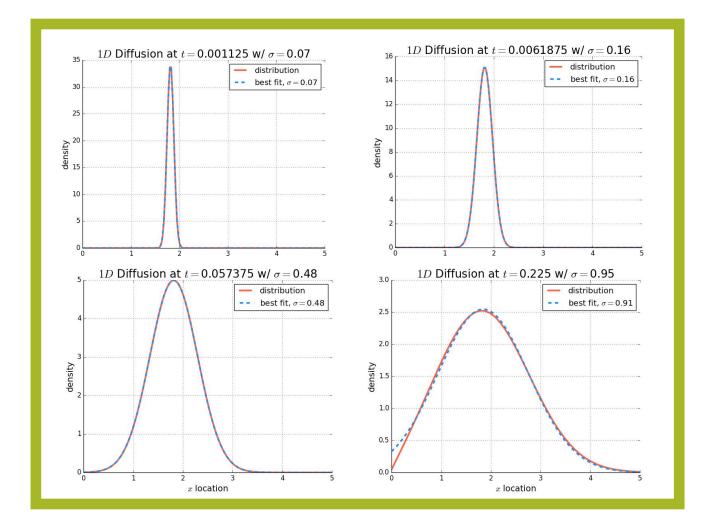
$$\langle x^2 \rangle = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma(t)^2}} \exp\left(-\frac{x^2}{2\sigma(t)^2}\right) x^2 dx$$
$$= 2 \int_0^{\infty} \frac{1}{\sqrt{2\pi\sigma(t)^2}} \exp\left(-\frac{x^2}{2\sigma(t)^2}\right) x^2 dx.$$

- After a change of variable  $\langle x^2 \rangle = \frac{4\sigma^2}{\sqrt{\pi}} \int_0^\infty x^2 \exp(-x^2) dx$
- Finally, after integrating by parts:  $\langle x^2 \rangle = \sigma^2$



### Initial Distribution

Important to put the box density far from the edges, otherwise you will affect the Gaussian and make it lopsided.



### Four Evolutions in Time

A sigma fit was performed for each time snapshot, and they match very well with the expected:

$$\sigma = \sqrt{2Dt}$$
.

Note: Edge effects distorting the fit at later times.

### Cluster Growth using DLA

#### **DLA Cluster**

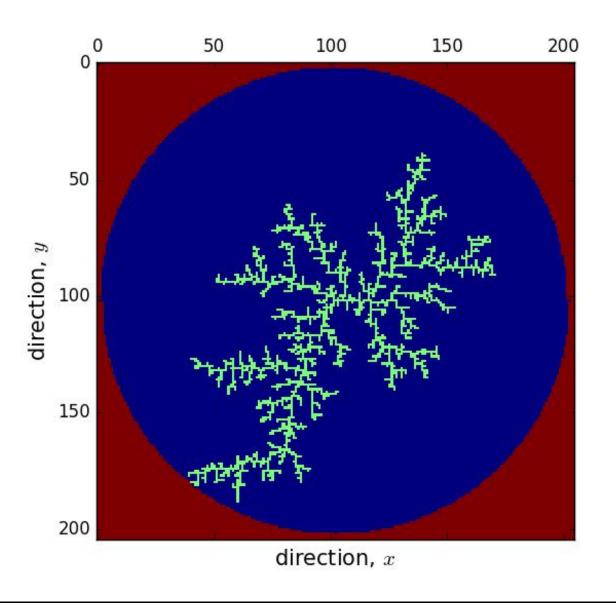
Many large open spaces, irregular perimeter

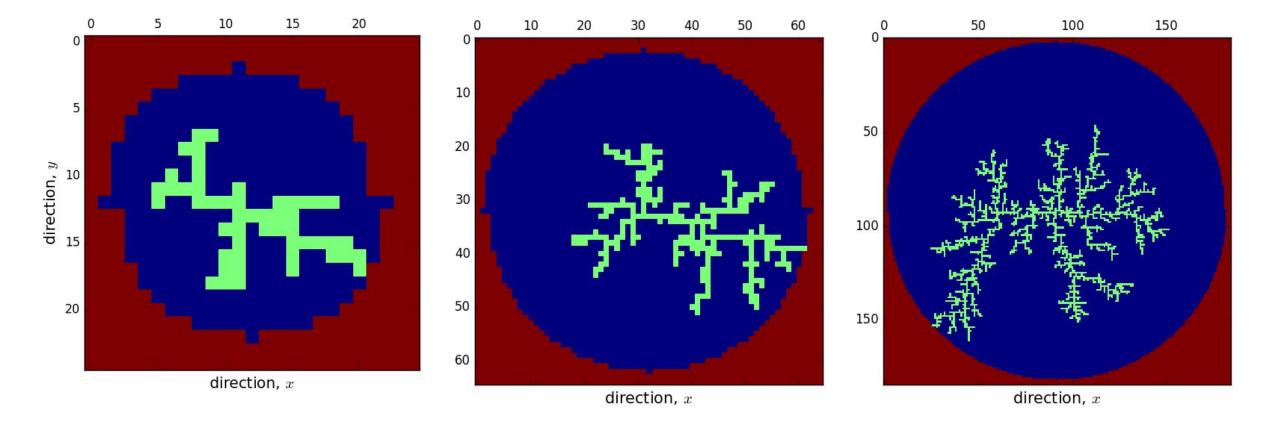
$$m(r) \sim r^{d_f}$$

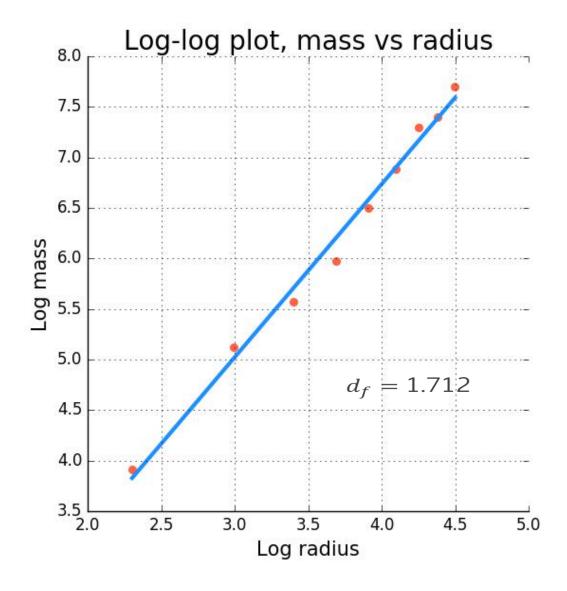
 $d_f = fractal\ dimensionality$ 

$$d_f = 1$$
 line, or curve

$$d_f = 2$$
 solid disk







#### Fractal dimensionality

$$\log m = d_f \log(r)$$

In 10 runs fractal dimensionality:

2.067, 1.653, 1.877, 1.833, 1.607, 1.832,1.782, 1.712, 1.843, 1.862

mean=1.807

## Thank you for your time!