

# Expectations on Fractal IFS Attractors

**Michael Rose**

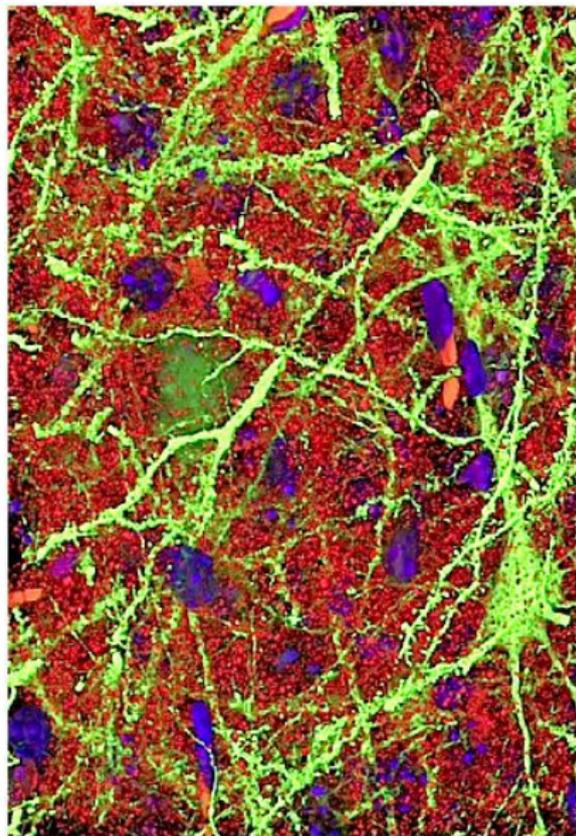
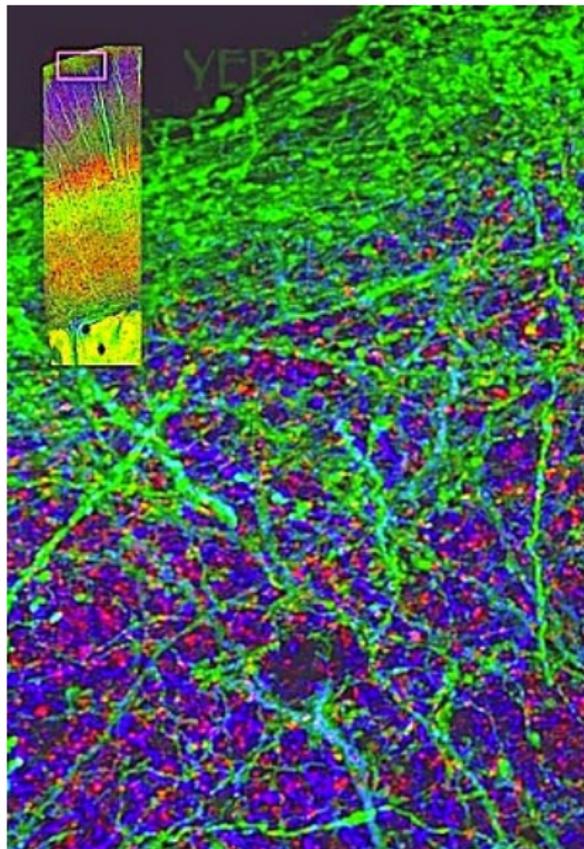
Principal Supervisor: Laureate Professor Jon Borwein

Co-supervisor: Associate Professor Brailey Sims

12th July 2014



## Synapse spatial distributions



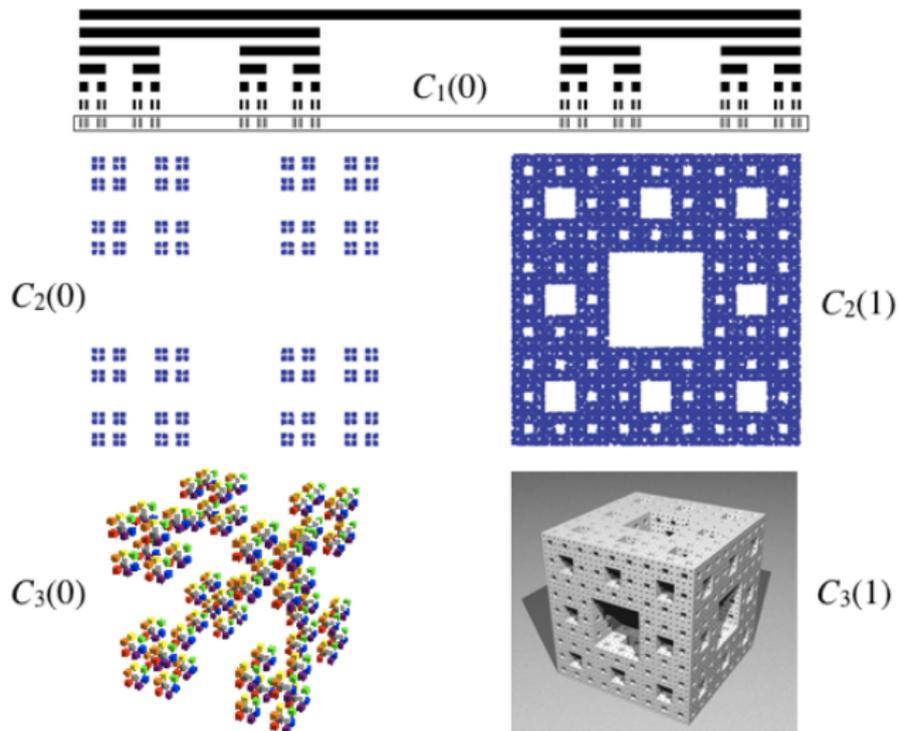
## Outline:

1. Summary of SCS results
2. Extension to IFS attractors
3. Examples



# Summary of SCS results

# String-generated Cantor Sets



D.H. Bailey, J.M. Borwein, R.E. Crandall and M.G. Rose,  
*Expectations on fractal sets*, J. Appl. Math. Comput. 220 (2013).

## String-generated Cantor Sets

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A helpful **counting function**:

$$U(c) := \#\{1\text{'s in ternary vector } c\}$$

$$Z(b) := \#\{0\text{'s in ternary vector } b\}$$

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with notational periodicity assumed:  $P_{p+k} := P_k$  for all  $k \geq 1$ .

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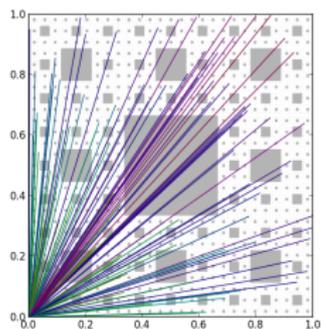
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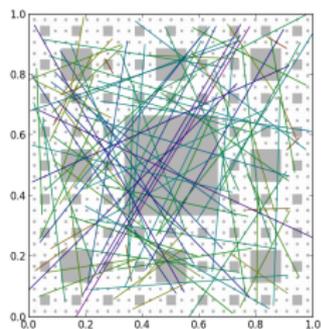
$\Delta_n(s)$  is the order- $s$  moment of separation between **two random points** in the  $n$ -cube:

$$\Delta_n(s) := \langle |r - q|^s \rangle_{r, q \in [0,1]^n} = \int_{r, q \in [0,1]^n} |r - q|^s \mathcal{D}r \mathcal{D}q$$

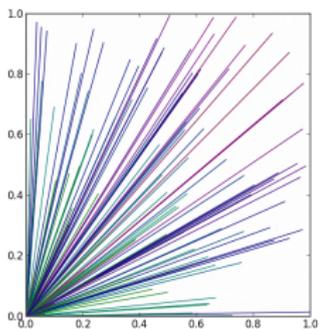
# Fractal Box Integrals



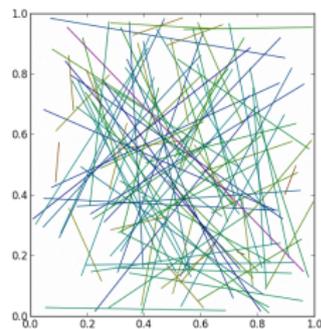
$$B(2, C_2(1)) = \frac{11}{16} = 0.6875$$



$$\Delta(2, C_2(1)) = \frac{3}{8} = 0.375$$



$$B(2, C_2(2)) = \frac{2}{3} = 0.66\dots$$



$$\Delta(2, C_2(2)) = \frac{1}{3} = 0.33\dots$$

## Definition of expectation

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$$\langle F(r) \rangle_{r \in C_n(P)} := \lim_{j \rightarrow \infty} \frac{1}{N_1 \cdots N_j} \sum_{U(c_i) \leq P_i} F(c_1/3 + c_2/3^2 + \cdots + c_j/3^j)$$

$$\langle F(r - q) \rangle_{r, q \in C_n(P)} := \lim_{j \rightarrow \infty} \frac{1}{N_1^2 \cdots N_j^2} \sum_{\substack{U(c_i) \leq P_i \\ U(d_i) \leq P_i}} F((c_1 - d_1)/3 + \cdots + (c_j - d_j)/3^j)$$

when the respective limits exist.

## Useful formulation of expectation

Next, determine a probability measure such that

$$\langle F(r) \rangle_{r \in C_n(P)} = \int_{r \in [0,1]^n} F(r) \phi(r) \mathcal{D}r$$

where  $\phi$  is a **probability density** that vanishes on inadmissible  $r \in [0, 1]^n \setminus C_n(P)$ .

## Scaling relations for probability densities

### Proposition (**Scaling relations for probability densities**)

*For  $r, q$  in  $R^n$  the probability densities pertaining to the box integrals  $B$  and  $\Delta$  satisfy the **scaling relations**:*

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$$\phi(r) = \frac{3^{pn}}{\prod_{k=1}^p N_k} \sum_{U(c_k) \leq P_k} \phi\left(3^p\left(r - \sum_{j=1}^p \frac{c_j}{3^j}\right)\right)$$

$$\Phi(d := r - q) = \frac{3^{pn}}{\prod_{k=1}^p N_k^2} \sum_{\substack{Z(b_k) \leq P_k \\ Z(a_k) \leq P_k}} \Phi\left(3^p\left(d - \sum_{j=1}^p \frac{(b_j - a_j)}{3^j}\right)\right)$$

# Functional equations for expectations

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$$\langle F(r) \rangle_{r \in C_n(P)} = \frac{1}{\prod_{j=1}^p N_j} \sum_{U(c_k) \leq P_k} \left\langle F\left(\frac{r}{3^p} + \sum_{j=1}^p \frac{c_j}{3^j}\right) \right\rangle$$

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The **functional expectation relations** directly yield all expectations  $B(2, C_n(P))$  as follows:

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**Theorem** (Closed forms for  $B(2, C_n(P))$  and  $\Delta(2, C_n(P))$ )

*For any embedding dimension  $n$  and SCS  $C_n(P)$  the box integral  $B(2, C_n(P))$  is **rational**, given by the closed form:*

$$B(2, C_n(P)) = \frac{n}{4} + \frac{1}{1 - 9^{-p}} \sum_{k=1}^p \frac{1}{9^k} \frac{\sum_{j=0}^{P_k} \binom{n}{j} 2^{n-j} (n-j)}{\sum_{j=0}^{P_k} \binom{n}{j} 2^{n-j}}$$

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*and the corresponding box integral  $\Delta(2, C_n(P))$  is also **rational**, given by:*

$$\Delta(2, C_n(P)) = 2B(2, C_n(P)) - \frac{n}{2}$$

## Special case - second moments

The first few cases for period-1 strings  $P$  are:

$$B(2, C_n(0)) = \frac{3}{8}n$$

$$B(2, C_n(1)) = \frac{n(3n + 5)}{8n + 16}$$

$$B(2, C_n(2)) = \frac{n(3n^2 + 7n + 22)}{8n^2 + 24n + 64}$$

$$B(2, C_n(n-1)) = \frac{n}{4} \left( 1 + \frac{3^{n-1}}{3^n - 1} \right)$$

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The [classical box integrals](#) over the unit  $n$ -cube are:

$$B_n(2) = \frac{n}{3} \quad \text{and} \quad \Delta_n(2) = \frac{n}{6}$$

which matches the output of our closed forms when  $P = n$ .

## Special case - complex poles

Powerful **self-similarity relations** for  $C_1(0)$  follow from the **functional expectation relations**:

$$B(s, C_1(0)) := \langle |r^s| \rangle_{r \in C_1(0)} = \frac{1}{2} \left\langle \left( \frac{r}{3} \right)^s \right\rangle + \frac{1}{2} \left\langle \left( \frac{r+2}{3} \right)^s \right\rangle$$
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Using the fact that  $\langle (r/3)^s \rangle$  is itself a scaled expectation leads to:

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### Theorem (Poles of $B(s, C_n(P))$ )

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Note that for the full unit  $n$ -cube  $[0, 1]^n$ , the pole is at  $s = -n$ . This is consistent with the classical theory.

Extension to IFS attractors

## IFS Attractors

Let  $(X, d)$  be a metric space and let  $(H(X), h(d))$  be the associated space of non-empty compact subsets of  $X$  equipped with the Hausdorff metric  $h(d)$ .

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### Definition

A mapping  $f : X \rightarrow X$  is said to be a *contraction mapping* with *contractivity factor*  $c$  if  $0 < c < 1$  and  $d(f(x), f(y)) \leq c \cdot d(x, y)$  for all  $x, y \in X$ .

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## Definition

For each  $i \in \{1, 2, \dots, m\}$  (where  $m \geq 2$ ), let  $f_i : X \rightarrow X$  be a contraction mapping with contractivity factor  $0 < c_i < 1$  and associated probability  $0 < p_i < 1$  (where  $\sum_{i=1}^m p_i = 1$ ). A **(hyperbolic) iterated function system (IFS) with probabilities** is the collection

$$\{X; w_1, \dots, w_m; c_1, \dots, c_m; p_1, \dots, p_m\}$$

# IFS Attractors

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Let  $\{X; w_1, \dots, w_m\}$  be an IFS with contractivity factor  $c$ . Then the transformation  $f : H(X) \rightarrow H(X)$  defined by  $f(S) = \bigcup_{n=1}^m f_n(S)$  for all  $S \in H(X)$  is a contraction mapping on  $H(X)$  with contractivity factor  $s$ .

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## Theorem (The Contraction Mapping Theorem)

The mapping  $f$  possesses a unique fixed point  $A \in H(X)$ , which satisfies:

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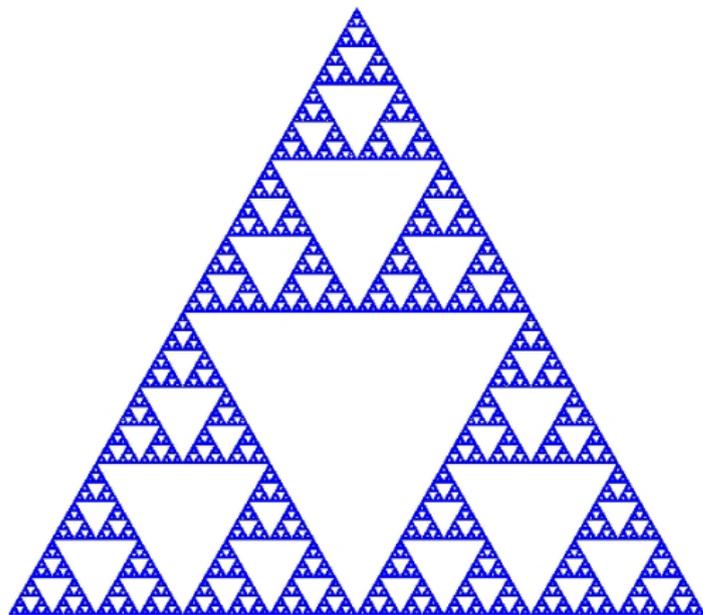
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We will take as our 'fractal sets' those sets that can be expressed as the attractor of a (non-overlapping) IFS.

# IFS Attractors



$$f_1(x, y) = \left(\frac{x}{2}, \frac{y}{2}\right)$$

$$f_2(x, y) = \left(\frac{x+1}{2}, \frac{y+\sqrt{3}}{2}\right)$$

$$f_3(x, y) = \left(\frac{x+2}{2}, \frac{y}{2}\right)$$

## SCS in IFS framework

Any given SCS can be expressed as the attractor of an IFS in the following manner:

### Proposition

*The IFS corresponding to the SCS  $C_n(P)$  is:*

$$\{[0, 1]^n \subset \mathbb{R}^n; f_1, f_2, \dots, f_i, \dots, f_m\} \quad (1)$$

*where  $f_i(x) = \left(\frac{1}{3}\right)^P x + \left(\frac{1}{3}\right) c_{1_i} + \left(\frac{1}{3}\right)^2 c_{2_i} + \dots + \left(\frac{1}{3}\right)^P c_{p_i}$  for  $i \in \{1, 2, \dots, m\}$  ranging over all admissible columns  $c_k$ , where  $m = \prod_{k=1}^P N_k$  and  $N_k = \sum_{j=0}^{P_k} \binom{n}{j} 2^{n-j}$ .*

# Expectations on IFS Attractors

Expectations over IFSs

Definition (Fundamental definition of expectation)

Let  $\{X; f_1, \dots, f_m\}$  be an IFS with attractor  $A \in H(X)$ . Let  $F : X \rightarrow \mathbb{C}$  be a complex-valued function over  $X$ . The *expectation of  $F$  over  $A$* ,  $\langle F(x) \rangle_{x \in A}$ , is defined as:

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$$\langle F(x) \rangle_{x \in A} := \lim_{j \rightarrow \infty} \frac{1}{m^j} \sum_{k_1=1}^m \sum_{k_2=1}^m \cdots \sum_{k_j=1}^m F(f_{k_j} \circ \cdots \circ f_{k_2} \circ f_{k_1}(x_0)) \quad (2)$$

for any  $x_0 \in A$ , when the limit exists.

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**Definition (Fundamental definition of expectation)**

Let  $\{X; f_1, \dots, f_m\}$  be an IFS with attractor  $A \in H(X)$ . Let  $F : X \rightarrow \mathbb{C}$  be a complex-valued function over  $X$ . The *expectation of  $F$  over  $A$* ,  $\langle F(x) \rangle_{x \in A}$ , is defined as:

$$\langle F(x) \rangle_{x \in A} := \lim_{j \rightarrow \infty} \frac{1}{m^j} \sum_{k_1=1}^m \sum_{k_2=1}^m \cdots \sum_{k_j=1}^m F(f_{k_j} \circ \cdots \circ f_{k_2} \circ f_{k_1}(x_0)) \quad (2)$$

for any  $x_0 \in A$ , when the limit exists.

Intuitively we evaluate the expectation over ever-finer pre-fractal sets and examine the limit as the resolution grows ever-finer. This definition is more elegantly stated using code-space ideas.

# Code Space

## Definition

Given an IFS  $\{X; f_1, \dots, f_m\}$ , the associated *code space*  $\Sigma_m$  is defined as:

$$\Sigma_m := \{\sigma = \sigma_1\sigma_2 \dots : \sigma_i \in \{0, 1, \dots, m-1\} \quad \forall i \in \mathbb{N}\}$$

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The *code space metric* is defined by:

$$d_{\Sigma}(\sigma, \omega) = d_{\Sigma}(\sigma_1\sigma_2\dots, \omega_1\omega_2\dots) := \sum_{k=1}^{\infty} \frac{|\sigma_k - \omega_k|}{(m+1)^k}$$

## Expectations on IFS Attractors

Definition (Fundamental definition of expectation (using code-space))

Let  $\{X; f_1, \dots, f_m\}$  be an IFS with attractor  $A \in H(X)$ . Let  $F : X \rightarrow \mathbb{C}$  be a complex-valued function over  $X$ . The *expectation of  $f$  over  $A$* ,  $\langle f(x) \rangle_{x \in A}$ , is defined as:

$$\langle F(x) \rangle_{x \in A} := \lim_{j \rightarrow \infty} \frac{1}{m^j} \sum_{\sigma_j \in \Sigma_m(j)} F(\phi(\sigma_j))$$

when the limit exists.

# Expectations on IFS Attractors

## Corollary

(Fundamental definition of separation (using code-space)) Let  $\{X; f_1, \dots, f_m\}$  be an IFS with attractor  $A \in H(X)$ . Let  $F : X \rightarrow \mathbb{C}$  be a complex-valued function over  $X$ . The *separation expectation of  $F$  over  $A$* ,  $\langle F(x - y) \rangle_{x, y \in A}$ , is defined as:

$$\langle F(x, y) \rangle_{x, y \in A} := \lim_{j \rightarrow \infty} \frac{1}{m^{2j}} \sum_{\sigma_j \in \Sigma_m(j)} \sum_{\tau_j \in \Sigma_m(j)} F(\phi(\sigma_j - \tau_j))$$

when the limit exists.

# The invariant IFS measure

## Definition

(Falconer) A measure  $\mu$  on  $X$  is **invariant** for a mapping  $f : X \rightarrow X$  if for every subset  $B \subset X$  we have

$$\mu(f^{-1}(A)) = \mu(A)$$

A measure  $\mu$  on  $X$  is **normalised** if  $\mu(X) = 1$ .

## Definition

Let  $B$  be a Borel subset of a metric space  $(X, d)$ . The **residence measure** is defined as:

$$\mu(B) := \lim_{n \rightarrow \infty} \frac{1}{n} \# \left\{ k : f^k(x) \in B, 1 \leq k \leq n \right\} \quad (3)$$

Ergodic theory shows that this limit exists and is identical for  $\mu$ -almost all points in the basin of attraction.

# The invariant IFS measure

## Corollary

*The residence measure is an invariant measure over the attractor of any IFS.*

## The invariant IFS measure

### Theorem (Elton's Theorem - special case)

Let  $(X, d)$  be a compact metric space and let  $\{X; w_1, \dots, w_m; c_1, \dots, c_m; p_1, \dots, p_m\}$  be a hyperbolic IFS. Let  $\{x_n\}_{n=0}^{\infty}$  denote a chaos game orbit of the IFS starting at  $x_0 \in X$ , that is,  $x_m = w_{\sigma_n} \circ \dots \circ w_{\sigma_1}(x_0)$  where the maps are chosen independently according to the probabilities  $p_1, \dots, p_m$  for  $n \in \mathbb{N}$ . Let  $\mu$  be the unique invariant measure for the IFS. Then, with probability 1 (i.e. for all code sequences excepting a set having probability 0),

$$\lim_{n \rightarrow \infty} \frac{1}{n+1} \sum_{k=0}^n f(x_k) = \int_X f(x) d\mu(x) \quad (4)$$

# Elton's Theorem

## Corollary

(Barnsley) Let  $B$  be a Borel subset of  $X$  and let  $\mu(B') = 0$  (where  $B'$  is the boundary of  $B$ ). Then, with probability 1,

$$\mu(B) = \lim_{n \rightarrow \infty} \frac{\#\{x_0, x_1, \dots, x_n\} \cap B}{n + 1} \quad (5)$$

for all  $x_0 \in X$ .

# Elton's Theorem

## Corollary

(Barnsley) Let  $B$  be a Borel subset of  $X$  and let  $\mu(B') = 0$  (where  $B'$  is the boundary of  $B$ ). Then, with probability 1,

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for all  $x_0 \in X$ .

It follows that our definition of the expectation leads naturally to the equivalence of integration with respect to the residence measure. Elton's Theorem and Barnsley's corollary implies a similarly fast Chaos-Game algorithms for numerical estimation of the residence measure of Borel sets, as well as our expectations.

# Expectations over IFS attractors

## Corollary

Let  $\{X; f_1, f_2, \dots, f_N\}$  be a contractive IFS with attractor  $A \in \mathbb{H}(X)$ . Given a complex-valued function  $F : X \rightarrow \mathbb{C}$ , the expectation of  $F$  over  $A$  is given by the integral:

$$\langle f(x) \rangle_{x \in A} = \int_X f(x) d\mu(x) \quad (6)$$

## Functional equations

If the IFS is non-overlapping, the measure separates as follows:

### Proposition (**Measure scaling relation**)

*The invariant measure  $\mu$  on a subset  $S$  of the attractor  $A$  of a totally-disconnected IFS satisfies the scaling relation:*

$$\mu(S) = \sum_{k=1}^m \mu(f_k(S)) \quad (7)$$

# Functional equations

The functional equations for expectations are:

## Proposition (**Function equations for expectations**)

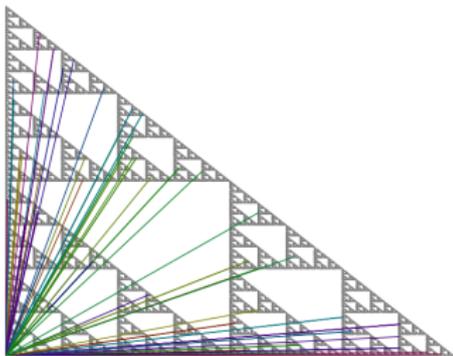
*For points  $x, y$  in the attractor  $A$  of a non-overlapping IFS, the expectations for a complex-valued function  $F$  satisfy the functional equations (respectively pertaining to the box-integrals  $B$  and  $\Delta$ ):*

$$\langle F(x) \rangle = \frac{1}{m} \sum_{j=1}^m \langle F(f_j(x)) \rangle \quad (8)$$

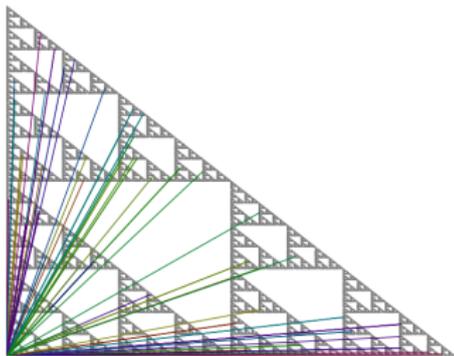
$$\langle F(x - y) \rangle = \frac{1}{m^2} \sum_{j=1}^m \sum_{k=1}^m \langle F(f_j(x) - f_k(y)) \rangle \quad (9)$$

# Examples

# Orthogonal Sierpinski Triangle

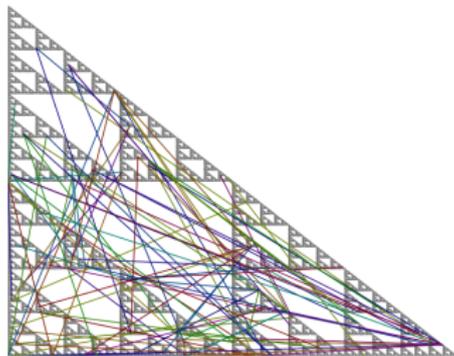
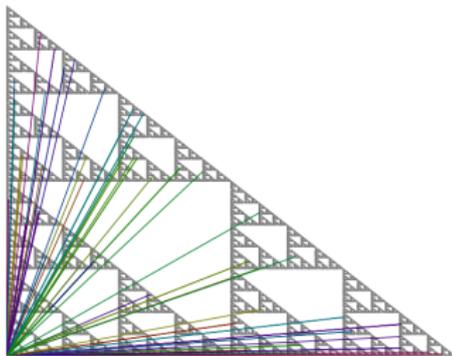


# Orthogonal Sierpinski Triangle



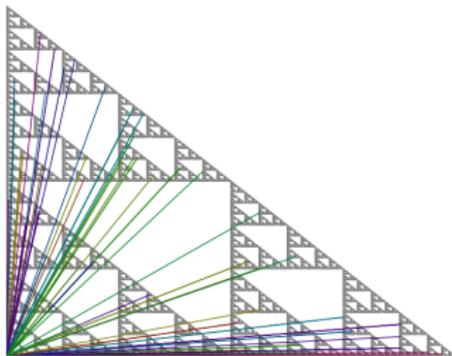
$$B_2 = \frac{10}{27}$$

# Orthogonal Sierpinski Triangle

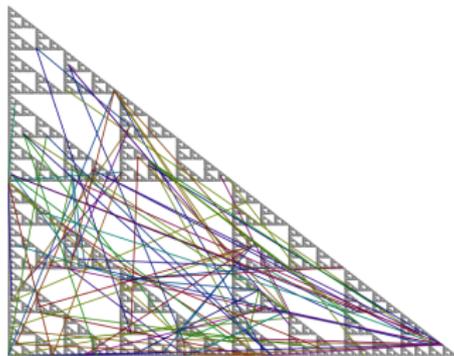


$$B_2 = \frac{10}{27}$$

# Orthogonal Sierpinski Triangle

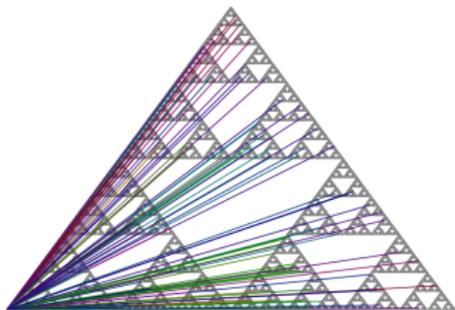


$$B_2 = \frac{10}{27}$$

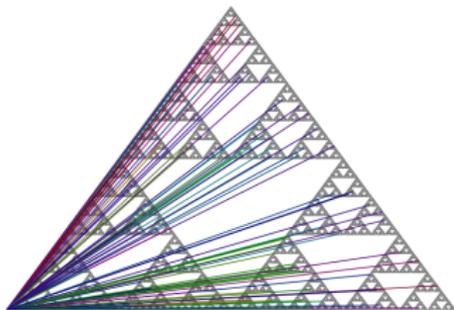


$$\Delta_2 = \frac{8}{27}$$

# Equilateral Sierpinski Triangle

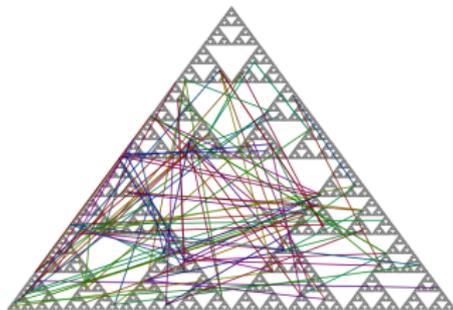
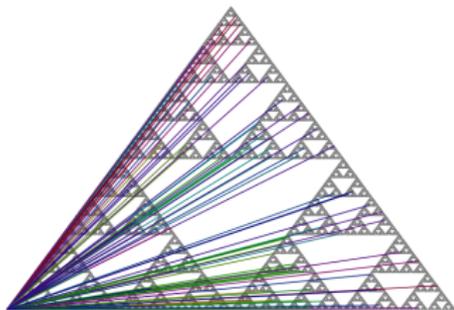


# Equilateral Sierpinski Triangle



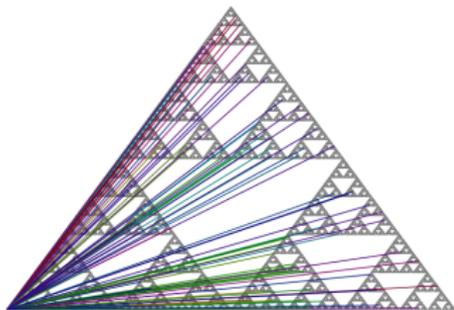
$$B_2 = \frac{4}{9}$$

# Equilateral Sierpinski Triangle

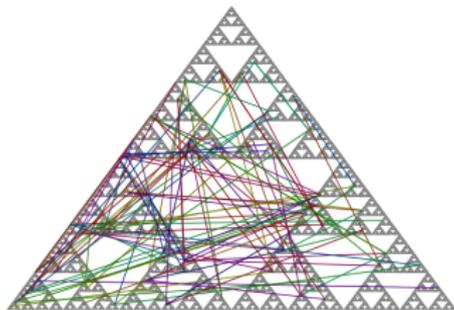


$$B_2 = \frac{4}{9}$$

# Equilateral Sierpinski Triangle

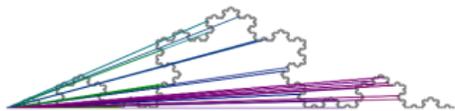


$$B_2 = \frac{4}{9}$$

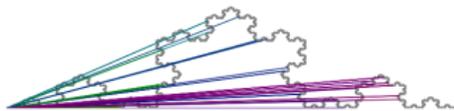


$$\Delta_2 = \frac{2}{9}$$

# Koch Curve

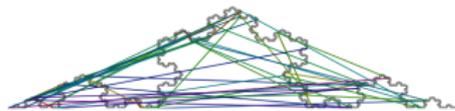
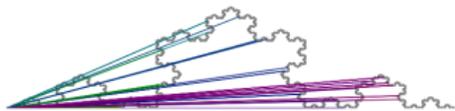


# Koch Curve



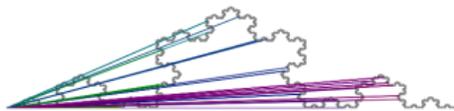
$$B_2 = \frac{1}{3}$$

# Koch Curve

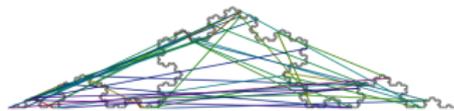


$$B_2 = \frac{1}{3}$$

# Koch Curve



$$B_2 = \frac{1}{3}$$



$$\Delta_2 = \frac{4}{27}$$

# Barnsley Fern



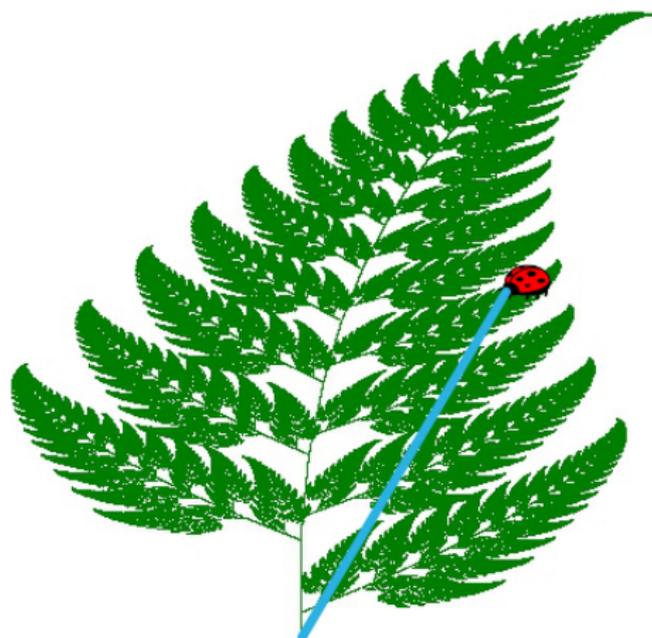
# Barnsley Fern



# Barnsley Fern



# Barnsley Fern



$$B_2 = \frac{2049440803137681904}{580160660775546421} \approx 3.5$$

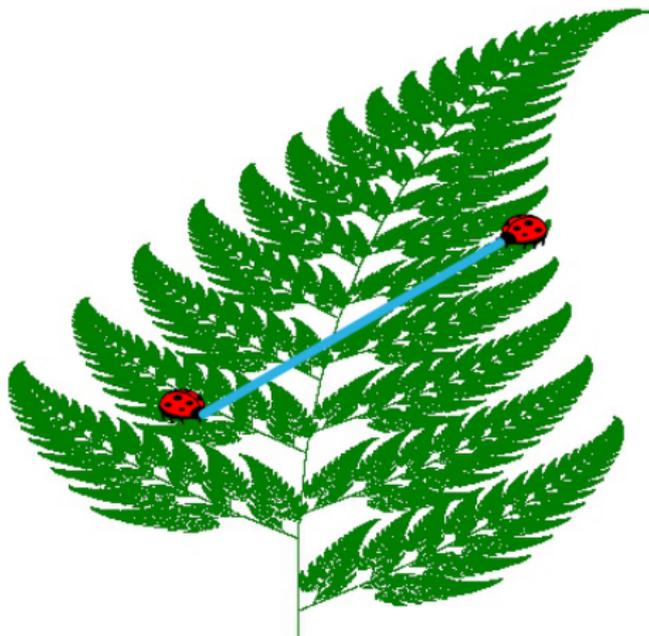
# Barnsley Fern



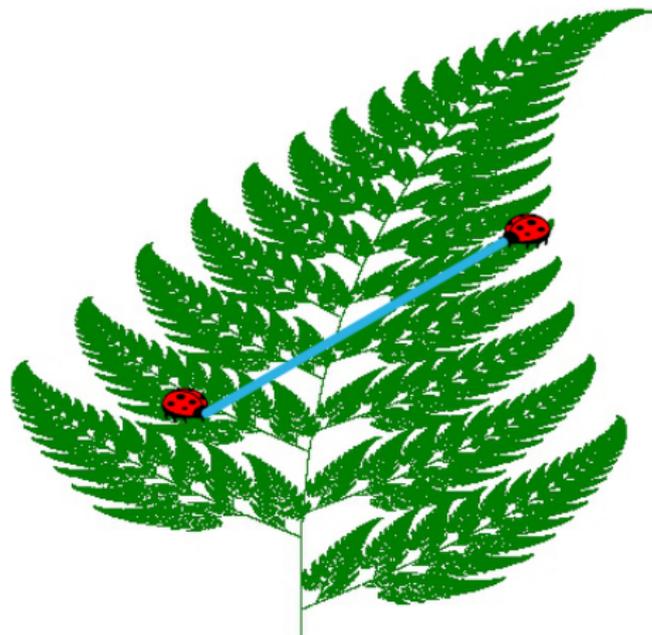
# Barnsley Fern



# Barnsley Fern



# Barnsley Fern



$$\Delta_2 = \frac{1561818604387599983932186}{541130352321871535527225} \approx 2.9$$

## Future directions

- ▶ Applications to Daubechies wavelets
- ▶ Evaluation of odd moments
- ▶ NMR diffusion studies

Thanks!

