Dynamics and time series: theory and applications

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Lecture 5, Feb 12, 2009

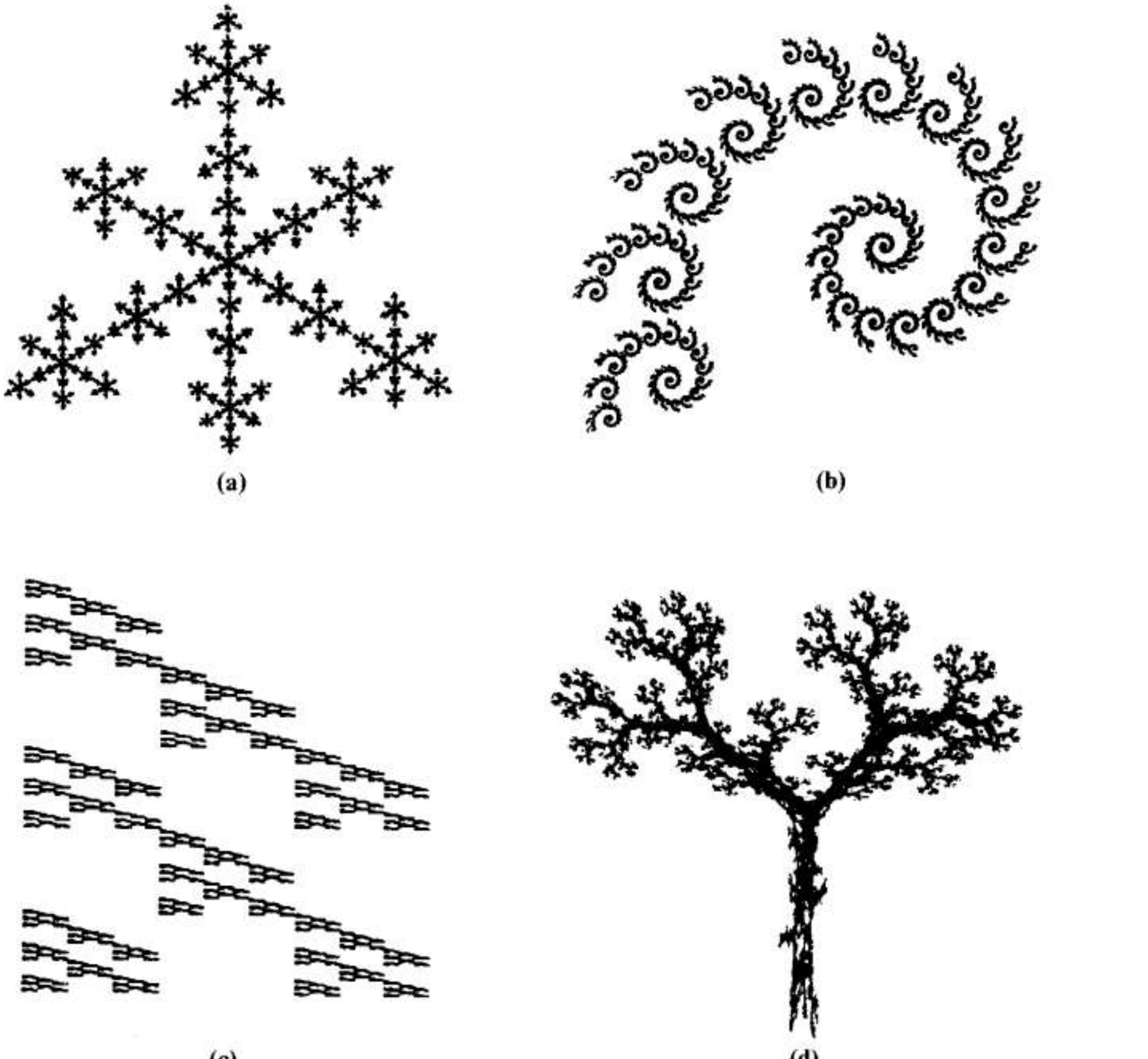
- Lecture 1: An introduction to dynamical systems and to time series. Periodic and quasiperiodic motions. (Tue Jan 13, 2 pm - 4 pm Aula Bianchi)
- Lecture 2: Ergodicity. Uniform distribution of orbits. Return times. Kac inequality Mixing (Thu Jan 15, 2 pm - 4 pm Aula Dini)
- Lecture 3: Kolmogorov-Sinai entropy. Randomness and deterministic chaos. (Tue Jan 27, 2 pm - 4 pm Aula Bianchi)
- Lecture 4: Time series analysis and embedology. (Thu Jan 29, 2 pm - 4 pm Dini)
- **Lecture 5: Fractals and multifractals. (Thu Feb 12, 2 pm - 4 pm Dini)**
- Lecture 6: The rhythms of life. (Tue Feb 17, 2 pm - 4 pm Bianchi)
- Lecture 7: Financial time series. (Thu Feb 19, 2 pm - 4 pm Dini)
- Lecture 8: The efficient markets hypothesis. (Tue Mar 3, 2 pm - 4 pm Bianchi)
- Lecture 9: A random walk down Wall Street. (Thu Mar 19, 2 pm - 4 pm Dini)
- Lecture 10: A non-random walk down Wall Street. (Tue Mar 24, 2 pm – 4 pm Bianchi)

- Seminar I: Waiting times, recurrence times ergodicity and quasiperiodic dynamics (D.H. Kim, Suwon, Korea; Thu Jan 22, 2 pm - 4 pm Aula Dini)
- Seminar II: Symbolization of dynamics. Recurrence rates and entropy (S. Galatolo, Università di Pisa; Tue Feb 10, 2 pm - 4 pm Aula Bianchi)
- Seminar III: Heart Rate Variability: a statistical physics point of view (A. Facchini, Università di Siena; Tue Feb 24, 2 pm - 4 pm Aula Bianchi)
- Seminar IV: Study of a population model: the Yoccoz-Birkeland model (D. Papini, Università di Siena; Thu Feb 26, 2 pm - 4 pm Aula Dini)
- Seminar V: Scaling laws in economics (G. Bottazzi, Scuola Superiore Sant'Anna Pisa; Tue Mar 17, 2 pm - 4 pm Aula Bianchi)
- Seminar VI: Complexity, sequence distance and heart rate variability (M. Degli Esposti, Università di Bologna; Thu Mar 26, 2 pm - 4 pm Aula Dini)
- Seminar VII: Forecasting (M. Lippi, Università di Roma; late april, TBA)

Self-similarity and fractals

A subset **A** of Euclidean space will be considered a “fractal” when it has most of the following features:

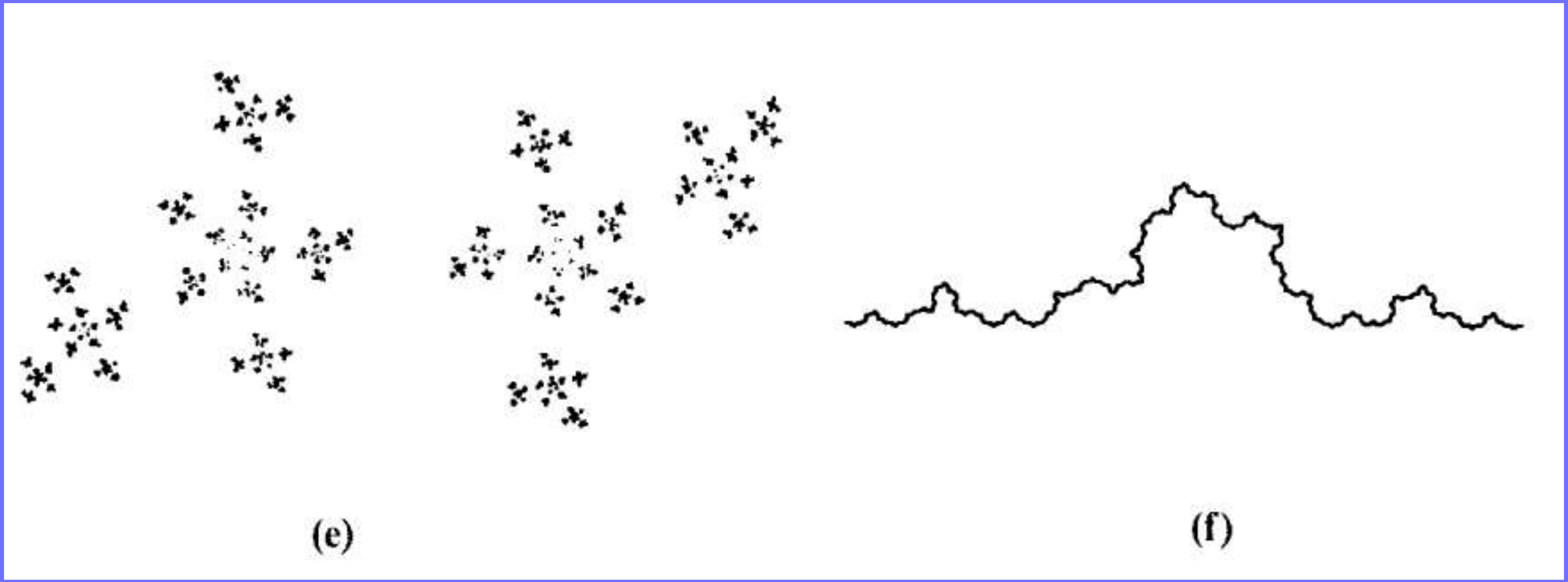
- **A** has fine structure (wiggly detail at arbitrarily small scales)
- **A** is too irregular to be described by calculus (e.g. no tangent space)
- **A** is self-similar or self-affine (maybe approximately or statistically)
- the fractal dimension of **A** is non-integer
- **A** may have a simple (recursive) definition
- **A** has a “natural” appearance: “Clouds are not spheres, mountains are not cones, coastlines are not circles, and bark is not smooth, nor does lightning travel in a straight line . . .” (B. Mandelbrot)



self-similar fractals

self-affine fractals

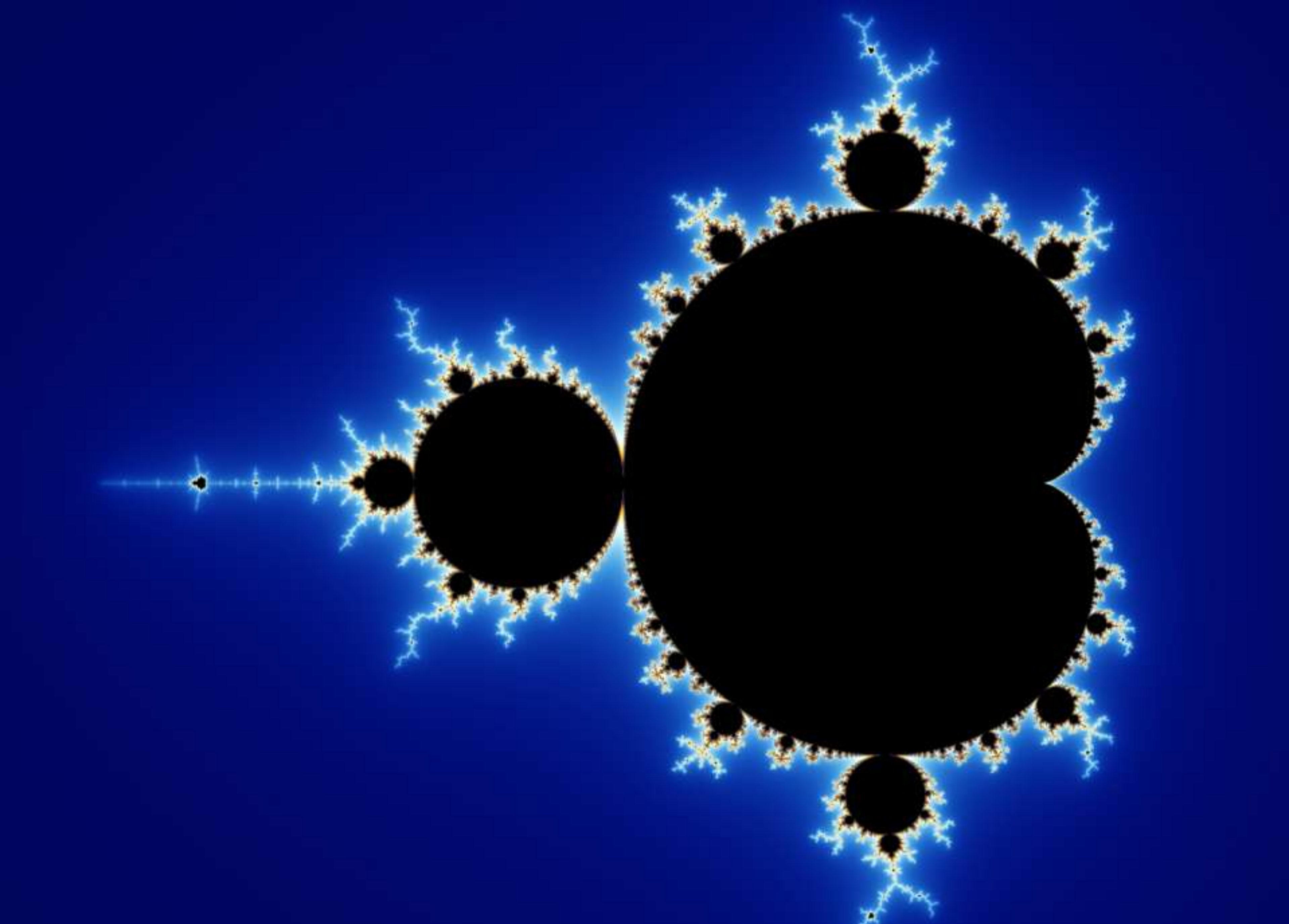
From: K. Falconer, Techniques in Fractal Geometry, Wiley 1997



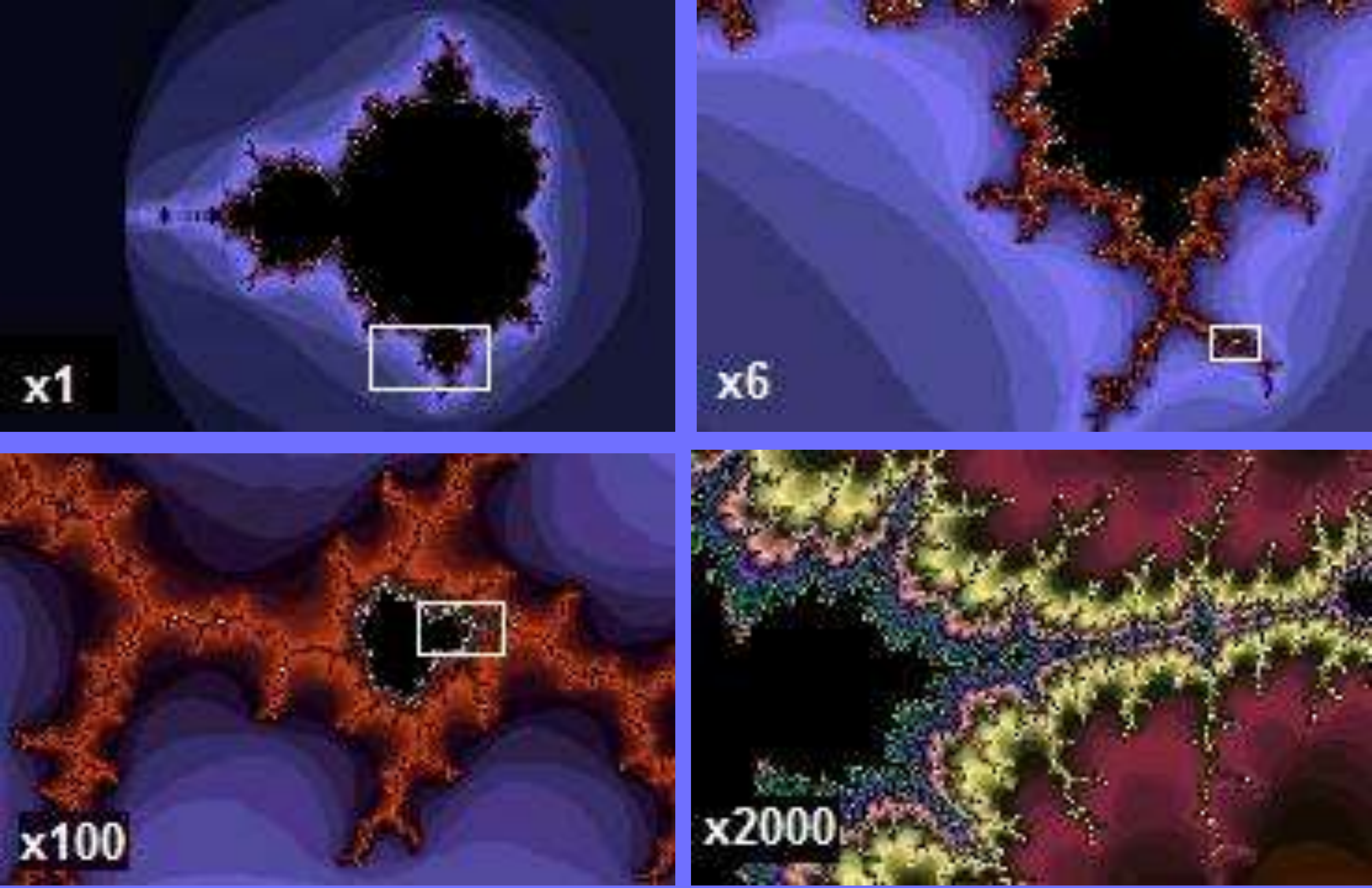
self-conformal fractals

Statistically self-similar fractals

From: K. Falconer, Techniques in Fractal Geometry, Wiley 1997

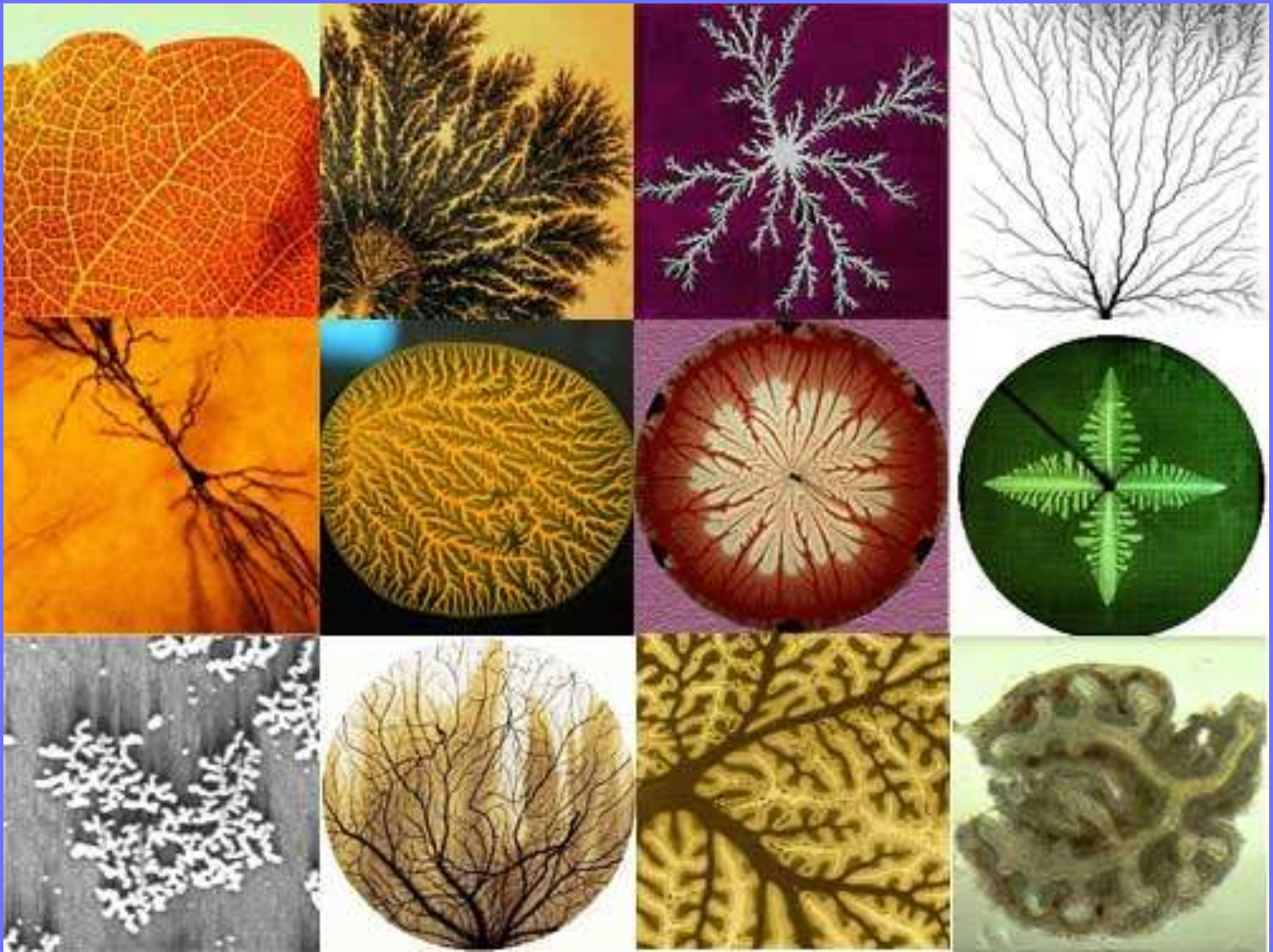


Source: Wikipedia



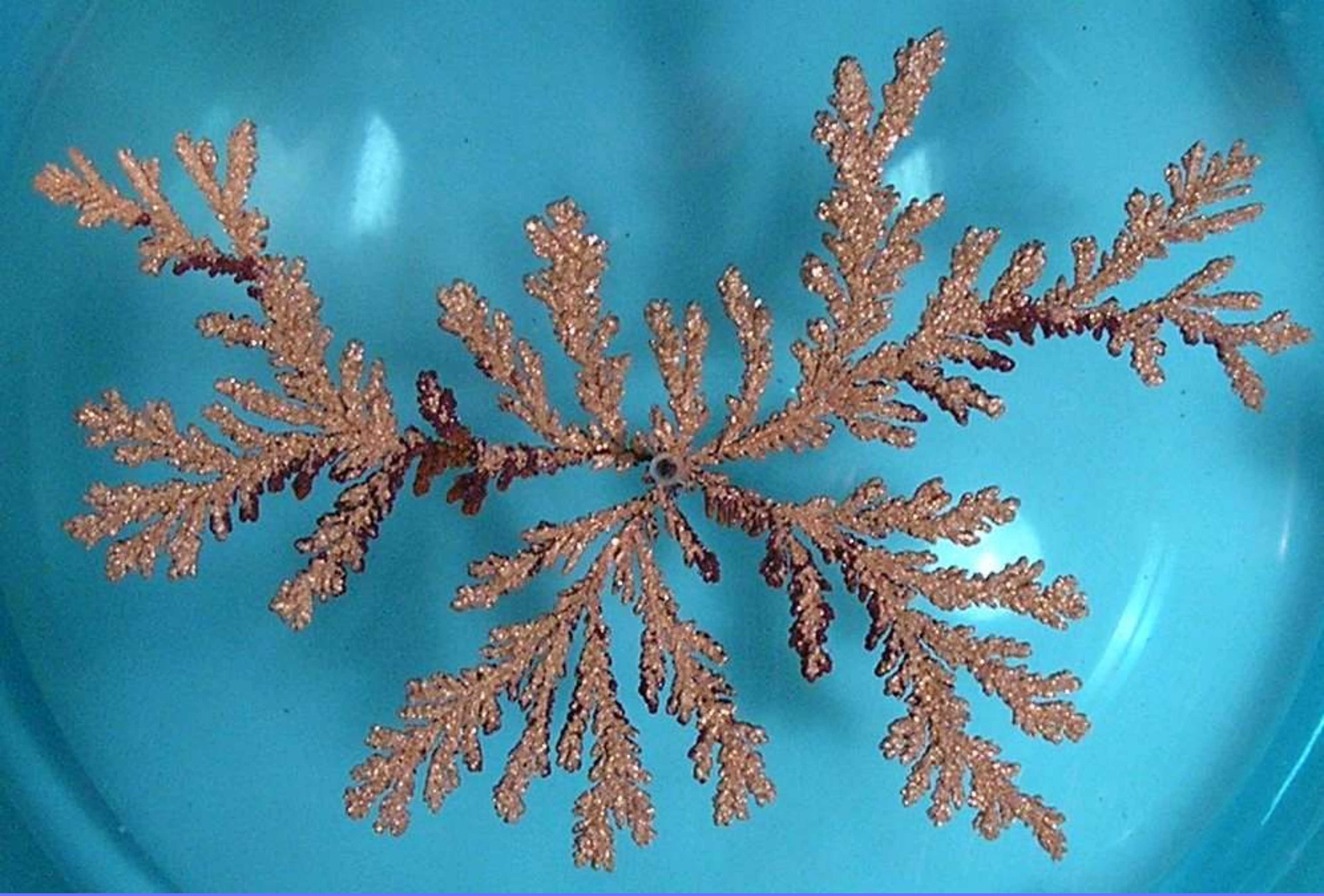
Source: Wikipedia

Mathematics, shapes and nature



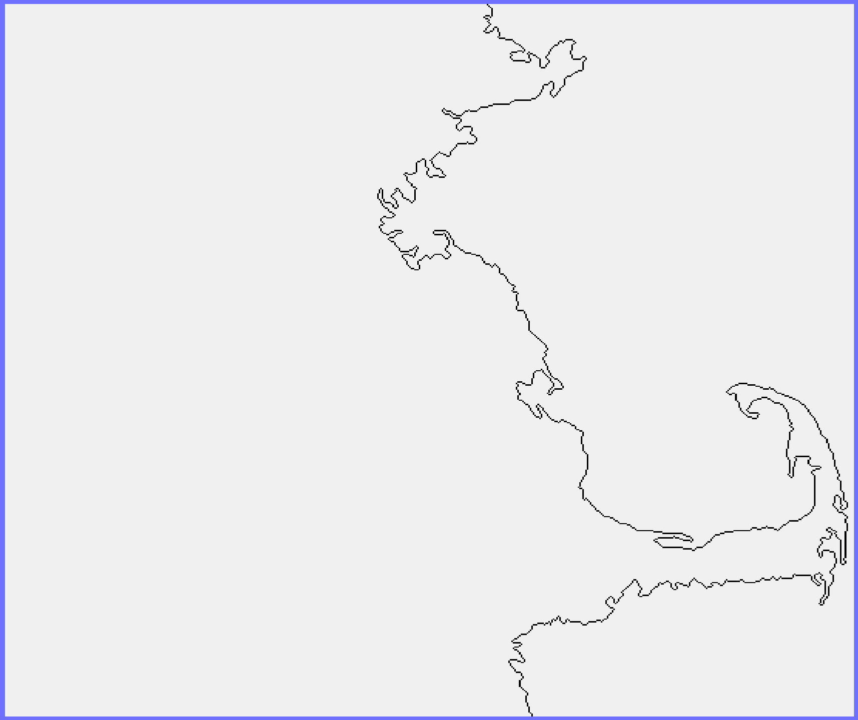
http://classes.yale.edu/fractals/Panorama/Nature/NatFracGallery/Gallery/Gallery.html

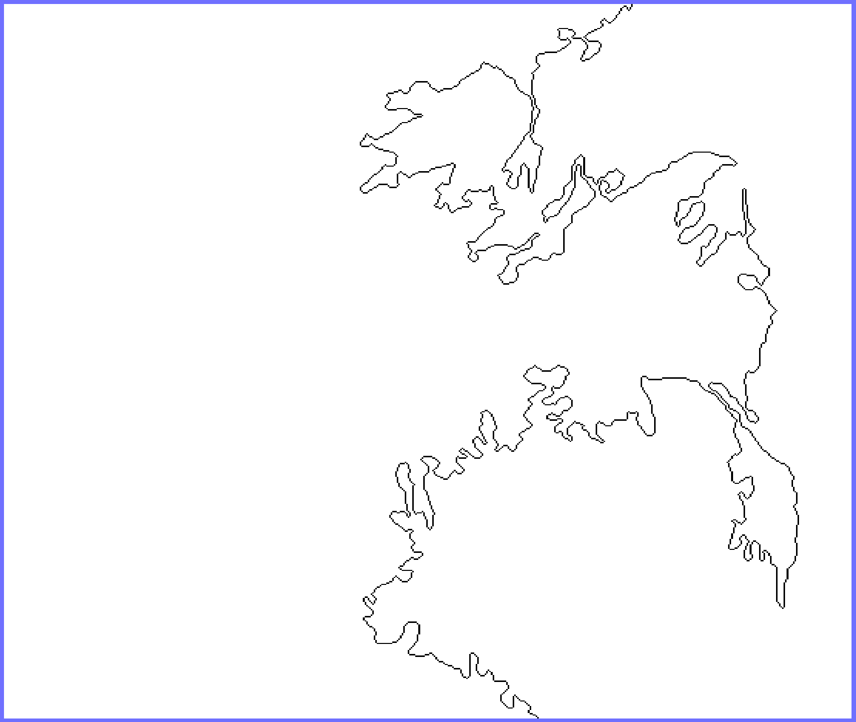
From http://en.wikipedia.org/wiki/Image:Square1.jpg
Lichtenberg Figure
High voltage dielectric breakdown within a block of plexiglas creates a beautiful fractal pattern called a Lichtenberg_figure. The branching discharges ultimately become hairlike, but are thought to extend down to the molecular level.
Bert Hickman, http://www.teslamania.com



A diffusion-limited aggregation (DLA) cluster. Copper aggregate formed from a copper sulfate solution in an electrode position cell. Kevin R. Johnson, Wikipedia

Coastlines





Massachusetts

D=1.15

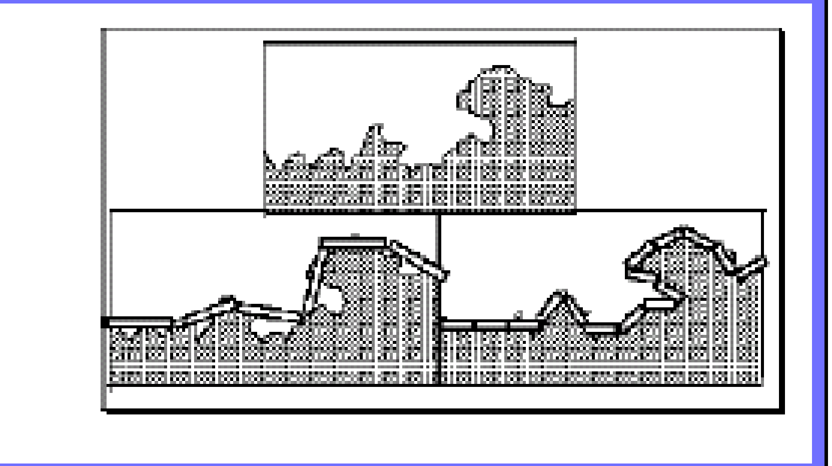
Greece

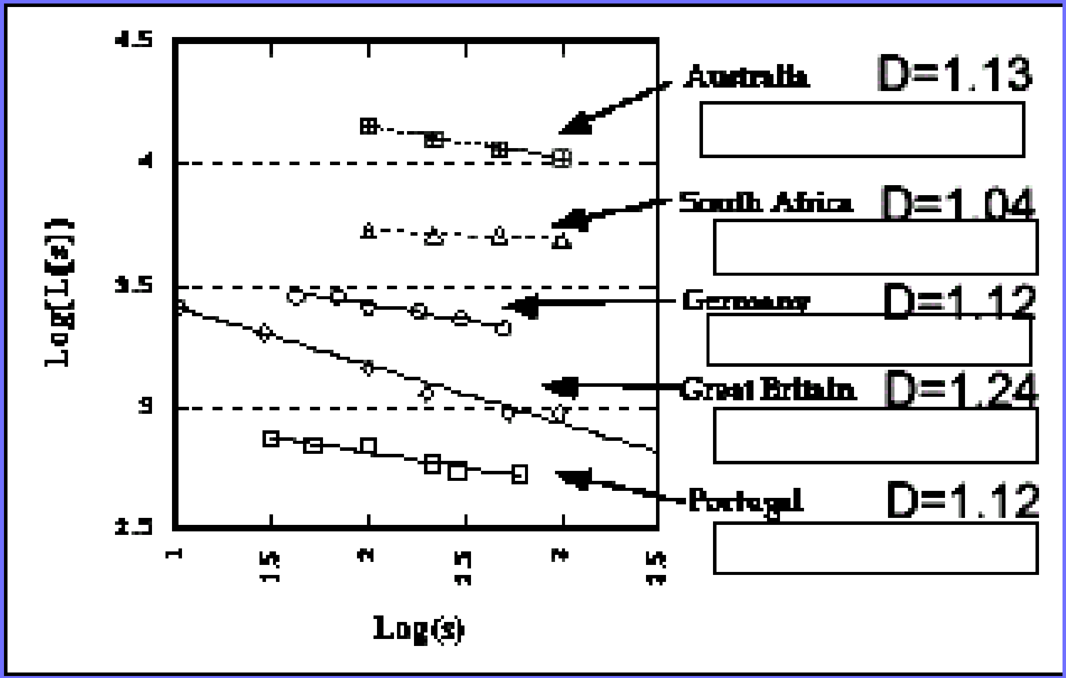
D=1.20

200 km 100 km 50 km

http://upload.wikimedia.org/wikipedia/commons/2/20/Britain-fractal-coastline-combined.jpg

How long is a coastline?





The answer depends on the scale at which the measurement is made: if s is the reference length the coastline length L(s) will be

$$\text{Log } L(s) = (1-D) \log s + \text{cost}$$

(Richardson 1961, Mandelbrot Science 1967)

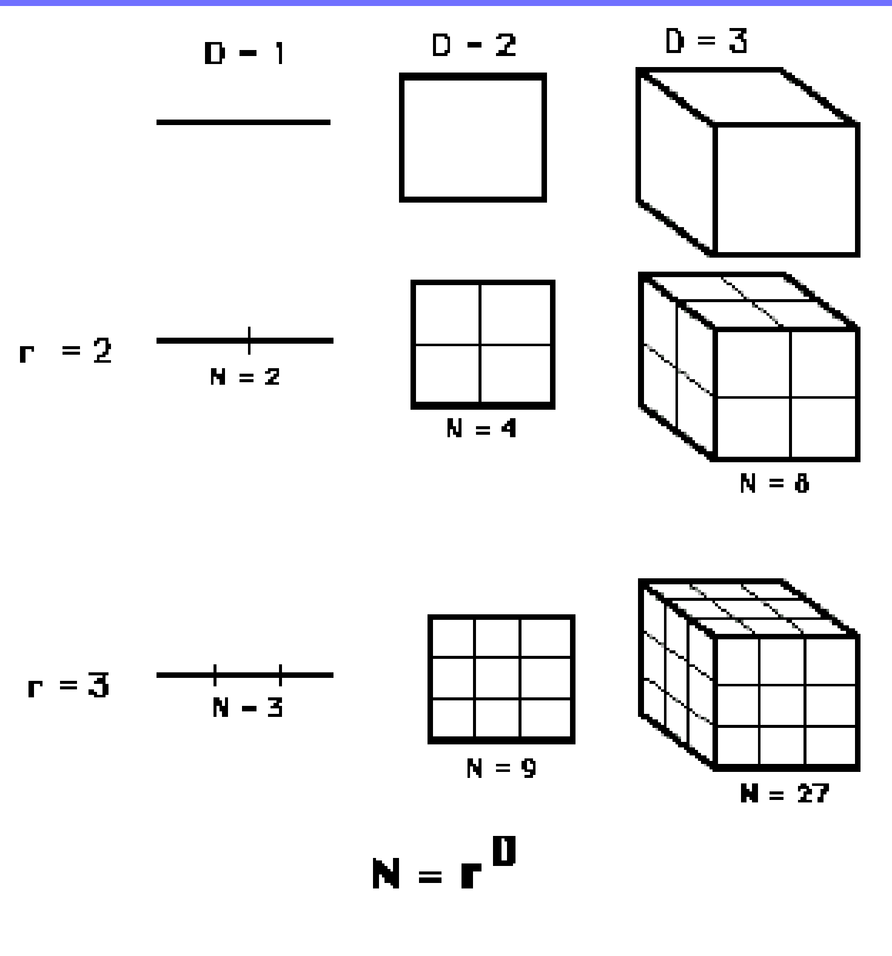
How long is the coast of Britain? Statistical self-similarity and fractional dimension Science: 156, 1967, 636-638 B. B. Mandelbrot

Seacoast shapes are examples of highly involved curves with the property that - in a statistical sense - each portion can be considered a reduced-scale image of the whole. This property will be referred to as ''statistical self-similarity.'' The concept of ''length'' is usually meaningless for geographical curves. They can be considered superpositions of features of widely scattered characteristic sizes; as even finer features are taken into account, the total measured length increases, and there is usually no clear-cut gap or crossover, between the realm of geography and details with which geography need not be concerned.

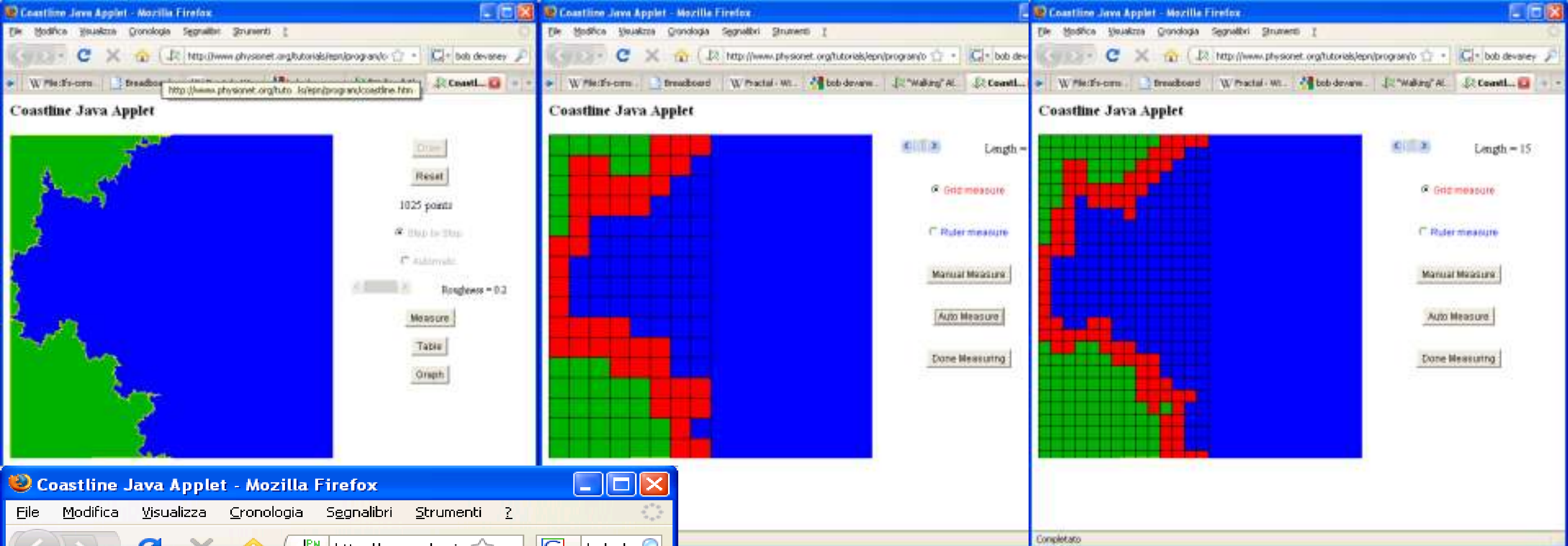
How long is the coast of Britain? Statistical self-similarity and fractional dimension Science: 156, 1967, 636-638 B. B. Mandelbrot

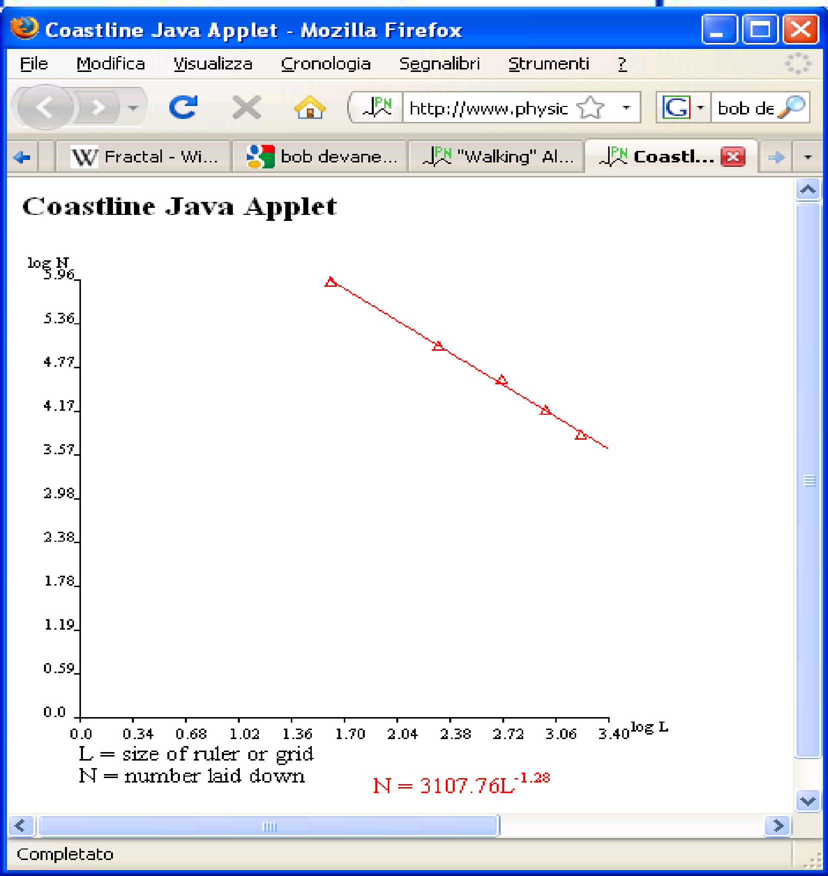
Quantities other than length are therefore needed to discriminate between various degrees of complication for a geographical curve. When a curve is self-similar, it is characterized by an exponent of similarity, D, which possesses many properties of a dimension, though it is usually a fraction greater that the dimension 1 commonly attributed to curves. I propose to reexamine in this light, some empirical observations in Richardson 1961 and interpret them as implying, for example, that the dimension of the west coast of Great Britain is D = 1.25. Thus, the so far esoteric concept of a "random figure of fractional dimension" is shown to have simple and concrete applications of great usefulness.

"Box counting" dimension



$$D = \lim_{s \to 0} \frac{\log N(s)}{\log(1/s)}$$





s	N(s)
25	47
20	67
15	100
10	159
5	386

Log N(s) = -D log s + cost

http://www.physionet.org/tutorials/epn/program/coastline.htm

Box counting (Minkowski) dimension

Let E be a non-empty bounded subset of $\mathbf{R}^n$ and let N_r (E) be the smallest number of sets of diameter r needed to cover E

- Lower dimension $\dim_B E = \liminf_{r\to 0} \log N_r(E) / -\log r$
- Upper dimension $\dim^B E = \limsup_{r\to 0} \log N_r(E) / -\log r$

- Box-counting dimension: if the lower and upper dimension agree then we define

$$\dim E = \lim_{r\to 0} \log N_r(E) / -\log r$$

The value of these limits remains unaltered if N_r (E) is taken to be the smallest number of balls of radius r (cubes of side r) needed to cover E, or the number of r-mesh cubes that intersect E

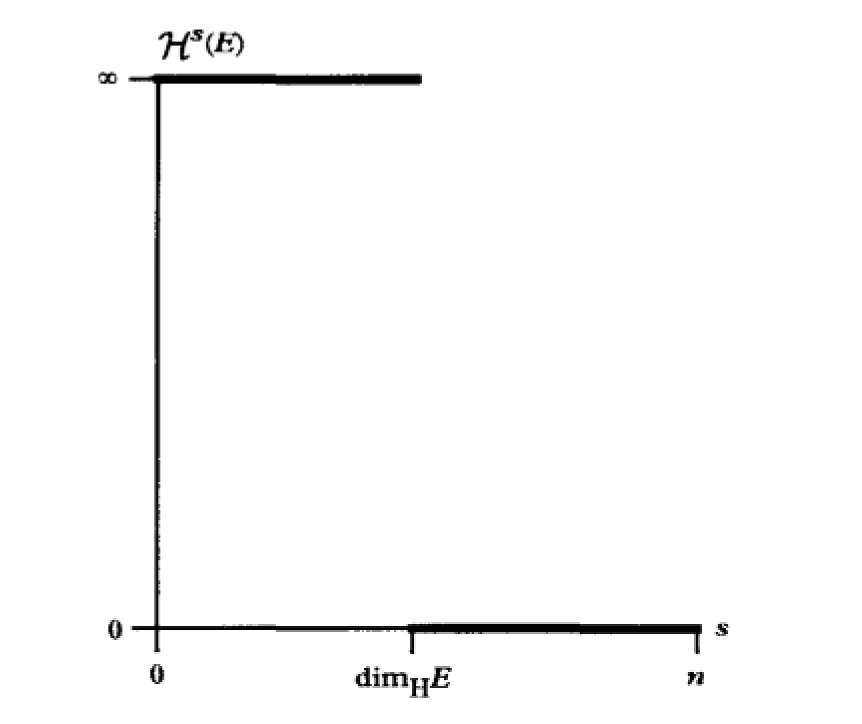
Hausdorff dimension

A finite or countable collection of subsets $\{U_i\}$ of $\mathbf{R}^n$ is a δ-cover of a set E if $|U_i| < \delta$ for all i and E is contained in $\bigcup_i U_i$

$H^s_\delta(E) = \inf\{\Sigma_i |U_i|^s, \{U_i\}$ is a a δ-cover of E$\}$

s-dimensional Hausdorff measure of E: $H^s(E) = \lim_{\delta\to 0} H^s_\delta(E)$

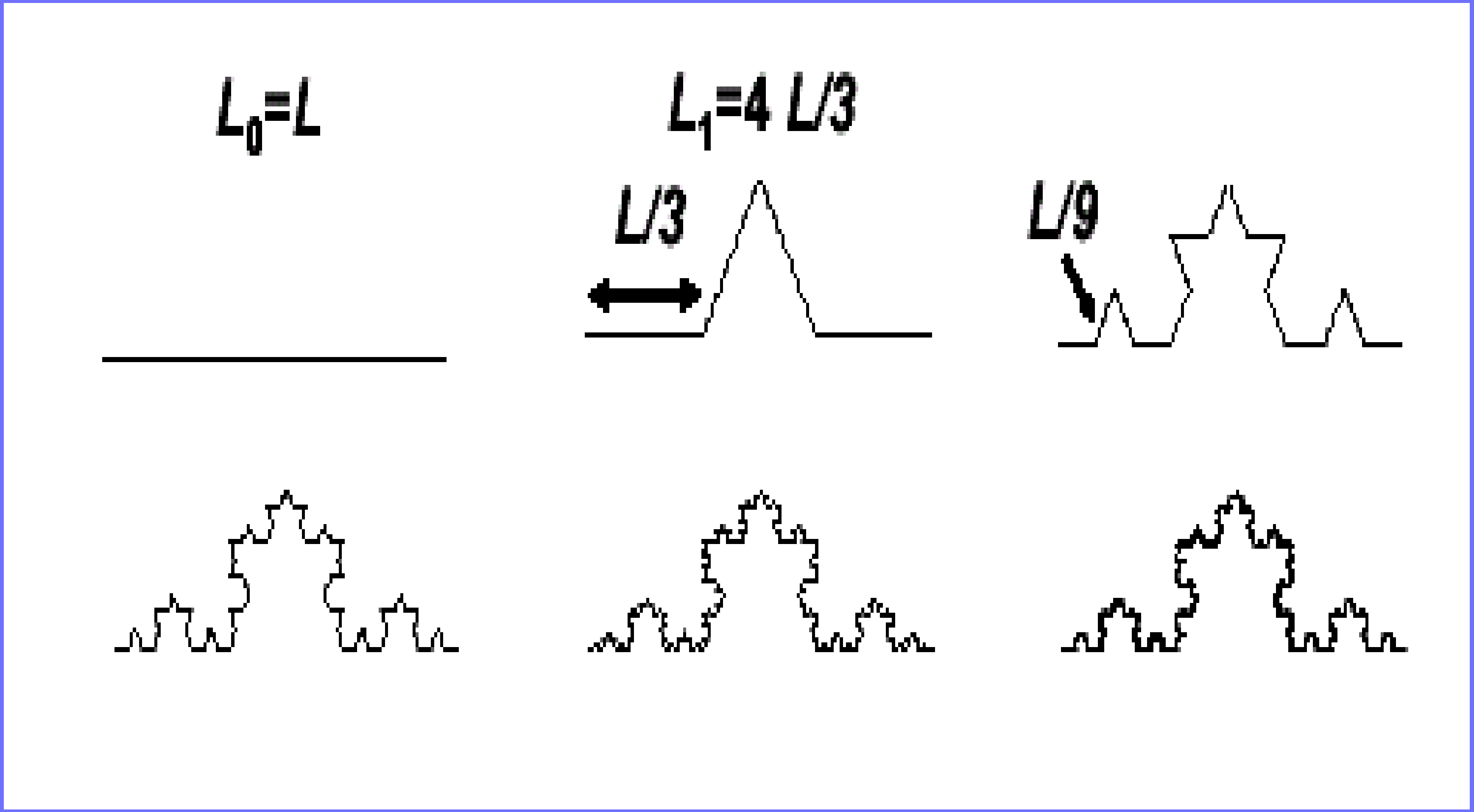
It is a Borel regular measure on $\mathbf{R}^n$, it behaves well under similarities and Lipschitz maps



The Hausdorff dimension $\dim_H E$ is the number at which the Hausdorff measure $H^s(E)$ jumps from ∞ to 0

$\dim_H E \le \dim_B E \le \dim^B E$

Von Koch curve (1904)



D=log4/log3=1.261859...

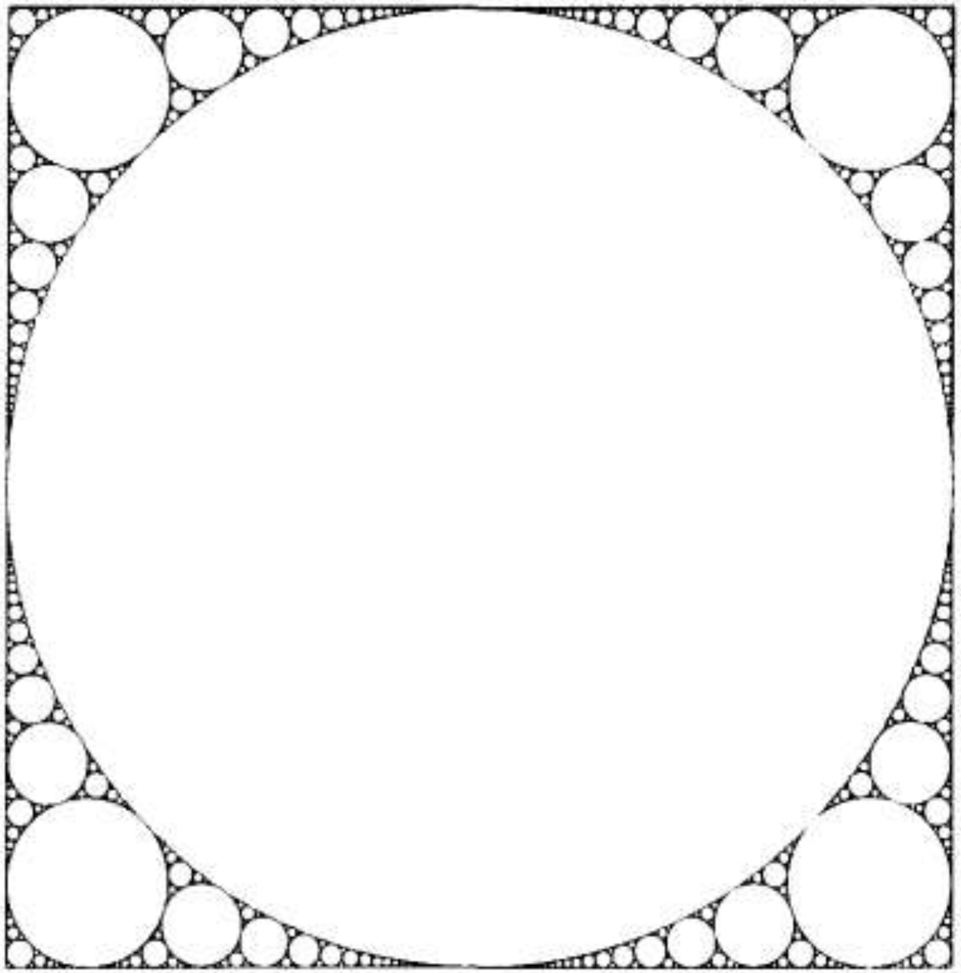
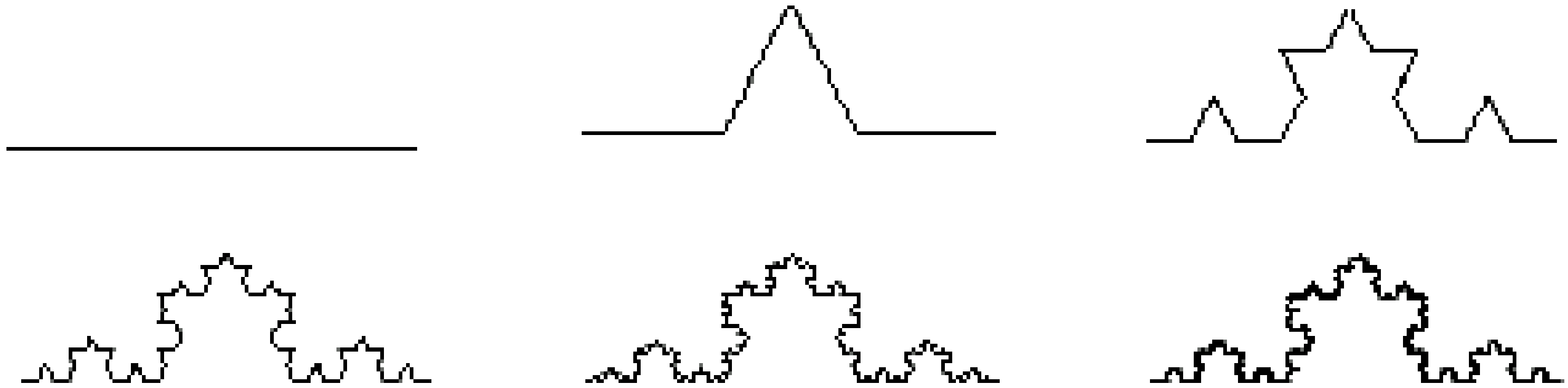


Figure 3.6 A cut-out set in the plane. Here, the largest possible disc is removed at each step. The family of discs removed is called the Apollonian packing of the square, and the cut-out set remaining is called the residual set, which has Hausdorff and box dimension about 1.31

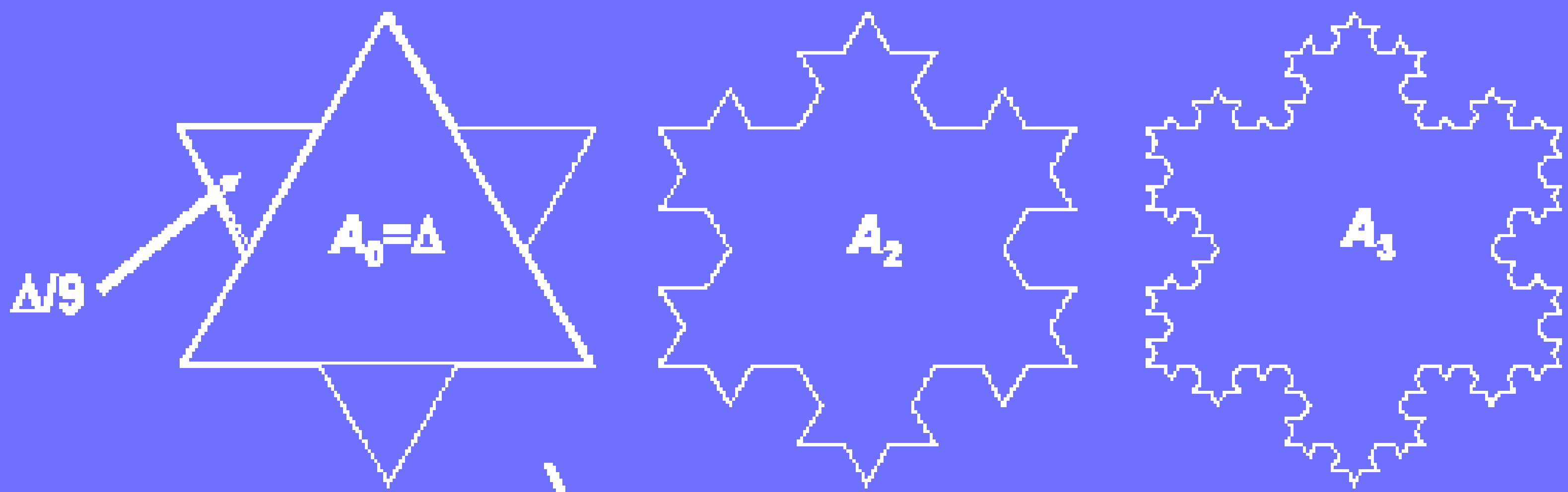
From: K. Falconer, Techniques in Fractal Geometry, Wiley 1997



$$L_0 = 1, \quad L_1 = 4/3, \quad L_2 = 4^2/3^2, \text{ etc... } L_k \to \infty$$

$$s = 1/3^k, \; N(s) = 4^k \to D = \frac{\log 4^k}{\log 3^k} = \frac{\log 4}{\log 3}$$

Fractal snowflake



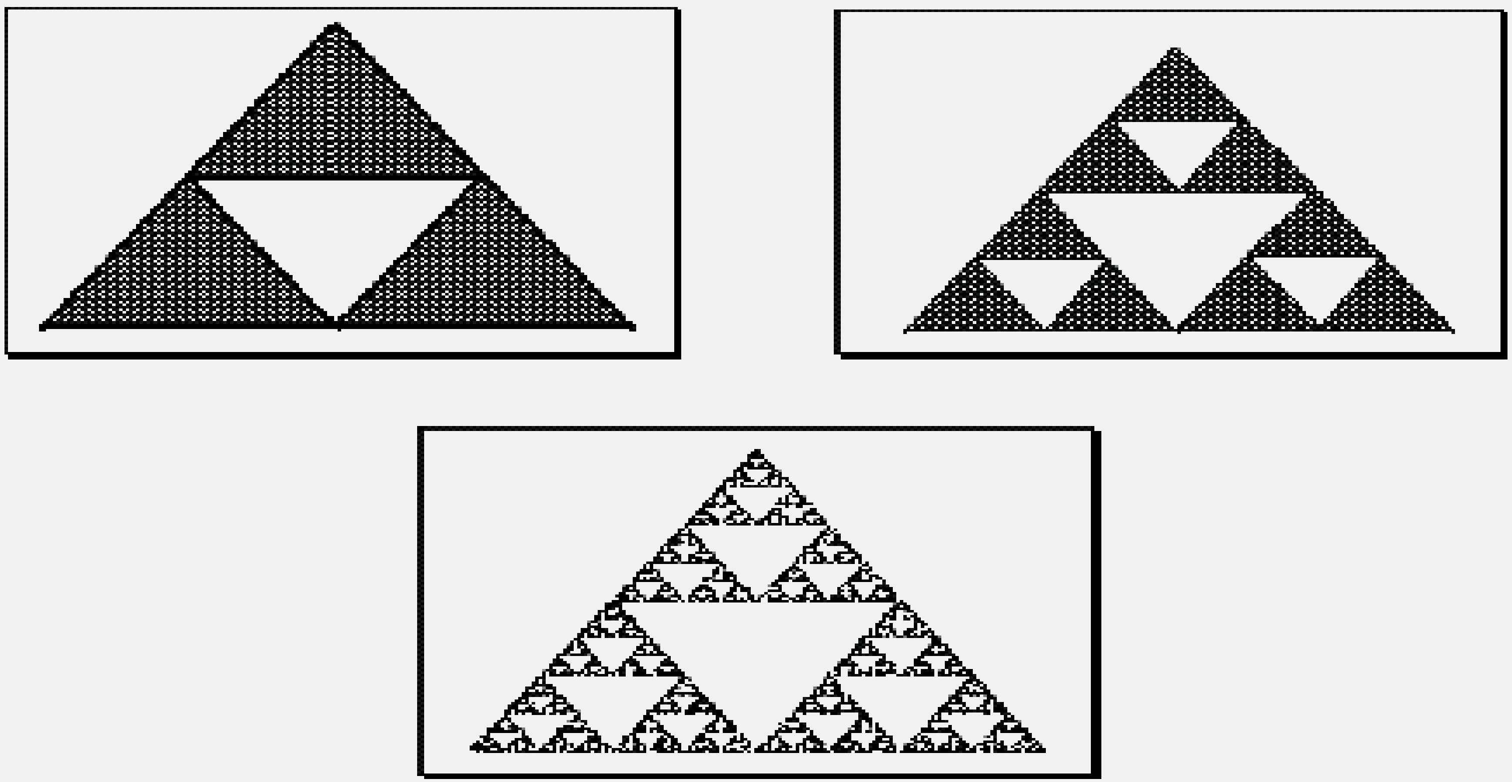
Area calculation:

$$A_0 = \Delta, \quad A_1 = \Delta + \frac{3}{9}\Delta = \Delta(1+\frac{1}{3}), \quad A_2 = \Delta + \frac{1}{3}\Delta + \frac{12}{81}\Delta = \Delta + \frac{1}{3}\Delta + \frac{1}{3}\frac{4}{9}\Delta$$

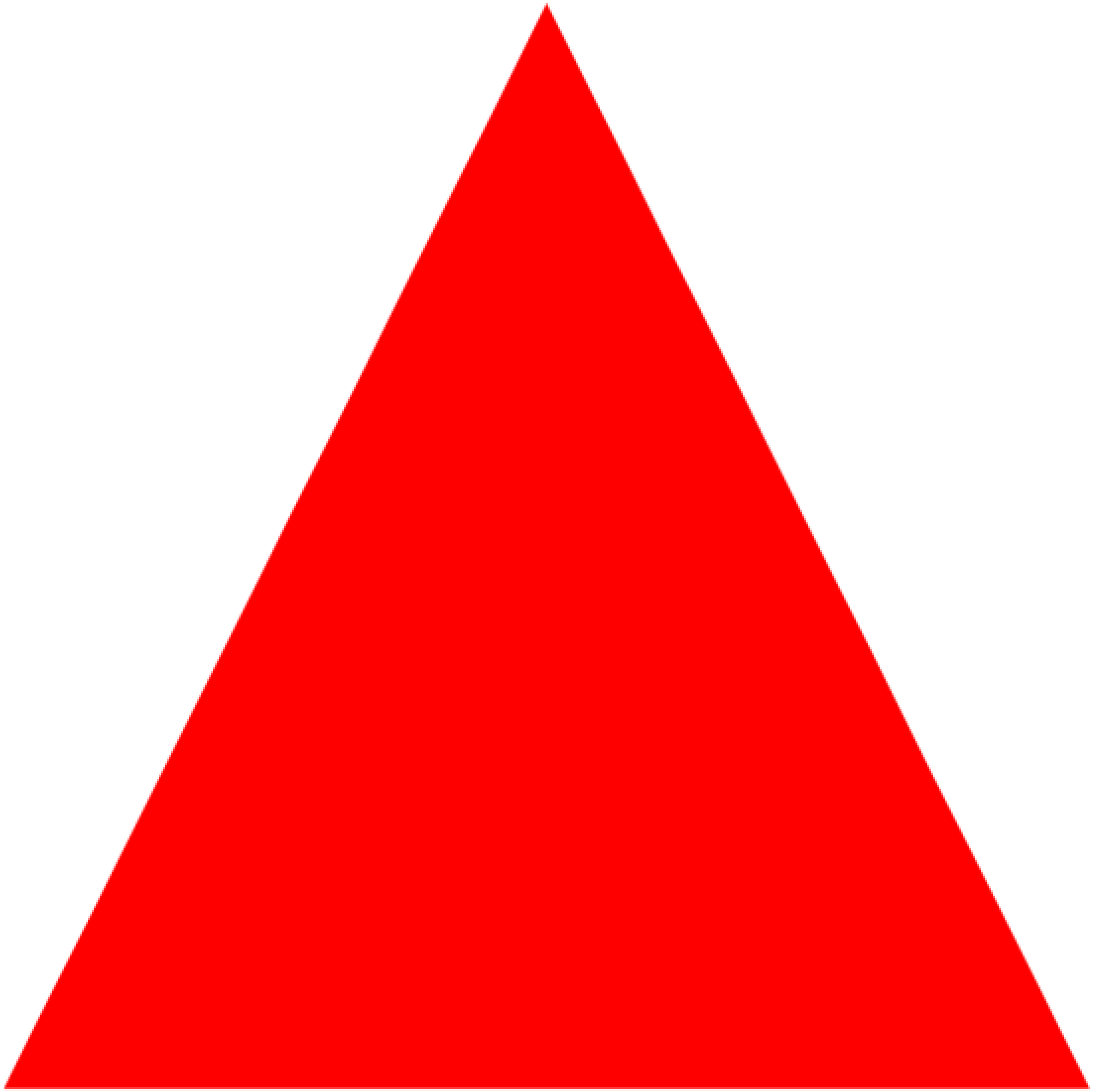
$$A_3 = \Delta + \frac{1}{3}\Delta + \frac{1}{3}\frac{4}{9}\Delta + \frac{1}{3}\frac{4}{9}\frac{4}{9}\Delta, \quad \text{etc...}$$

Infinite perimeter, finite area, D=log4/log3=1.261859...

Sierpinski triangle (1916)

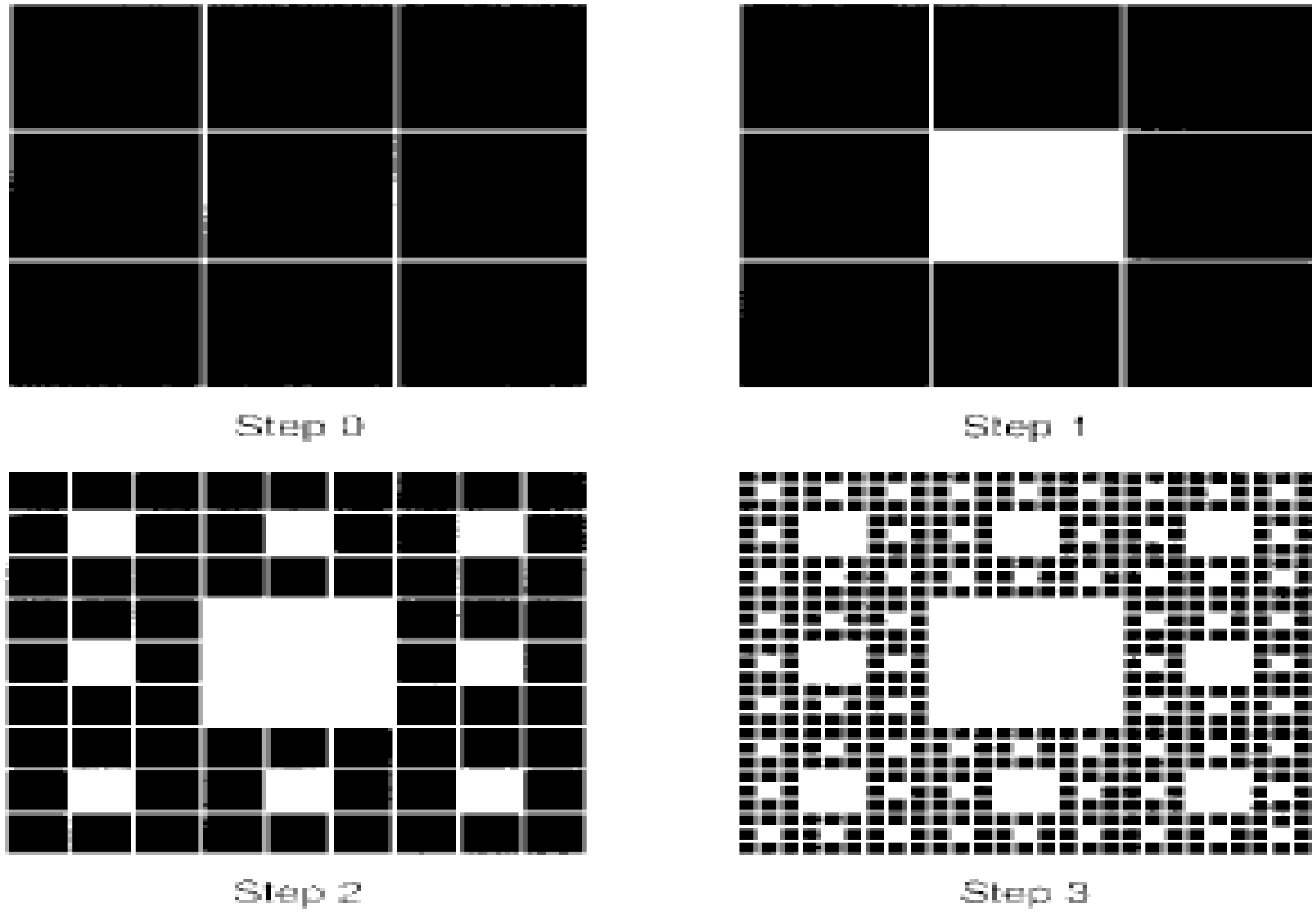


D=log3/log2=1.5849625...



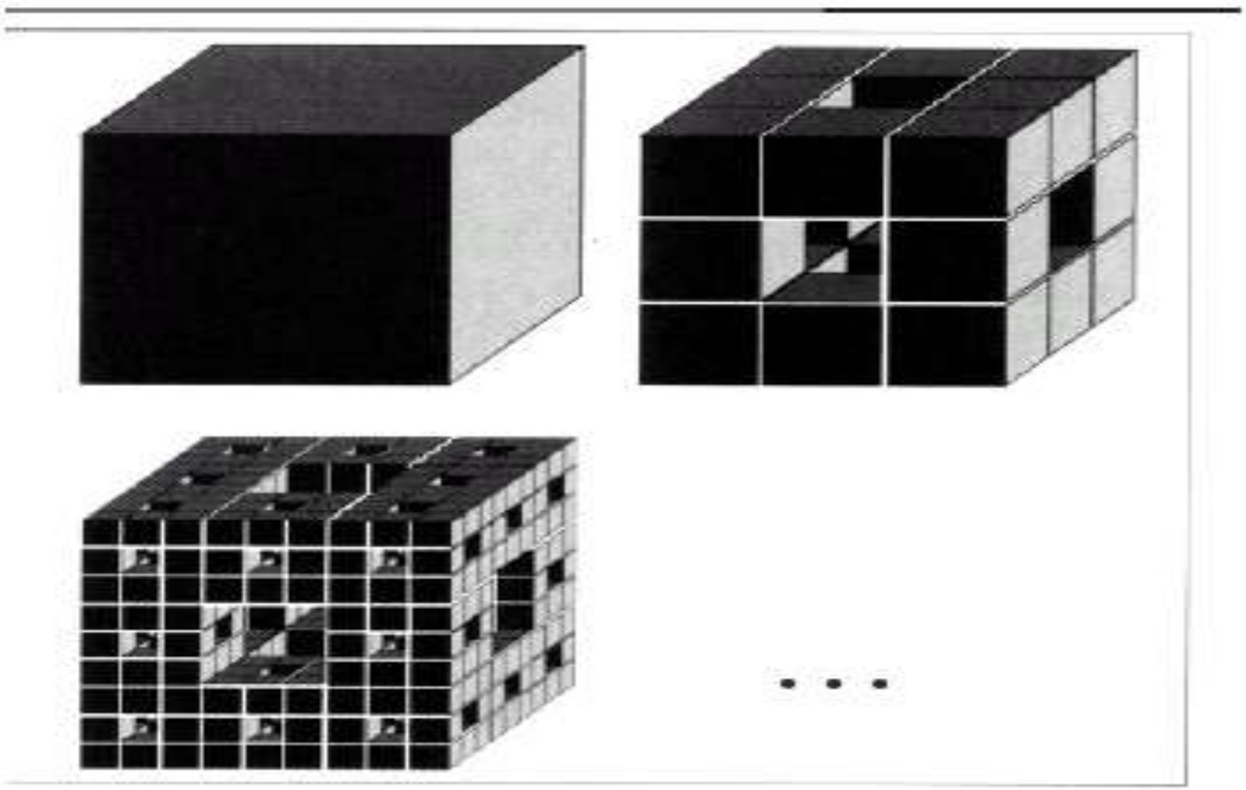
Source:
Wikipedia

A fractal carpet (zero area)

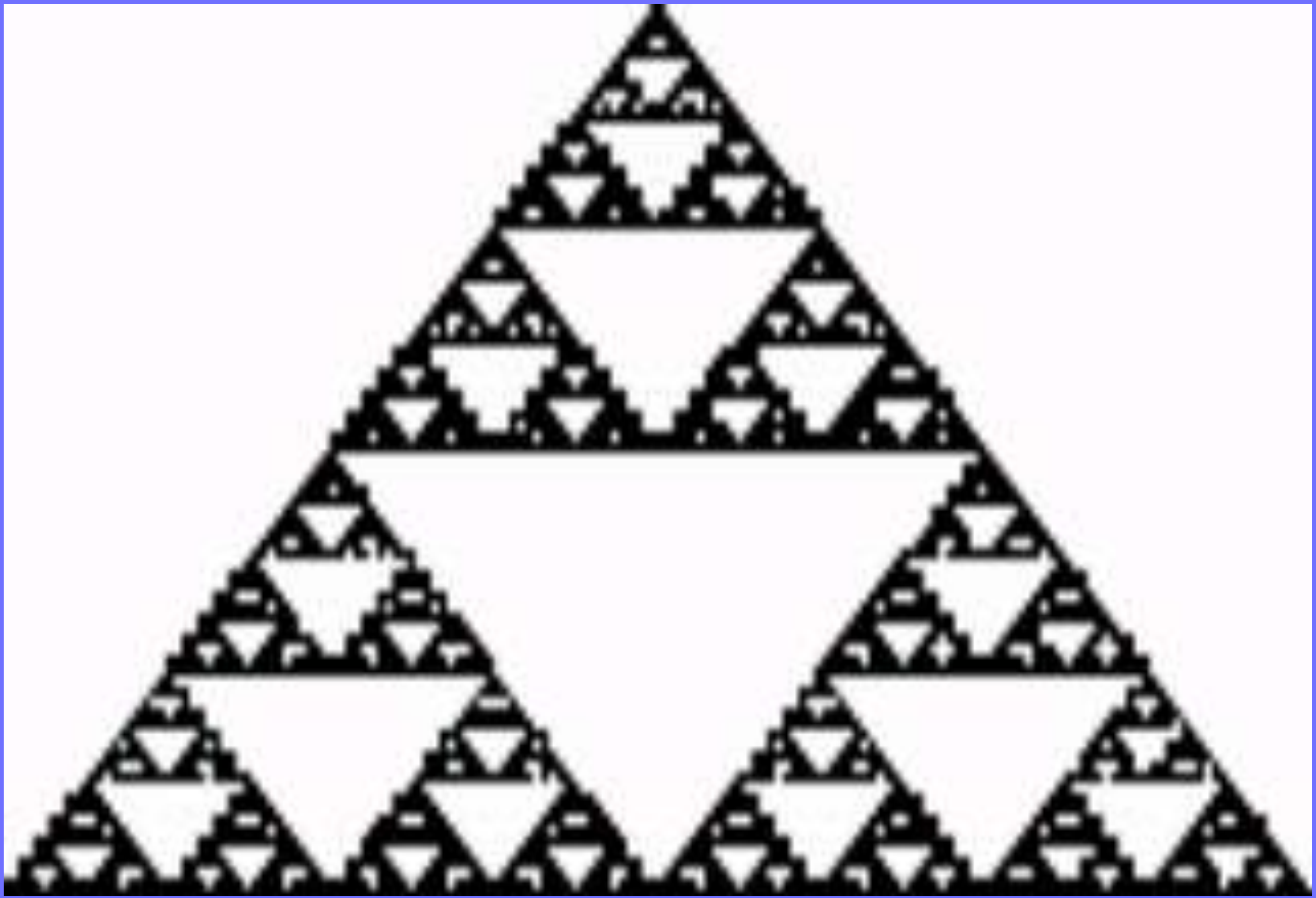


D=3log2/log3=1.892789...

A fractal sponge

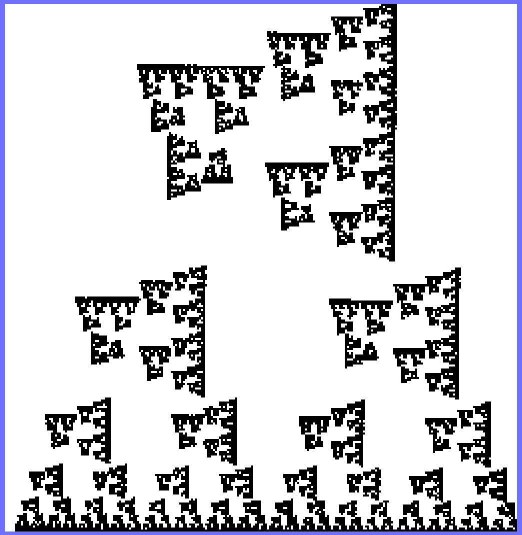


Zooming in

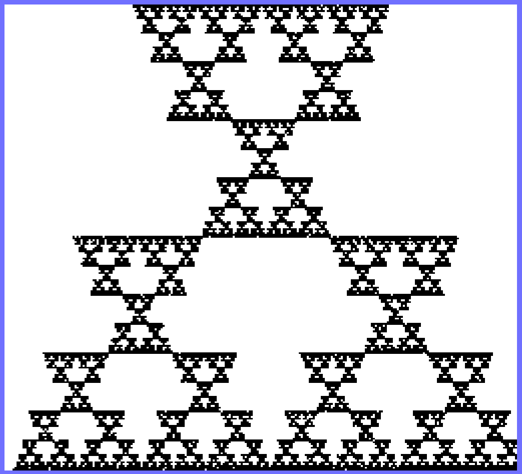


Changing parameters

- The triangle of Sierpinski is the attractor of an iterated function system (i.f.s).
- The i.f.s. is made of three affine maps (each contracting by a factor ½ and leaving one of the initial vertices fixed)
- Combining the affine maps with rotations one can change the shape considerably



90° anticlockwise rotation about the top vertex



180° rotation about the same vertex

Hausdorff metric and compact sets

$X=[0,1]^2$

$d((x,y),(x',y'))=|x-x'|+|y-y'|$ Manhattan metric

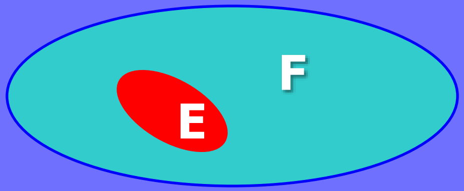
$\mathcal{H}(X)=\{E$ compact nonempty subsets of $X\}$

$h(E,F)=\max(d(E,F),d(F,E))$

$d(E,F)=\max_{x\in E}\min_{y\in F} d(x,y)$ $d(E,F)\neq d(F,E)$

$d(E,F)>0$

$d(F,E)=0$



Theorem: $(\mathcal{H}(X),h)$ is a complete metric space

→ Cauchy sequences have a limit!

Contractions and Hausdorff metric

Proposition: if $w:X \to X$ is a contraction with Lipschitz constant s then w is also a contraction on $(\mathcal{H}(X),h)$ with Lipschitz constant s

To each family $\mathcal{F}$ of contractions on X one can associate a family of contractions on $(\mathcal{H}(X),h)$. By Banach-Caccioppoli to each such $\mathcal{F}$ will correspond a compact nonempty subset $\mathcal{A}$ of X: the attractor associated to $\mathcal{F}$

$$d(w(E),w(F)) = \max_{y \in E} \min_{z \in F} d(y,z) = \max_{e \in E} \min_{f \in F} d(w(e),w(f))$$

$$\leq s \max_{e \in E} \min_{f \in F} d(e,f) = s\, d(E,F)$$

Iterated function systems

$\mathcal{F} = \{w_1, \ldots, w_N\}$ each $w_i : X \to X$ is a contraction of constant s_i, $0 \leq s_i < 1$

Let $\mathcal{W} : \mathcal{H}(X) \to X$

$$\mathcal{W}(E) = \bigcup_{1 \leq i \leq N} w_i(E)$$

Then $\mathcal{W}$ contracts the Hausdorff metric h with Lipschitz constant $s = \max_{1 \leq i \leq N} s_i$. We denote by $\mathcal{A}$ the corresponding attractor

Given any subset E of X, the iterates $\mathcal{W}^n(E) \to \mathcal{A}$ exponentially fast, in fact $h(\mathcal{W}^n(E), \mathcal{A}) \approx s^n$ as $n \to \infty$

Self similarity and fractal dimension

If the contractions of the i.f.s. $\mathcal{F} = \{w_1, \ldots, w_N\}$ are

- Similarities ⇒ the attractor $\mathcal{A}$ will be said self-similar
- Affine maps ⇒ the attractor $\mathcal{A}$ will be said self-affine
- Conformal maps (i.e. their derivative is a similarity) then the attractor $\mathcal{A}$ will be said self-conformal

If the open set condition is verified, i.e. there exists an open set U such that $w_i(U) \cap w_j(U) = \emptyset$ if $i \neq j$ and $\bigcup_i w_i(U)$ is an open subset of U then the dimension d of the attractor $\mathcal{A}$ is the unique positive solution of $s_1^d + s_2^d + \ldots + s_N^d = 1$

Inverse problem

Inverse problem: given $\varepsilon>0$ and a target (fractal) set $\mathcal{T}$ can one find an i.f.s $\mathcal{F}$ such that the corresponding attractor $\mathcal{A}$ is ε-close to $\mathcal{T}$ w.r.t. the Hausdorff distance h?

Collage Theorem (Barnsley 1985) Let $\varepsilon>0$ and let $\mathcal{T}\in\mathcal{H}(X)$ be given. If the i.f.s. $\mathcal{F} = \{w_1, \ldots, w_N\}$ is such that

$$h(\cup_{1\le i\le N} w_i(\mathcal{T}), \mathcal{T}) < \varepsilon$$

then

$$h(\mathcal{T}, \mathcal{A}) < \varepsilon / (1-s)$$

where s is the Lipschitz constant of $\mathcal{F}$

Fractal image compression ?

The Collage Theorem tells us that to find an i.f.s. whose attractor "looks like" a give set one must find a set of contracting maps such that the union (collage) of the images of the given set under these maps is near (w.r.t. Hausdorff metric) to the original set.

The collage theorem sometimes allows incredible compression rates of images (of course with loss). It can be especially useful when the information contained in details is not considered very very important

Fractal image compression !

The top-selling multimedia encyclopedia Encarta, published by Microsoft Corporation, includes on one CD-ROM seven thousand color photographs which may be viewed interactively on a computer screen. The images are diverse; they are of buildings, musical instruments, people's faces, baseball bats, ferns, etc. What most users do not know is that all of these photographs are based on fractals and that they represent a (seemingly magical) practical success of mathematics.

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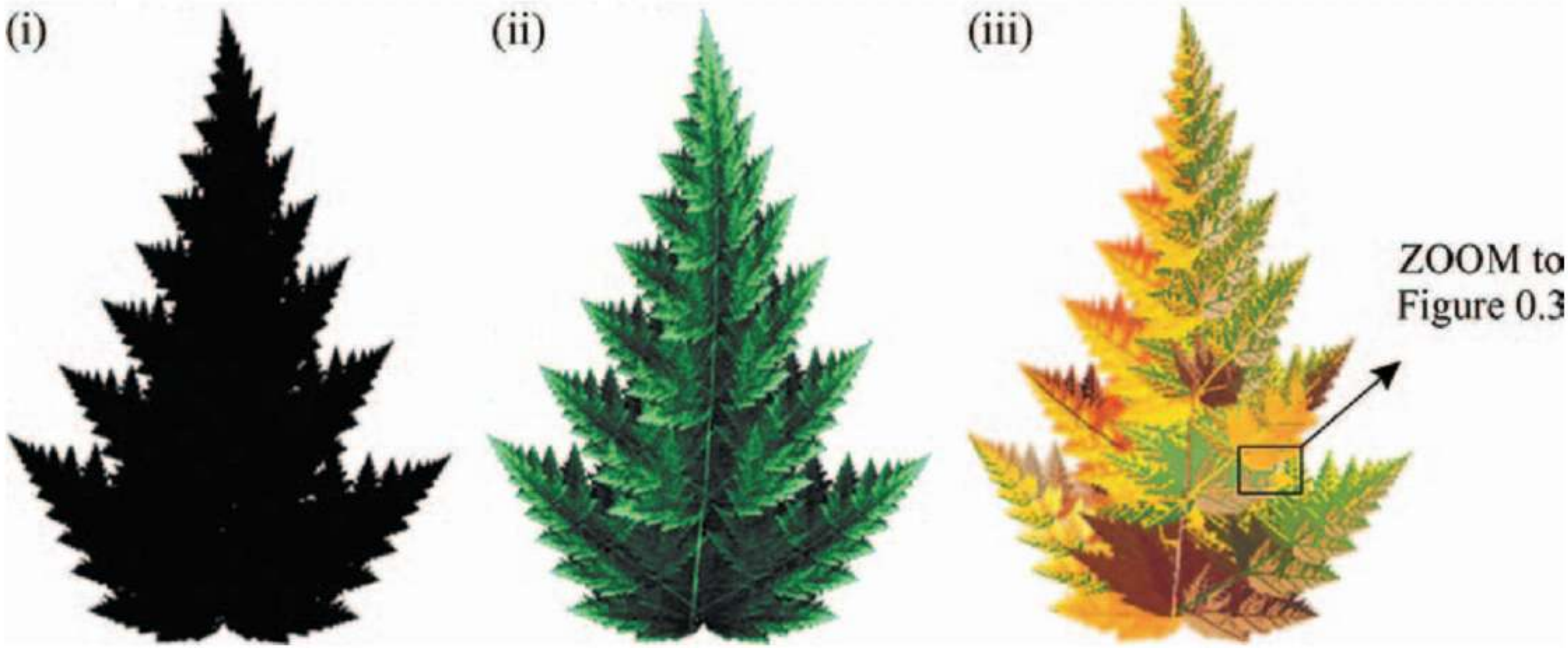
Fractal Image Compression by Michael F. Barnsley

e.g: Barnsley's fern: can be encoded with 160 bytes= 4*10*4

4 maps 10 parameters (each parameter using 4 bytes)

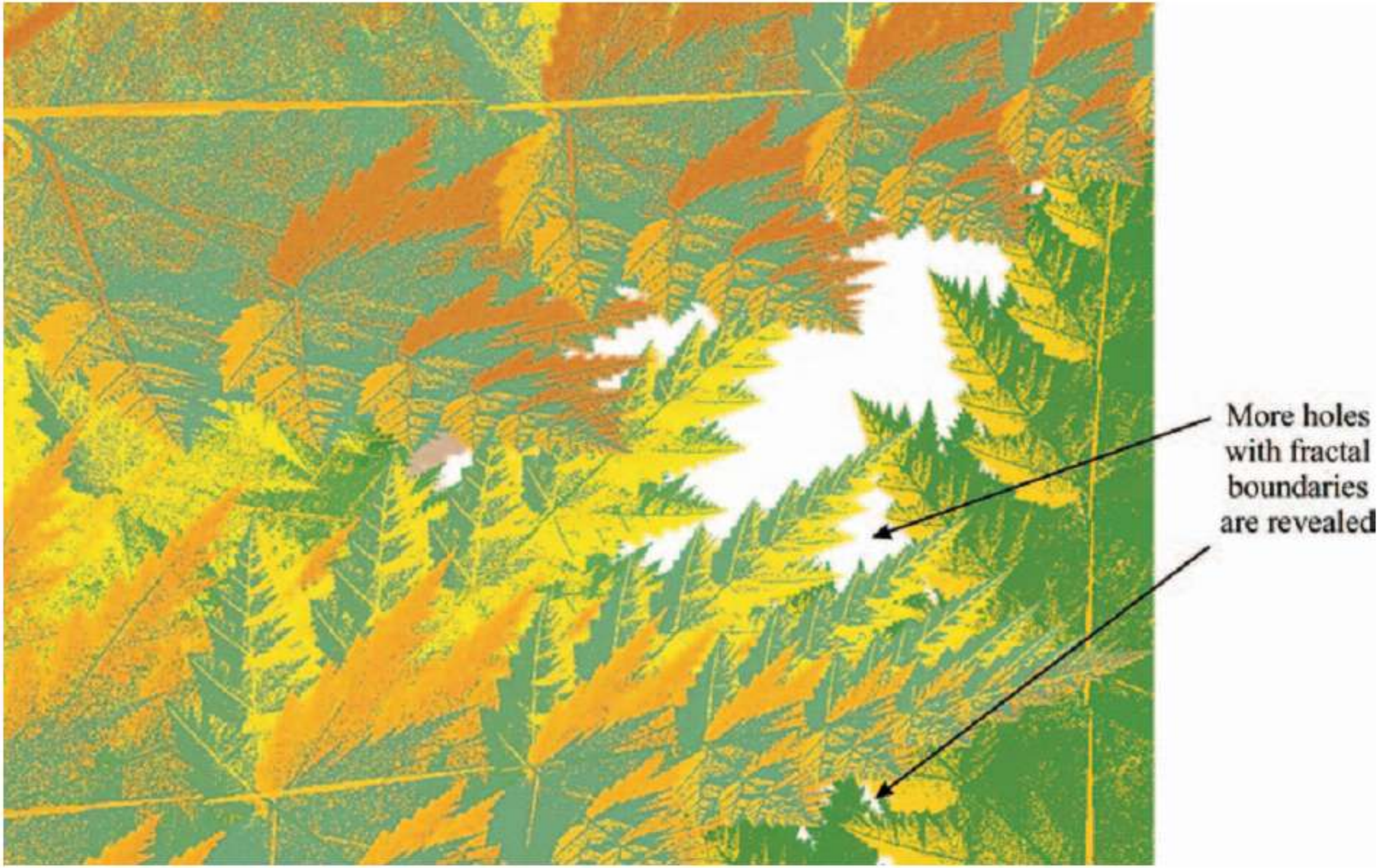


the measure attractor and (iii) the

$$f_n(x, y) = \left(\frac{a_n x + b_n y + c_n}{g_n x + h_n y + j_n}, \frac{d_n x + e_n y + k_n}{g_n x + h_n y + j_n} \right)$$

n	a_n	b_n	c_n	d_n	e_n	k_n	g_n	h_n	j_n	p_n
1	19.05	0.72	1.86	−0.15	16.9	−0.28	5.63	2.01	20.0	$\frac{60}{100}$
2	0.2	4.4	7.5	−0.3	−4.4	−10.4	0.2	8.8	15.4	$\frac{1}{100}$
3	96.5	35.2	5.8	−131.4	−6.5	19.1	134.8	30.7	7.5	$\frac{20}{100}$
4	−32.5	5.81	−2.9	122.9	−0.1	−19.9	−128.1	−24.3	−5.8	$\frac{19}{100}$

From M. Barnsely SUPERFRACTALS Cambridge University Press 2006



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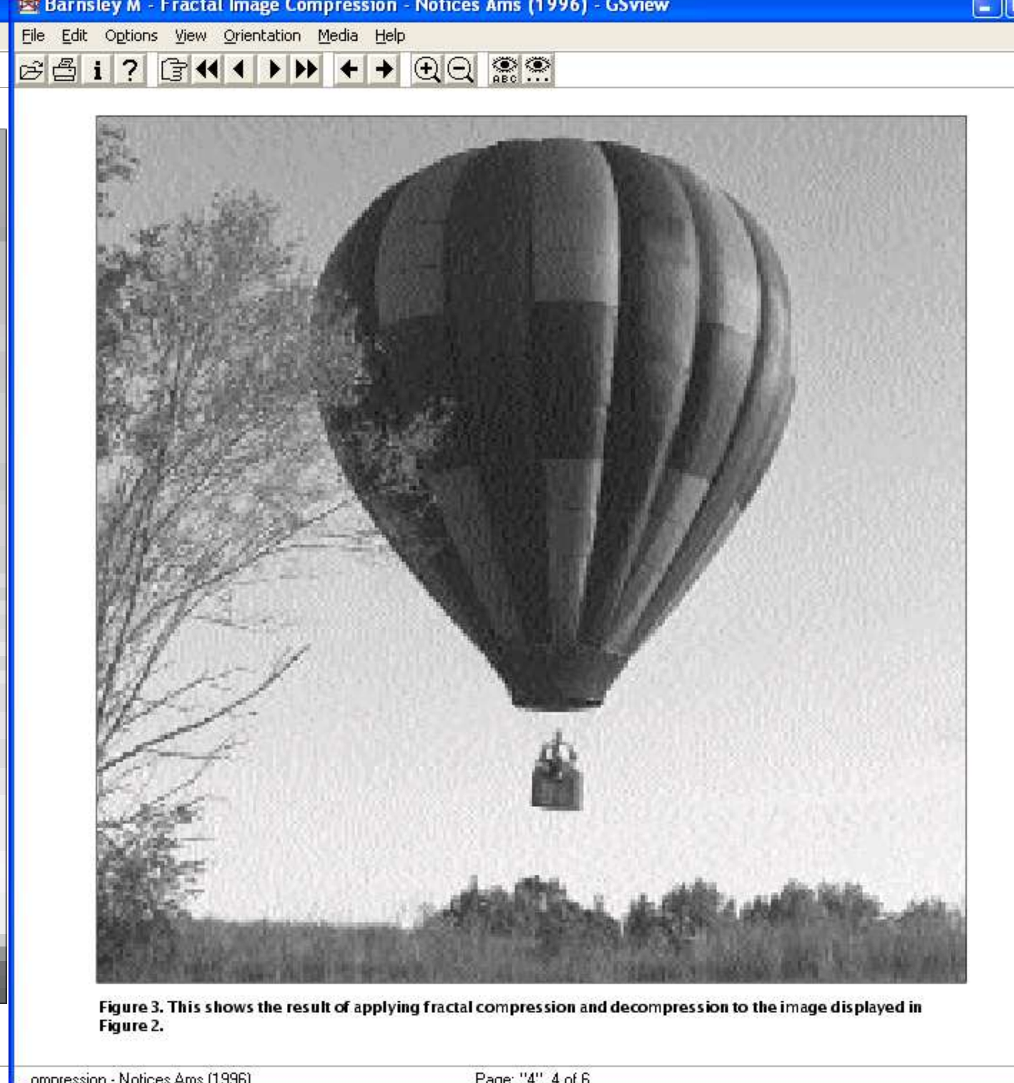
Cambridge University Press
2006



LEFT: the original digital image of Balloon, 512 pixels by 512 pixels, with 256 gray levels at each pixel. RIGHT: shows the same image after fractal compression. The fractal transform file is approximately one fifth the size of the original.

JUNE 1996 NOTICES OF THE AMS 657 Fractal Image Compression by Michael F. Barnsley

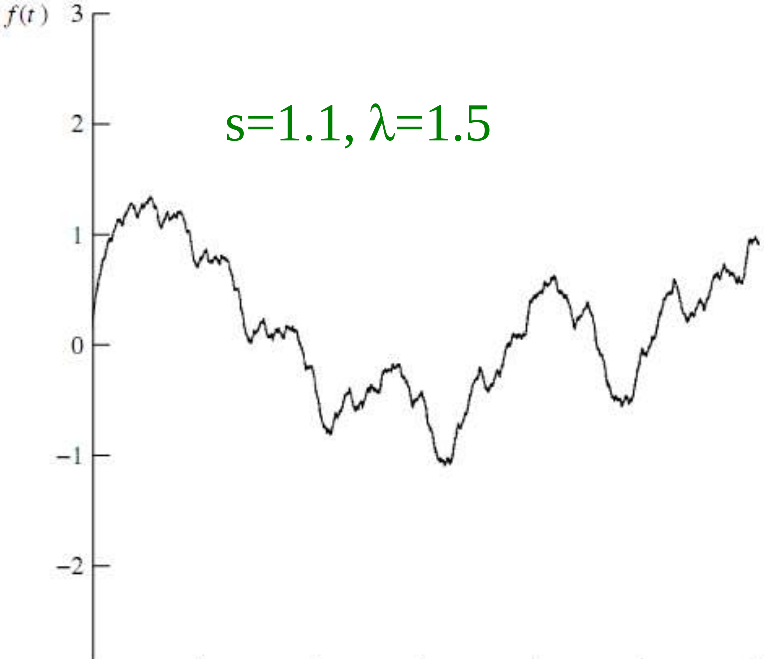
Fractal graphs of functions

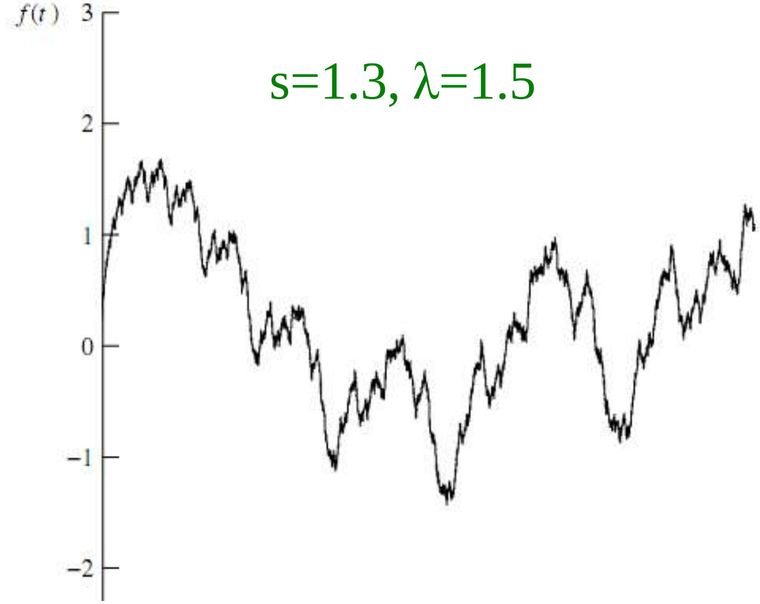
Many interesting fractals, both of theoretical and practical importance, occur as graphs of functions. Indeed many time series have fractal features, at least when recorded over fairly long time spans: examples include wind speed, levels of reservoirs, population data and some financial time series market (the famous Mandelbrot cotton graphs)

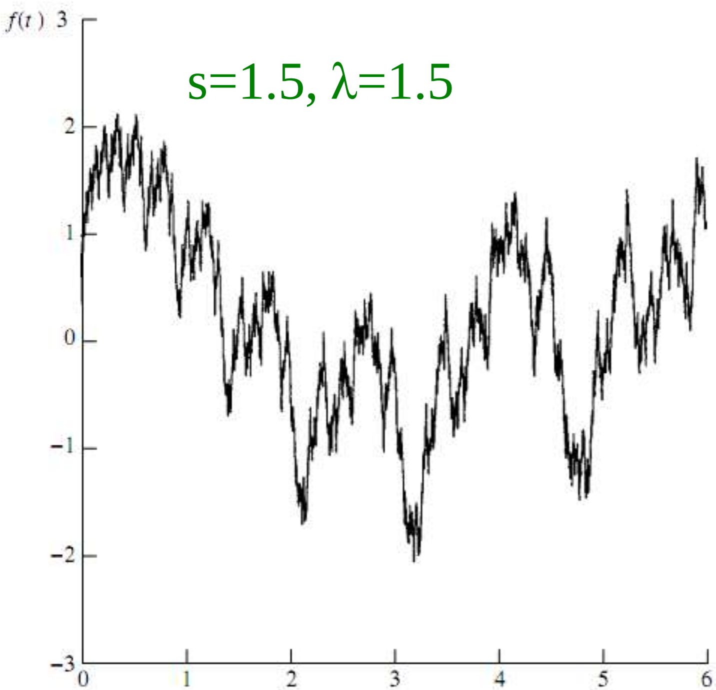
Weierstrass nowhere differentiable continuous function:

$$f(t)=\Sigma_{1\leq k\leq\infty}\ \lambda^{(s-2)k} \sin (\lambda^k\ t) \qquad 1<s<2,\ \lambda>2$$

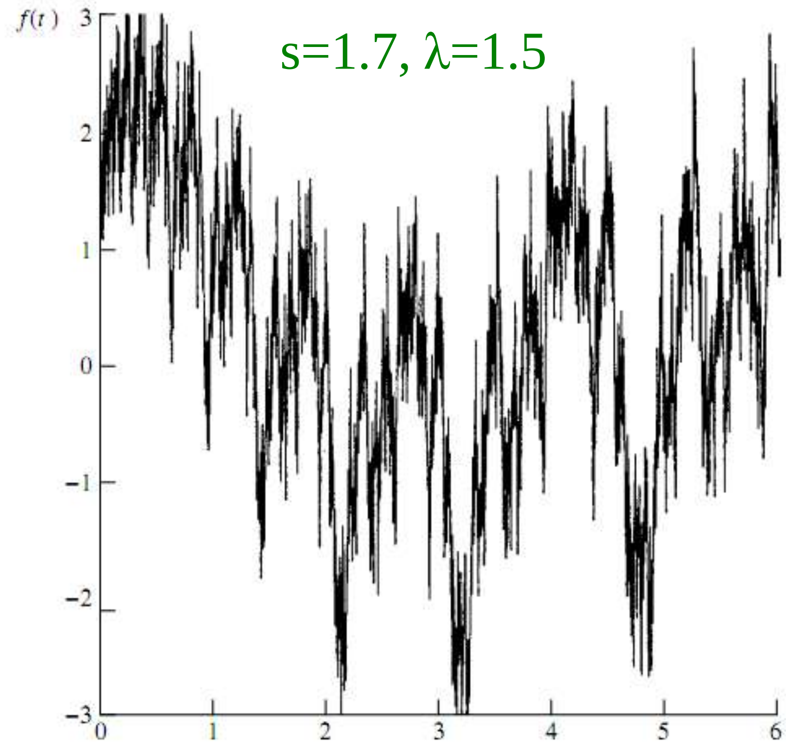
The graph of f has box dimension s for λ large enough.







(c)



(d)

From “Fractal Geometry”, K. Falconer, p. 164-165

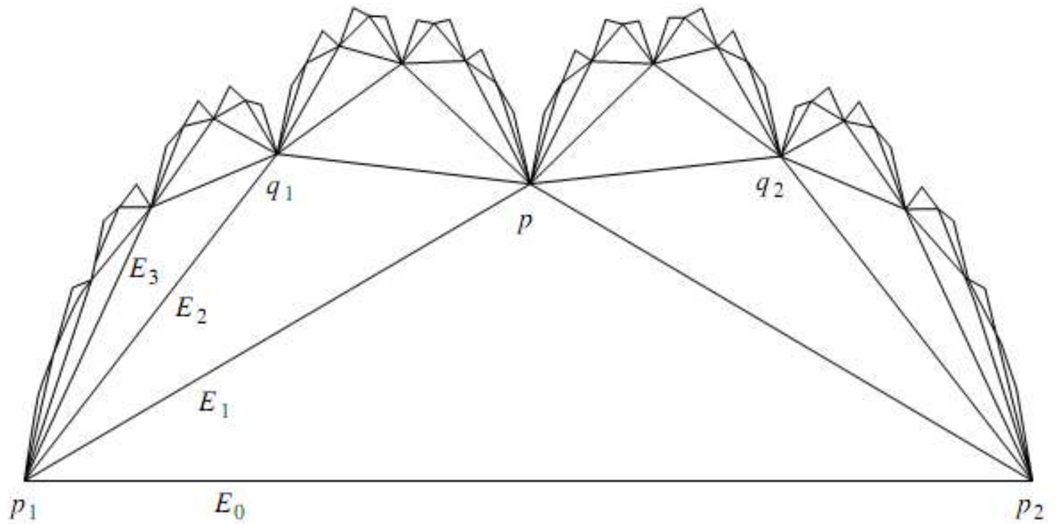


Figure 11.3 Stages in the construction of a self-affine curve F. The affine transformations S_1 and S_2 map the generating triangle p_1pp_2 onto the triangles p_1q_1p and pq_2p_2, respectively, and transform vertical lines to vertical lines. The rising sequence of polygonal curves $E_0, E_1, \ldots$ are given by $E_{k+1} = S_1(E_k) \cup S_2(E_k)$ and provide increasingly good approximations to F (shown in figure 11.4(a) for this case)

Fractal graphs and i.f.s.

(from K. Falconer, Fractal Geometry, Wiley (2003))

$$S_i(t, x) = (t/m + (i-1)/m,\ a_i t + c_i x + b_i).$$

Thus the S_i transform vertical lines to vertical lines, with the vertical strip $0 \leqslant t \leqslant 1$ mapped onto the strip $(i-1)/m \leqslant t \leqslant i/m$. We suppose that

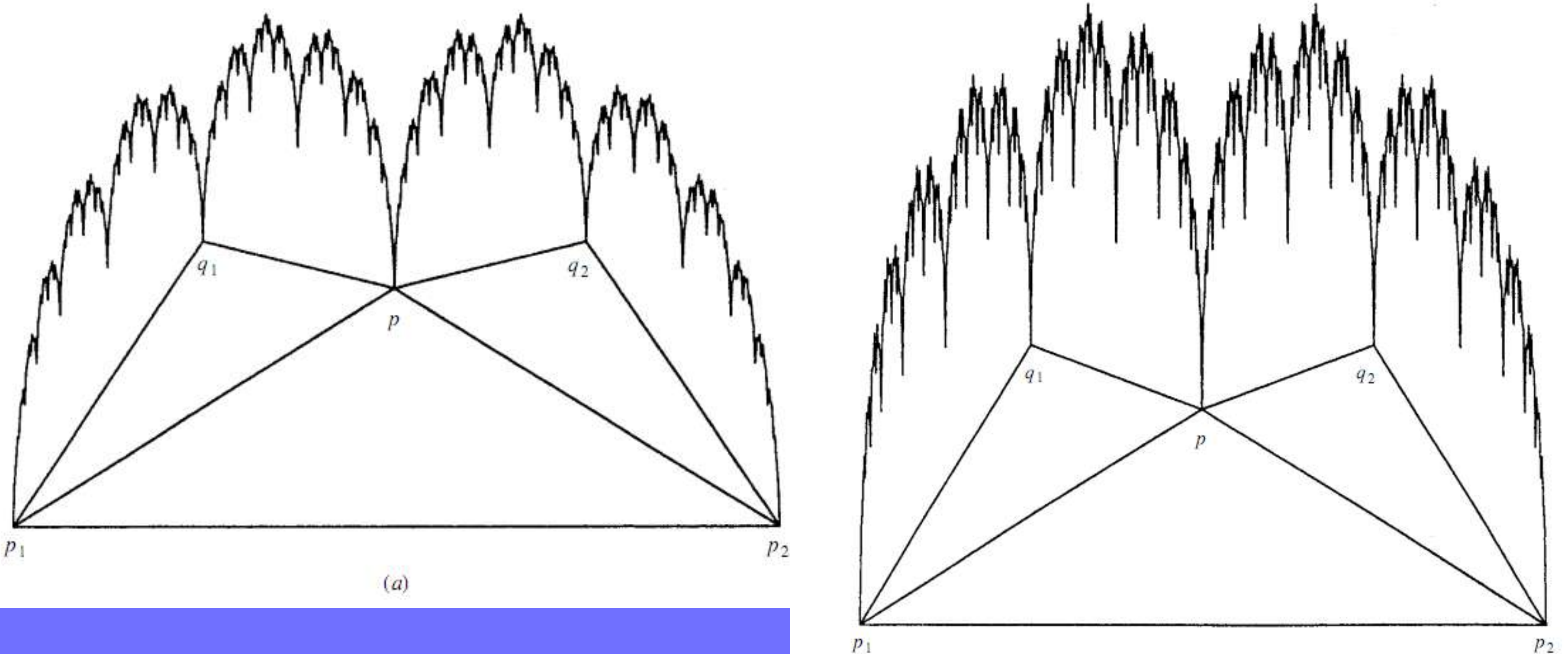
$$1/m < c_i < 1 \qquad (11.9)$$

so that contraction in the t direction is stronger than in the x direction.

Let $p_1 = (0, b_1/(1-c_1))$ and $p_m = (1, (a_m + b_m)/(1-c_m))$ be the fixed points of S_1 and S_m. We assume that the matrix entries have been chosen so that

$$S_i(p_m) = S_{i+1}(p_1) \qquad (1 \leqslant i \leqslant m-1) \qquad (11.10)$$

so that the segments $[S_i(p_1), S_i(p_m)]$ join up to form a polygonal curve E_1. To



Self-affine curves defined by the two affine transformations that map the triangle p_1pp_2 onto p_1q_1p and pq_2p_2 respectively. In (a) the vertical contraction of both transformations is 0.7 giving dim graph f = 1.49, and in (b) the vertical contraction of both transformations is 0.8, giving dim graph f = 1.68

from K. Falconer, Fractal Geometry, Wiley (2003)

Probabilistic i.f.s.

$\mathcal{F} = \{w_1, \ldots, w_N\}$, $w_i : X \to X$ contraction of constant s_i, $0 \leq s_i < 1$

$(p_1,\ldots,p_N)$ probability vector $0 \leq p_i \leq 1$, $p_1+\ldots+p_N = 1$

Iteration: at each step with probability p_i one applies w_i

i.f.s.: k iterates of a point → N^k points $\mathcal{W} : \mathcal{H}(X) \to X$

$\mathcal{W}(E) = \cup_1 w_i(E)$

Probabilistic i.f.s.: k iterates of a point → k points

Theorem: each probabilistic i.f.s. has a unique Borel probability invariant measure μ with support = $\mathcal{A}$

Invariance: $\mu(E)= \Sigma_{1\leq i\leq N}\, p_i \mu(w_i^{-1}(E))$ for all Borel sets E, equivalently

$\int_X g(x)d\mu(x)= \Sigma_{1\leq i\leq N}\, p_i \int_X g(w_i(x))d\mu(x)$ for all continuous functions g

Probabilistic i.f.s.

If $\mathcal{M}$ denotes the space of Borel probability measures on X endowed with the metric

$$d(\nu_1,\nu_2)=\sup\{|\int_X g(x)d\nu_1(x)-\int_X g(x)d\nu_2(x)|, \text{ g Lipschitz, } Lip(g)\leq 1\}$$

Then a probabilistic i.f.s. acts on measures as follows

$$L_{p,w}\,\nu=\Sigma\, p_i \nu \circ w_i^{-1}$$

And by duality acts con continuos functions $g:X\rightarrow \mathbf{R}$

$$\int_X g(x)d(L_{p,w}\,\nu)(x)=\Sigma_{1\leq i\leq N}\, p_i \int_X g(w_i(x))d\nu(x)$$

It is easy to verify that

$$d(L_{p,w}\,\nu_1 , L_{p,w}\,\nu_2) \leq s\, d(\nu_1,\nu_2)$$

from which the previous theorem follows

Multifractal analysis of measures

Local dimension (local Hölder exponent) of a measure μ at a point x:

$\dim_{loc} \mu(x)=\lim_{r\to 0} \log \mu(B(x,r))/\log r$ (when the limit exists)

$\alpha>0$, $E_\alpha = \{x \in X, \dim_{loc} \mu(x)= \alpha\}$

For certain measures μ the sets E_α may be non-empty over a range of values of α: multifractal measures

multifractal spectrum (singularity spectrum) of the multifractal measure μ: is the function $\alpha \to f(\alpha)=\dim E_\alpha$

With equal probabilities, the Random Algorithm for the IFS with these rules

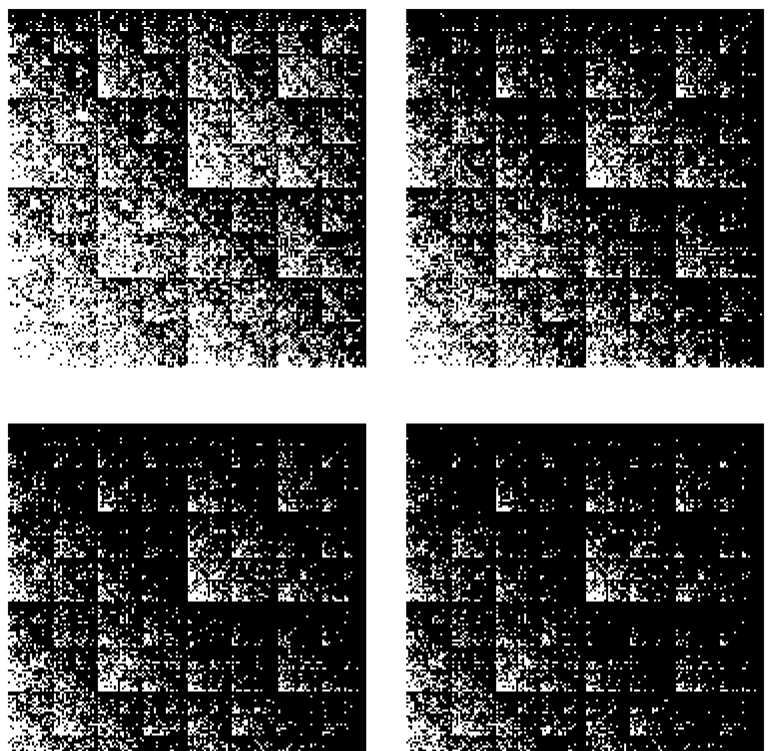
$T_3(x, y) = (x/2, y/2) + (0, 1/2)$	$T_4(x, y) = (x/2, y/2) + (1/2, 1/2)$
$T_1(x, y) = (x/2, y/2)$	$T_2(x, y) = (x/2, y/2) + (1/2, 0)$

fills in the unit square uniformly.

The pictures below were generated with these probabilities

$$p_1 = 0.1,\ p_2 = p_3 = p_4 = 0.3.$$

Successive pictures show increments of 25000 points. With enough patience, the whole square will fill in, but some regions fill in more quickly than others.



Multifractals

Variable Probability Histograms

The probabilities of applying each transformation represent the fraction of the total number of iterates in the region determined by the transformation.

With the IFS and probabilities of the last example, in a typical picture about 0.1 of the points will lie in the square with address 1, and about 0.3 of the points will lie in each of the squares with address 2, 3, and 4.

Arguing in the same way, about 0.01 = 0.1*0.1 of the points will lie in the square with address 11, about 0.03 = 0.1*0.3 of the points will lie in the square with address 12, and so on.

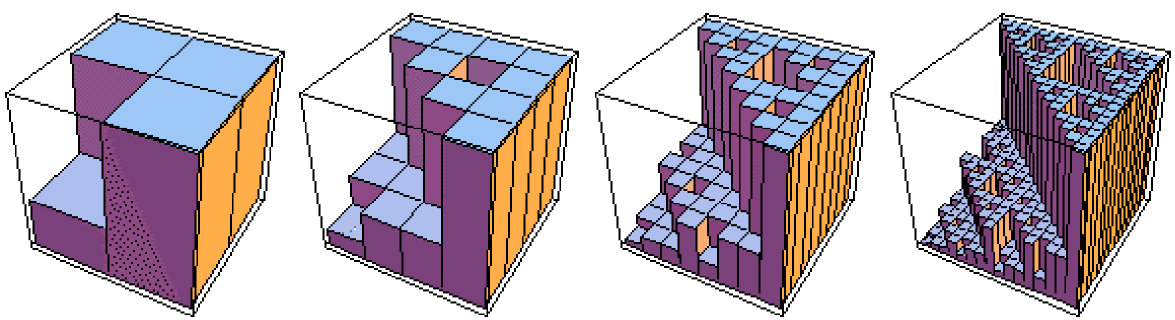
.3	.3
.1	.3

.09	.09	.09	.09
.03	.09	.03	.09
.03	.03	.09	.09
.01	.03	.03	.09

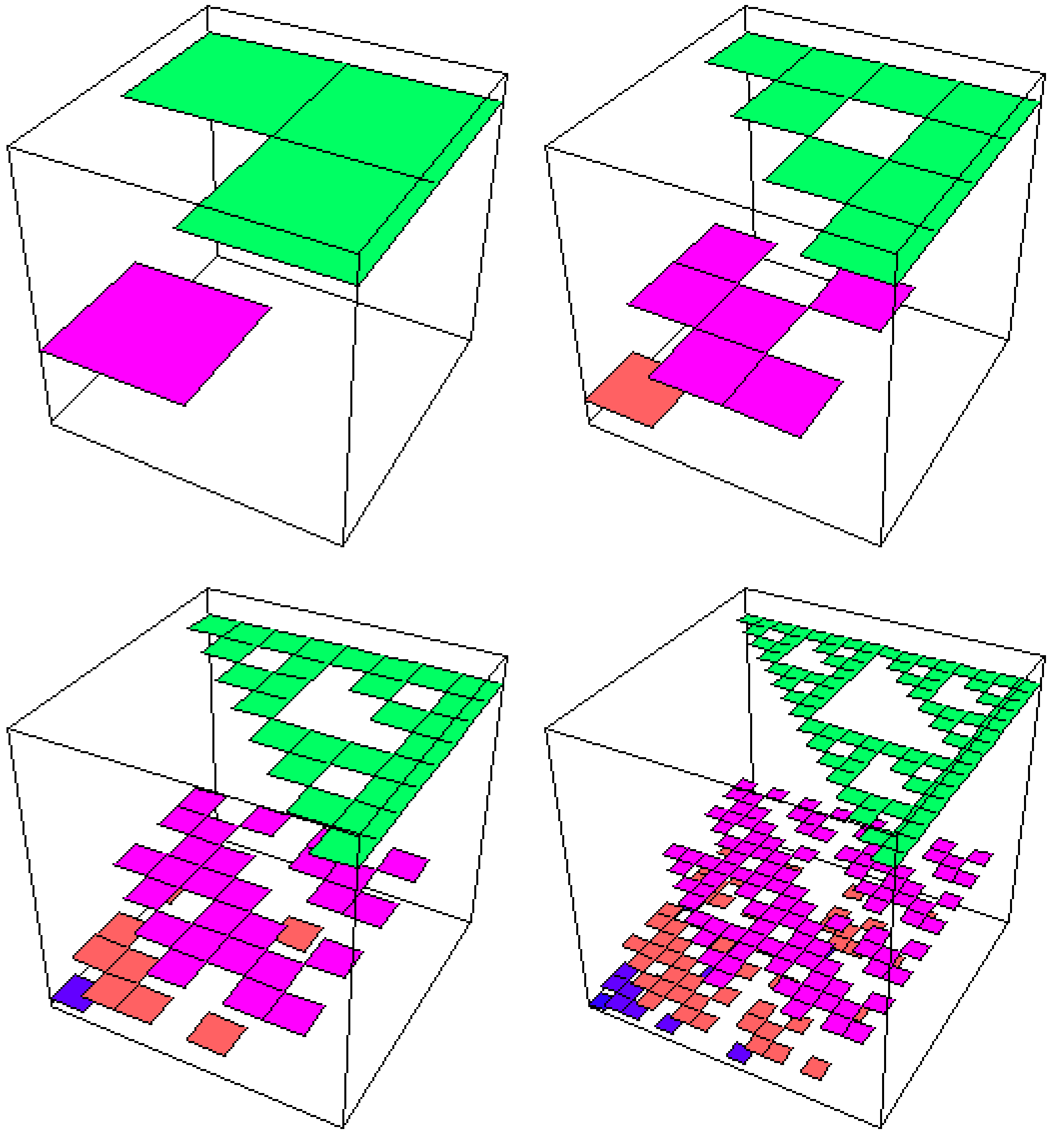
Higher iterates are easier to understand visually.

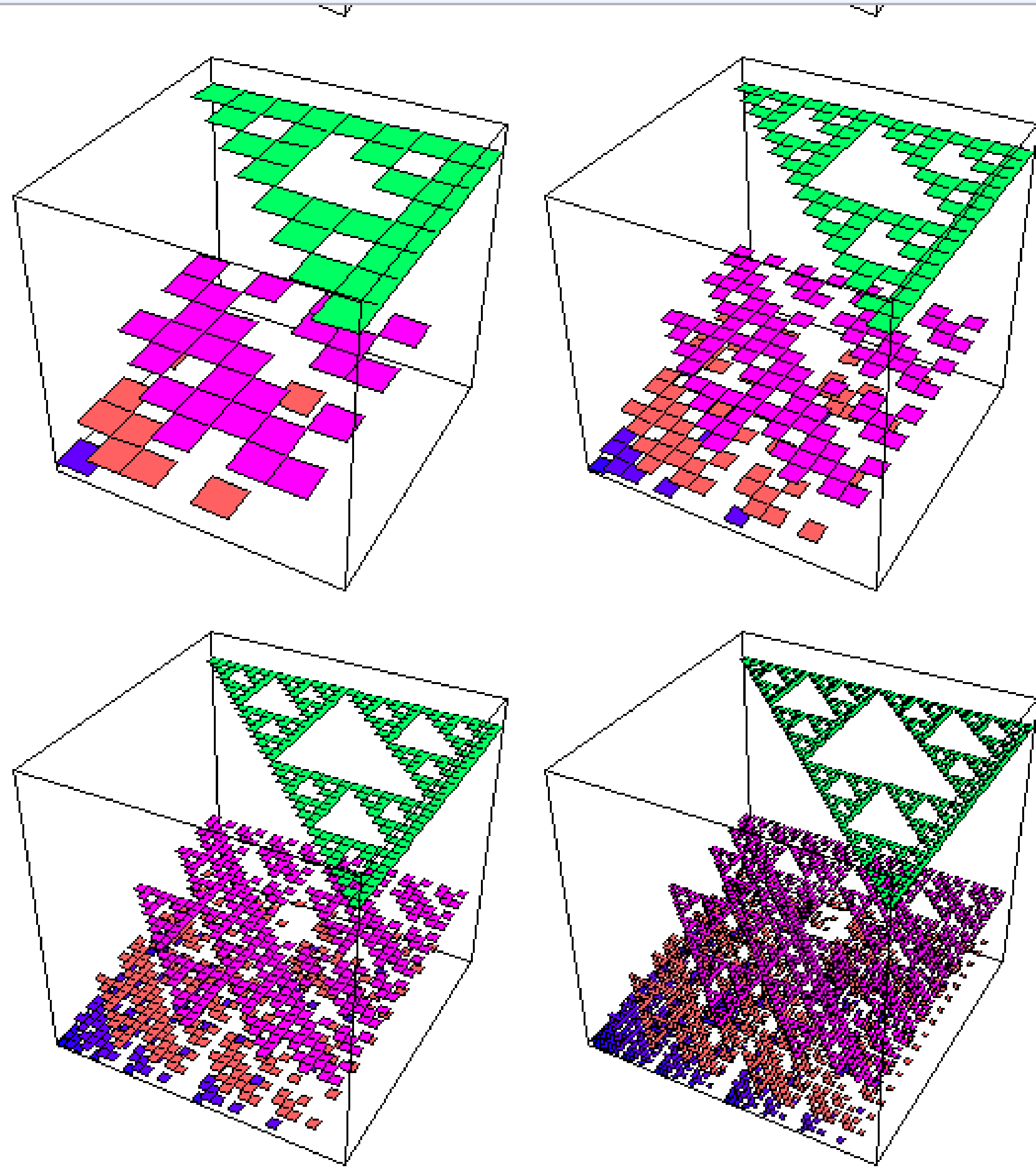
Here we show the first four generations, with the height of the box in a region representing the fraction of the points in that region.

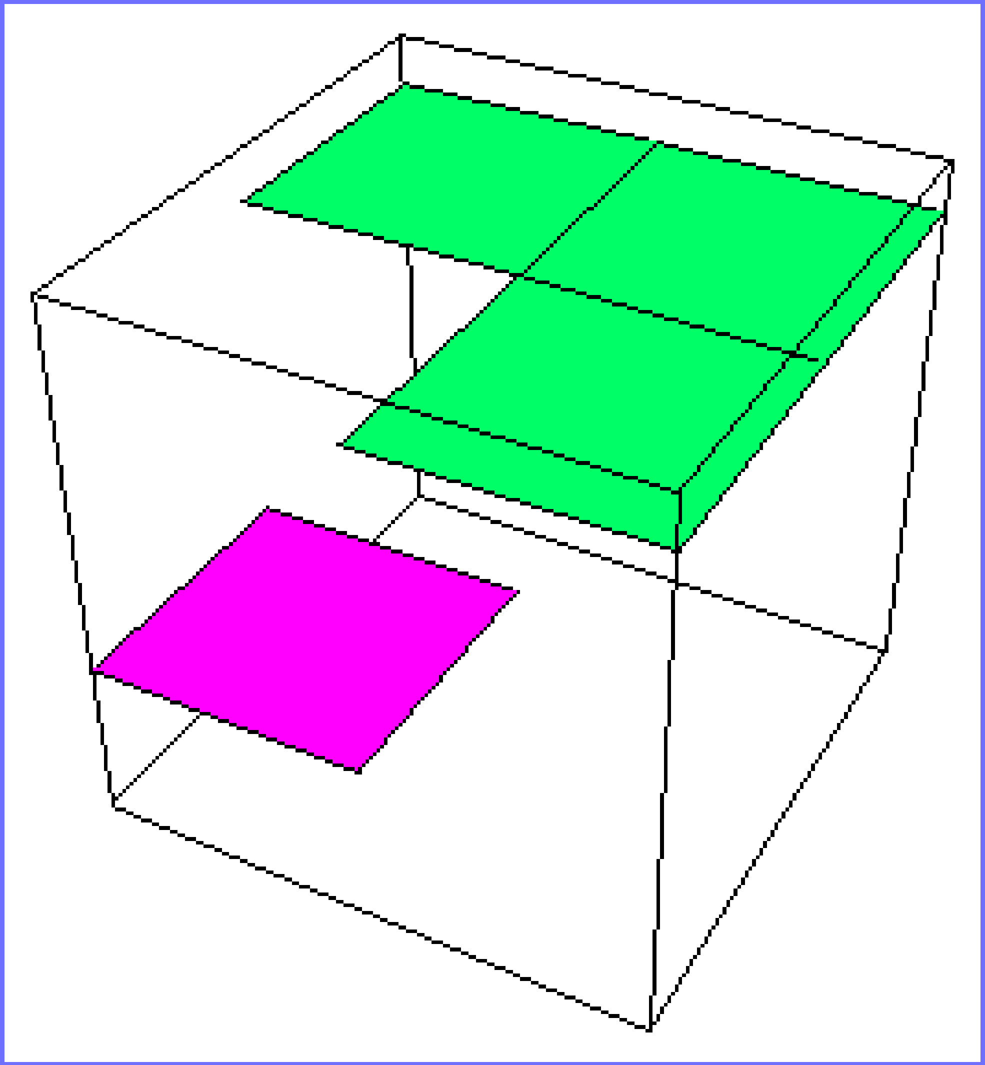
All the pictures have been adjusted to have the same height, whereas square 4 has 0.3 of the points, square 44 has 0.09 of the points, square 444 has 0.027 of the points, and so on.



So again the height represents the fraction of the points landing in that region.







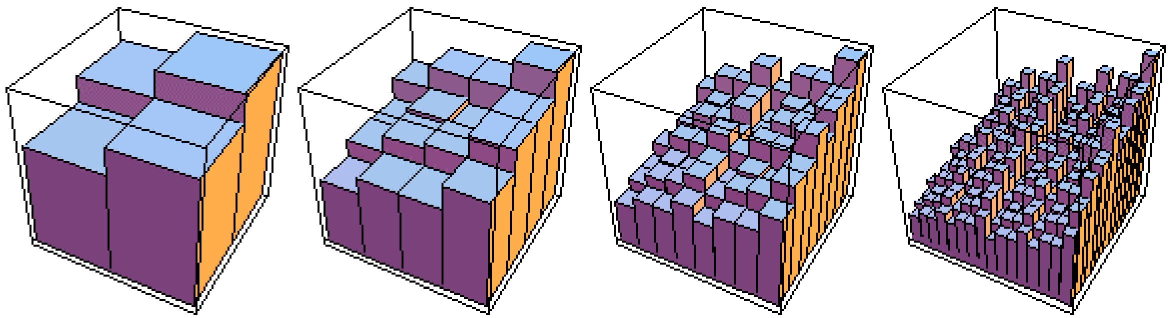
http://classes.yale.edu/fractals/MultiFractals/MFGaskSect/MFGaskSectMv.gif

Different Probabilities, Another Example

In this example, we introduce more variability in the probabilities:

$$p_1 = 0.2,\ p_2 = 0.25,\ p_3 = 0.25, \text{ and } p_4 = 0.3.$$

Among other things, the number of values of the probabilities of regions increases more rapidly.



Smaller regions have smaller probabilities; if these graphs weren't rescalled vertically they would appear to become closer and closer to a flat surface of heig 0. Click here for an animation of the first four iterates, all drawn to the same vertical scale.

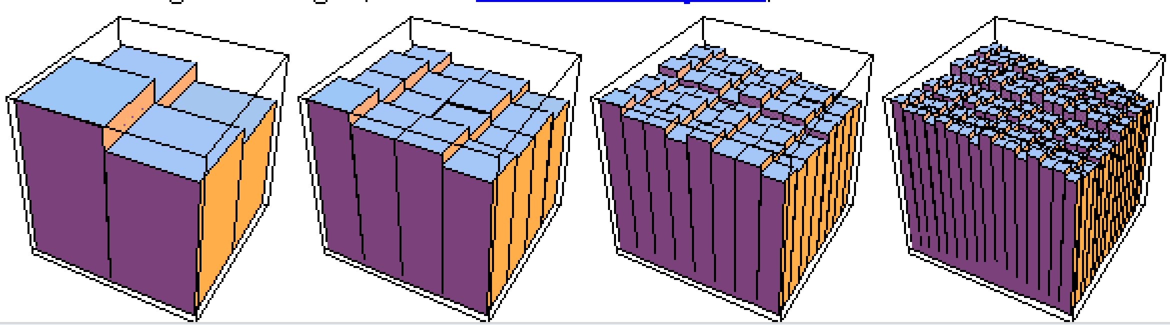
For each region we expect that

$$\text{prob scales as (side length)}^{\text{some power}}$$

So instead of letting the height of the graph represent the probability of the region, now we assign height Log(prob)/Log(side length) to the region.

Because the probability measures the fraction of the points that occupy a region, we think of this ratio as a dimension.

Being viewed at the resolution of the side length of the region, this is a coarse Holder exponent; it is also called the coarse dimension.



Multifractals

Local Holder Exponents

Taking limits as the side length of the regions go to zero, the coarse Holder exponent can be refined to the local Holder exponent (or *roughness*) at (x, y) is

$$d_{loc}(x,y) = \lim_{n \to \text{infinity}} \text{Log}(\text{Prob}(i_1 \ldots i_n))/\text{Log}(2^{-n})$$

where $\text{Prob}(i_1 \ldots i_n)$ is the probability $pr(i_1)* \ldots *pr(i_n)$, if (x,y) lies in the square with address $i_1 \ldots i_n$.

The value for a square of finite length address is called the coarse Holder exponent. So the local Holder exponent of a point (x, y) is the limit as N -> infinity of the coarse Holder exponents of the length N address squares containing (x, y).

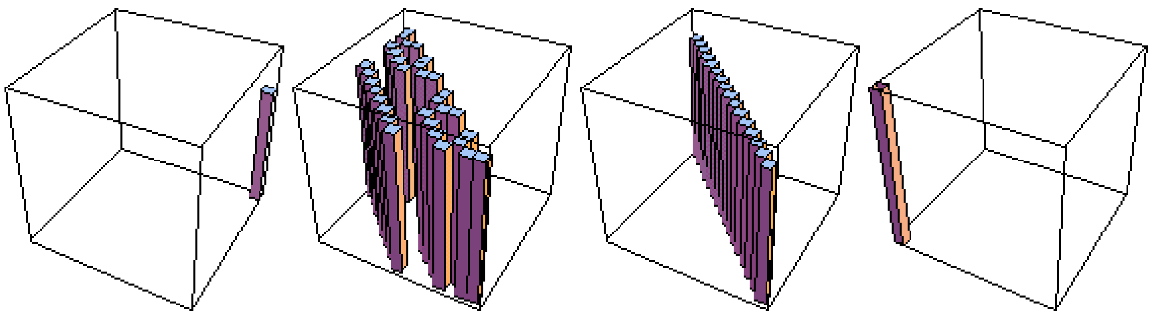
Now define

$$E_{alpha} = \{(x, y): d_{loc}(x, y) = alpha\},$$

the collection of all points of the fractal having local Holder exponent alpha.

As alpha takes on all values of the local Holder exponent, we decompose the fractal into these sets E_{alpha}.

Here are examples, E_{alpha} (alpha = column height) for the lowest value of alpha (on the left), two intermediate values, and the highest value.

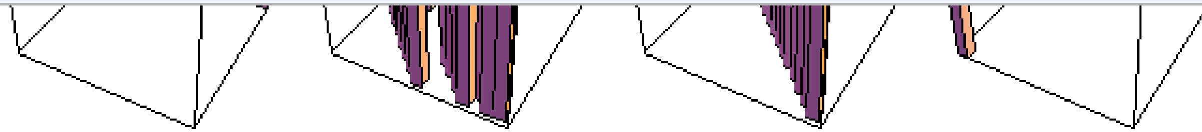


Click here for an animation scanning through all the values of alpha, from lowest to highest, resolved to boxes have side length $1/2^4$.

Because each local Holder exponent alpha is the exponent for a power law, a multifractal is a process exhibiting scaling for a range of different power laws.

The multifractal structure is revealed by plotting $\dim(E_{alpha})$ as a function of alpha.

(In general, a dimension more subtle than the box-counting dimension must be used. We ignore this complication here.)



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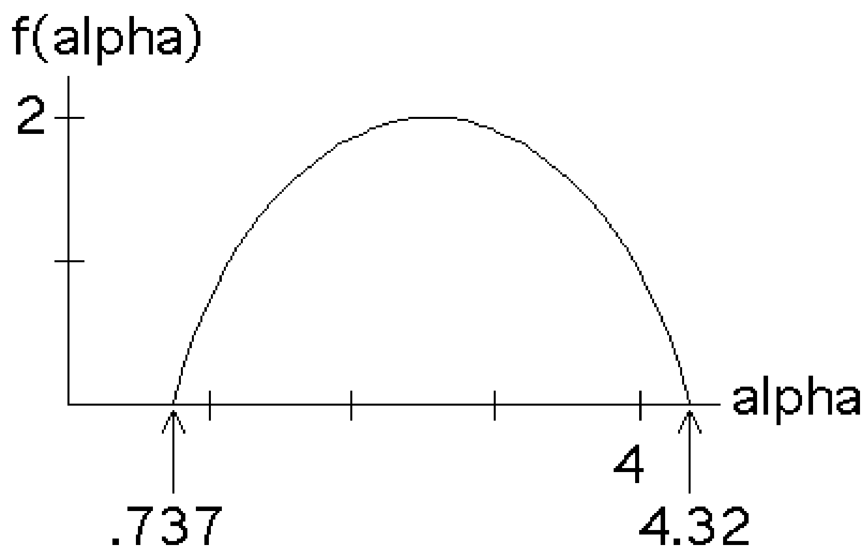
The multifractal structure is revealed by plotting $\dim(E_{alpha})$ as a function of alpha.

(In general, a dimension more subtle than the box-counting dimension must be used. We ignore this complication here.)

This graph is called the f(alpha) curve.

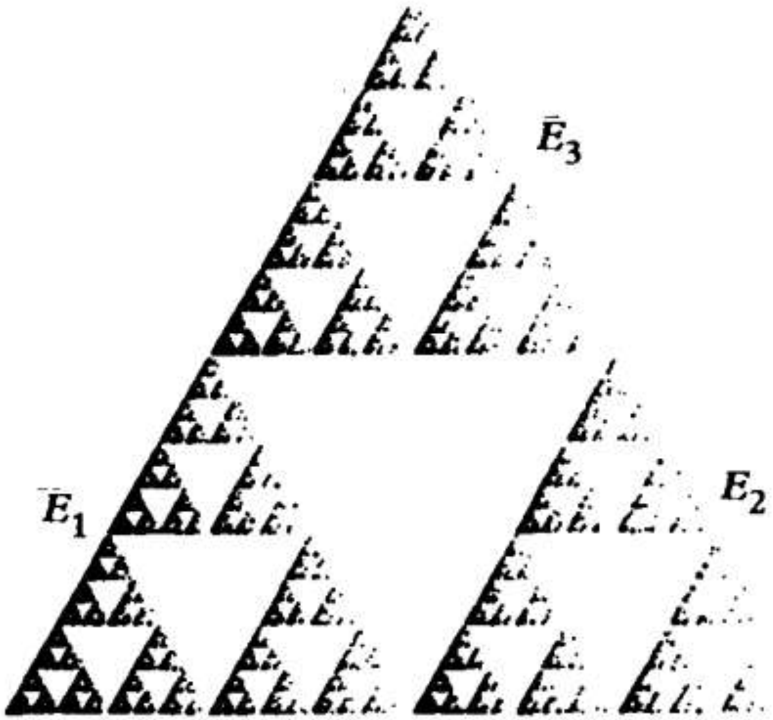
Here is the f(alpha) curve for the example with $p_1 = 0.2$, $p_2 = p_3 = 0.25$, and $p_4 = 0.3$.

At least in this example, sets E_{alpha} for the lowest and highest values of alpha reduce to points in the limit, hence have dimension f(alpha) = 0. This is represented in the left and right endpoints of the curve lying on the x-axis.



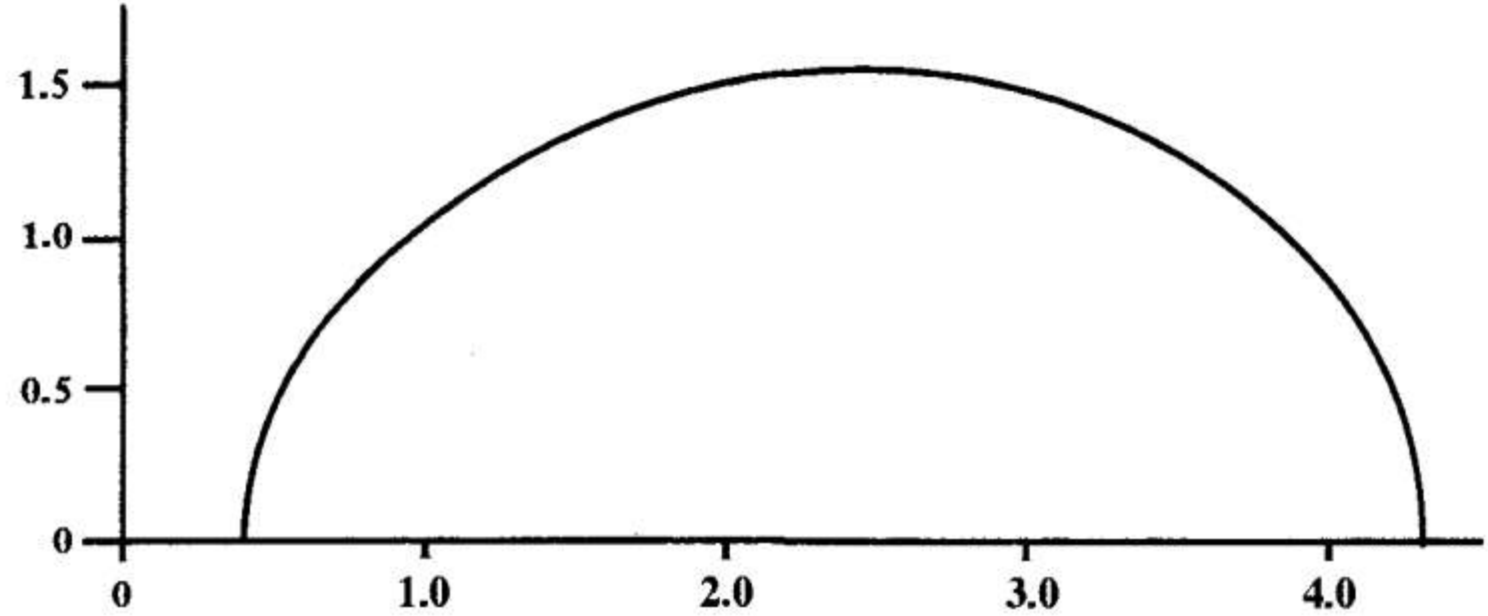
This result is derived under more general conditions in a later section.

Return to Multifractals.



K. Falconer, Techniques in Fractal geometry

P=(0.8,0.05,0.15)



The Legendre transform of f(α)

$\mathcal{F} = \{w_1, \ldots, w_N\}$, $w_i : X \to X$ contraction of constant s_i, $0 \le s_i < 1$

$(p_1,\ldots,p_N)$ probability vector $0 \le p_i \le 1$, $p_1+\ldots+p_N = 1$

The dimension d of the attractor $\mathcal{A}$ is the solution of the equation

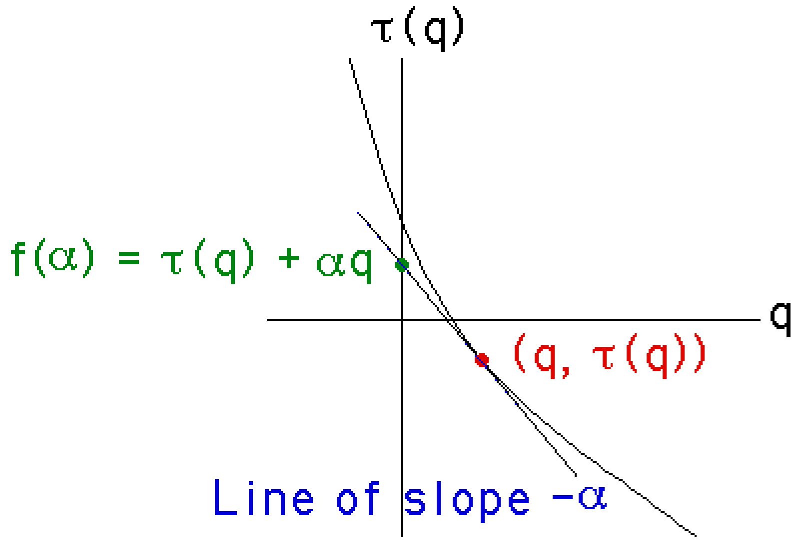
$$s_1^d + s_2^d + \ldots + s_N^d = 1$$

The singularity spectrum $\alpha \to f(\alpha)$ of a probabilistic i.f.s. is the Legendre transform of the function $q \to \tau(q)$ obtained solving the functional equation

$$p_1^q \, s_1^{\tau(q)} + p_2^q \, s_2^{\tau(q)} + \ldots + p_N^q \, s_N^{\tau(q)} = 1$$

Defining f(α)

For each point (q, τ(q)) say the slope of the tangent line is -α. That is, α = -dτ/dq.



This tangent line passes through the point (q, τ(q)) and the point (0, y). Consequently,

$$-\alpha = (y - \tau(q))/(0 - q)$$

Solving for y,

$$y = q\cdot\alpha + \tau(q)$$

Call this y-value f(α):

$$f(\alpha) = q\cdot\alpha + \tau(q)$$

Return to Multifractals from IFS.

Lecture_5_MFGaskSect....gif

The singularity spectrum α→f(α) of a probabilistic i.f.s. is the Legendre transform of the function q→τ(q)