

# Statistical Analysis of Diffusion over Fractal Sets

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# Waypoints

- Dimension(s)
- Diffusion over fractal sets
- Alternative numerical approach

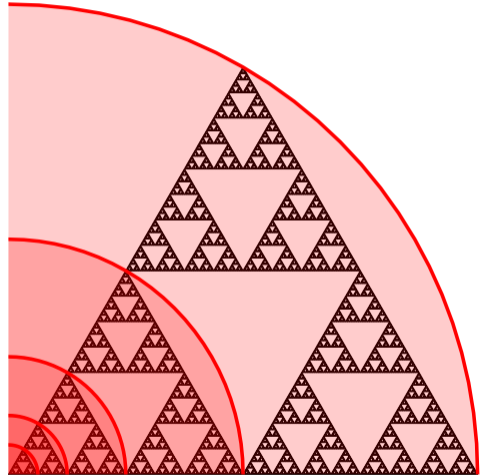
# Fractal Dimension

- Sierpinski Gasket
- double the distance, triple the mass
- $d_f = \log 3 / \log 2$

## Mass Scaling

$$M \sim L^{d_f}$$

- Similarity dimension
- Hausdorff dimension



# Diffusion on Fractals

## Fractal Dimension

$$M \sim L^{d_f}$$

## Walk Dimension

$$t \sim L^{d_w}$$

## Spectral Dimension

$$d_s = 2 \frac{d_f}{d_w}$$

## Observables

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- Return Probability

$$\Pr(X_t = \mathbf{x}_0) \sim t^{-d_s/2}$$

- Absolute Moments

$$\mathbb{E} \|X_t - \mathbf{x}_0\|_2^\alpha \sim t^{\alpha/d_w}$$

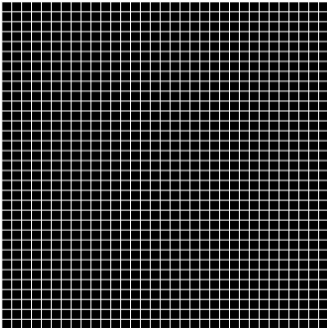
# Porous Media Diffusion



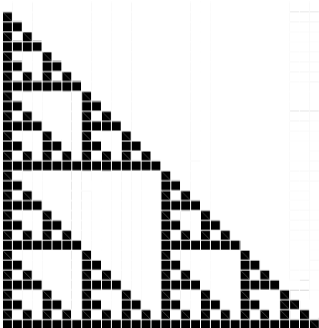
[https://en.wikipedia.org/wiki/Porous\\_medium](https://en.wikipedia.org/wiki/Porous_medium)

# Grid Based Models

$$d = 2$$



$$d_f = \log 3 / \log 2$$



# Random Walk on Graph

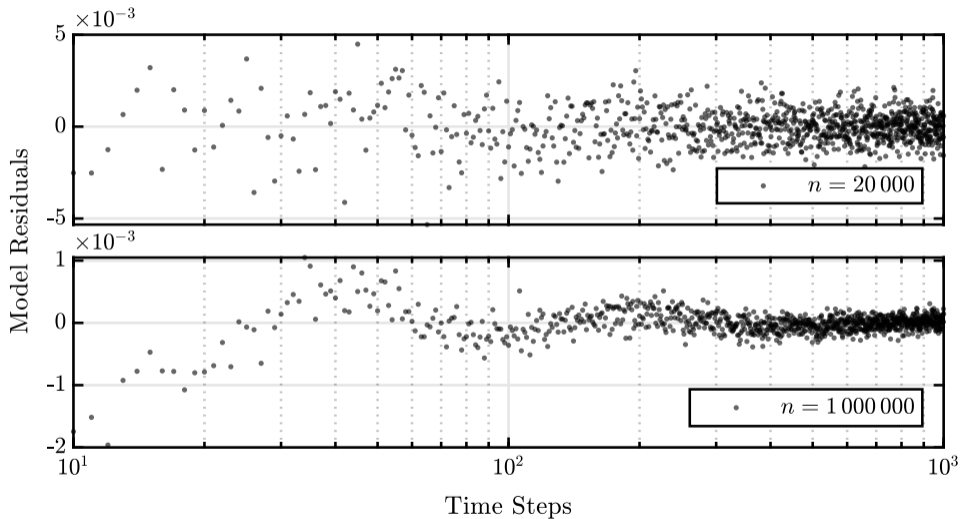
$$\mathcal{G} = (\mathcal{F}, \mathcal{E}), \quad \mathcal{F} \subset \mathbb{Z}^d, \quad \mathcal{T} \subset \mathbb{Z}^d$$

$$p \in (0, 1), \quad c(\mathbf{x}) = \text{card } \mathcal{N}(\mathbf{x}), \quad \mathcal{N}(\mathbf{x}) = (\mathbf{x} \oplus \mathcal{T}) \cap \mathcal{F}$$

$$\Pr(X_{t+1} = \mathbf{y} \mid X_t = \mathbf{x}) = \begin{cases} p, & \mathbf{y} \in \mathcal{N}(\mathbf{x}) \\ 1 - c(\mathbf{x})p, & \mathbf{y} = \mathbf{x} \\ 0, & \text{otherwise} \end{cases}$$

$$\mathbf{x}, \mathbf{y} \in \mathcal{F}$$

# Monte Carlo Simulations: Return Probability Model





# Full Space Numerical Approach

- $P_t : \mathbb{Z}^d \mapsto [0, 1]$
- $P_t(\mathbf{x}) = \Pr(X_t = \mathbf{x} | X_0 = \mathbf{x}_0)$
- $P_0(\mathbf{x}) = 1(\mathbf{x} = \mathbf{x}_0)$

- $N_{\text{square}} = \begin{pmatrix} 0 & p & 0 \\ p & 1 - 4p & p \\ 0 & p & 0 \end{pmatrix}$

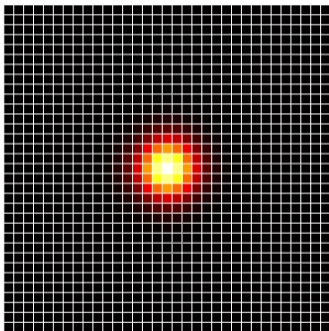
## Full Grid Probability Evolution

$$P_{t+1} = N * P_t$$

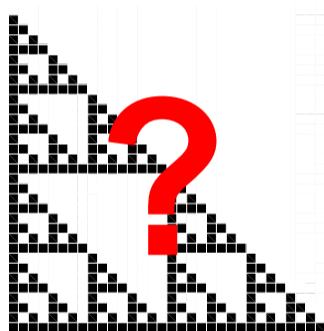
- $N_{\text{hexa}} = \begin{pmatrix} p & p & 0 \\ p & 1 - 6p & p \\ 0 & p & p \end{pmatrix}$

# Random Walk Over Grid Based Models

$$d = 2$$



$$d_f = \log 3 / \log 2$$



# Constrained Convolution Schema

- $P_t, F, C : \mathbb{Z}^d \mapsto \mathbb{R}$
- $P_t(x) = \Pr(X_t = x | X_0 = x_0)$
- $P_0(x) = I(x = x_0)$
- $F(x) = I(x \in \mathcal{F})$
- $N(x) = I(x \in \mathcal{T})$
- $C = F(N * F)$

- $N_{\text{square}} = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix}$

## Sparse Grid Probability Evolution

$$P_{t+1} = P_t(1 - pC) + pF(N * P_t)$$

- $N_{\text{hexa}} = \begin{pmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 1 \end{pmatrix}$

# Constrained Convolution Schema

- Markov Chain transition probabilities

$$p_{t+1}(\mathbf{x}) = \sum_{\mathbf{y} \in \mathcal{F}} p_t(\mathbf{y}) p(\mathbf{y} \rightarrow \mathbf{x}) \quad (1)$$

$$= p_t(\mathbf{x}) p(\mathbf{x} \rightarrow \mathbf{x}) + \sum_{\mathbf{y} \in \mathcal{F}, \mathbf{y} \neq \mathbf{x}} p_t(\mathbf{y}) p(\mathbf{y} \rightarrow \mathbf{x}) \quad (2)$$

$$= p_t(\mathbf{x}) (1 - p_c(\mathbf{x})) + \sum_{\mathbf{y} \in \mathcal{F}} p_t(\mathbf{y}) p(\mathbf{y} \in \mathcal{N}(\mathbf{x})) \quad (3)$$

# Constrained Convolution Schema

$$P_{t+1}(\mathbf{x}) = \left(P_t(1 - \rho C)\right)(\mathbf{x}) + \rho \sum_{\mathbf{y} \in \mathbb{Z}^d} P_t(\mathbf{y}) \mathbb{I}(\mathbf{y} \in \mathcal{N}(\mathbf{x})) \mathbb{I}(\mathbf{x} \in \mathcal{F}) \quad (4)$$

$$= \left(P_t(1 - \rho C)\right)(\mathbf{x}) + \rho \sum_{\mathbf{y} \in \mathbb{Z}^d} P_t(\mathbf{y}) \mathbb{I}(\mathbf{y} \in (\mathbf{x} \oplus \mathcal{T}) \cap \mathcal{F}) F(\mathbf{x}) \quad (5)$$

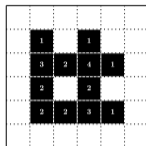
$$= \left(P_t(1 - \rho C)\right)(\mathbf{x}) + \rho F(\mathbf{x}) \sum_{\mathbf{y} \in \mathbb{Z}^d} P_t(\mathbf{y}) \mathbb{I}(\mathbf{y} \in (\mathbf{x} \oplus \mathcal{T})) \mathbb{I}(\mathbf{y} \in \mathcal{F}) \quad (6)$$

$$= \left(P_t(1 - \rho C)\right)(\mathbf{x}) + \rho F(\mathbf{x}) \sum_{\mathbf{y} \in \mathbb{Z}^d} P_t(\mathbf{y}) \mathbb{I}((\mathbf{x} - \mathbf{y}) \in \mathcal{T}) F(\mathbf{y}) \quad (7)$$

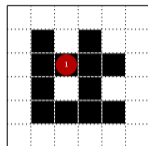
$$= \left(P_t(1 - \rho C)\right)(\mathbf{x}) + \rho F(\mathbf{x}) \sum_{\mathbf{y} \in \mathbb{Z}^d} P_t(\mathbf{y}) N(\mathbf{x} - \mathbf{y}) \quad (8)$$

$$= \left(P_t(1 - \rho C)\right)(\mathbf{x}) + \rho F(\mathbf{x}) (P_t * N)(\mathbf{x}) \quad (9)$$

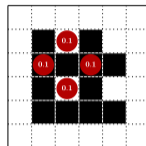
# Time Evolution (Sub)Steps: Square Topology



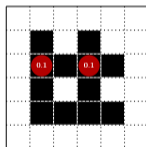
$F, C$



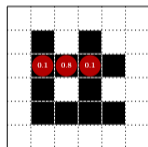
$P_0$



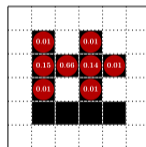
$\rho(P_0 * N)$



$\rho F(P_0 * N)$

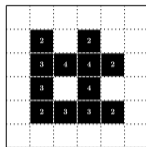


$P_1$

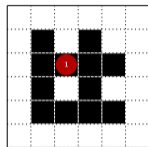


$P_2$

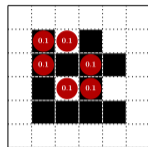
# Time Evolution (Sub)Steps: Hexagonal Topology



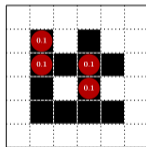
$F, C$



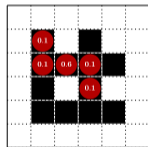
$P_0$



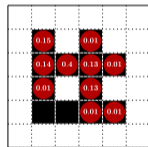
$\rho(P_0 * N)$



$\rho F(P_0 * N)$



$P_1$



$P_2$

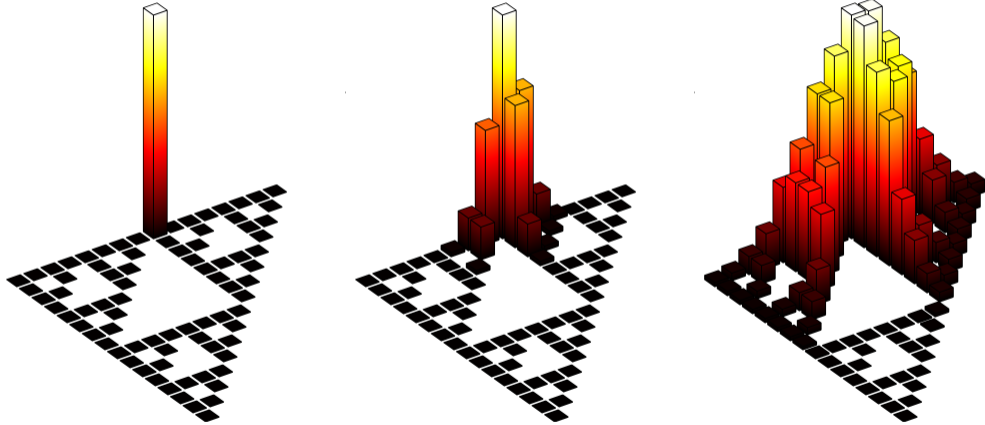
# MATLAB Implementation

```
1  % parameters
2  time_steps = 1e2;
3  p = 0.1;
4
5  % load set model
6  data = load("data_SierpGasket.mat");
7  F = data.F;
8  start_idx = data.start_idx;
9  % neighbourhood
10 N = [1, 1, 0;
11      1, 0, 1;
12      0, 1, 1];
13 % precalculated arrays
14 C = conv2(F, N, "same") .* F;
15 S = 1 - p .* C;
16 pF = p .* F;
17
18 % initial probability
19 P = zeros(size(F));
20 P(start_idx) = 1;
21 % checks
22 assert(sum(P, "all") == 1)
23 assert(sum(P .* F, "all") == 1)
24
25 % resulting return probabilities
26 ret_probabs = nan(time_steps, 1);
27 % GPU support
28 gpuType = @(a) gpuArray(double(a));
29 if canUseGPU()
30     P = gpuType(P);
31     pF = gpuType(pF);
32     N = gpuType(N);
33     S = gpuType(S);
34     ret_probabs = gpuType(ret_probabs);
35 end
36
37 for t = 1:time_steps
38     P = P .* S + pF .* conv2(P, N, "same");
39     ret_probabs(t) = P(start_idx);
40 end
```

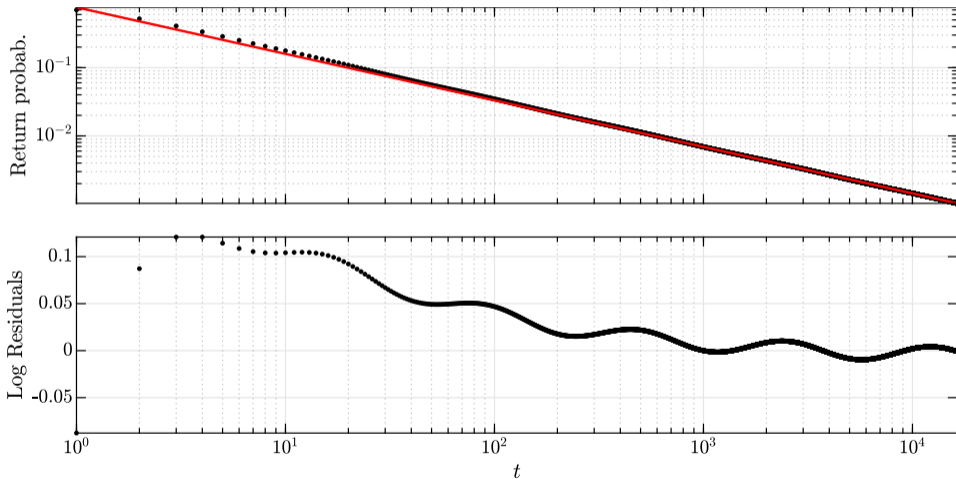


# Probability on Sierpinski Gasket

# Probability on Sierpinski Gasket



# Return Probability



- Dimension(s)
- Random walks
- Constrained convolution schema

Thank you for your attention!