

Lecture : Self-Similarity and Scale Invariance \Rightarrow RW. (Random Walks)

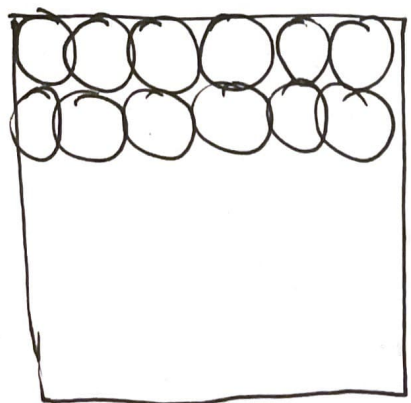
As we discussed last time, a central role is played by fixed points which are invariant under scale transformation. . . . In other words, they are self-similar. . . . (Scale invariance at all scales)

Such self-similar structures are often "fractal" and defined by a fractal dimension

To understand this

D - fractal or Hausdorff dimension

Consider an object (say the plane in \mathbb{R}^2)



Let $N(a)$ be the minimum number of d -dim. balls needed to cover the object (min is over position)

$$N(a) \sim a^{-D}$$

(agrees with usual idea of dimension for objects)

Notice that

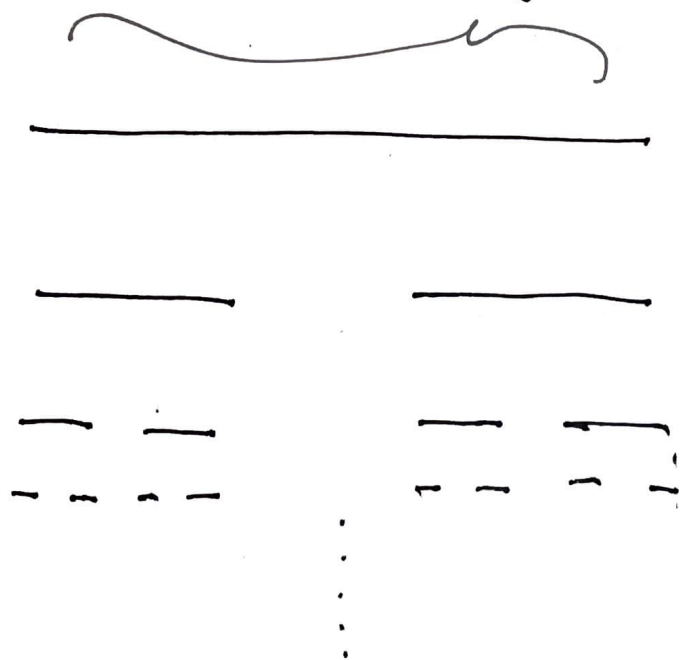
$$d_T \leq D \leq d$$

Topological dimension $\rightarrow d_T$
 (1 for curve)
 dimension of embedding space \checkmark
 (\mathbb{R}^2)



So how can we create objects where $D \neq d_T, d$

Classic example is "Cantor Set"



Take a line segment
 $d=1$
 of length a_0

Remove middle third
 \downarrow Repeat

Now choose $a = a_0 3^{-n}$, $n=1, 2, \dots$

$$\begin{aligned}
 N(a) &= 2^n = 2^{\frac{-\log \frac{a}{a_0}}{\log 3}} = 2^{-\frac{\ln(a/a_0)}{\ln 3}} = e^{-\frac{(\ln 2)(\ln(a/a_0))}{(\ln 3)^2}} \\
 &= \left(\frac{a}{a_0}\right)^{-\frac{\ln 2}{\ln 3}} \Rightarrow D = \frac{\ln 2}{\ln 3} = 0.6309
 \end{aligned}$$

As promised $d_T = 0$ (points)
 $d = 1$ (embedded in 1D)

$$D = 0,6309 = \frac{\ln 2}{\ln 3}$$

Useful to reformulate this using self-similarity recursively

$$N(a) = 2N(3a) \leftarrow \text{Same function i.e. self similar when we zoom out}$$

Assume scaling

$$N(a) \sim a^{-D}$$

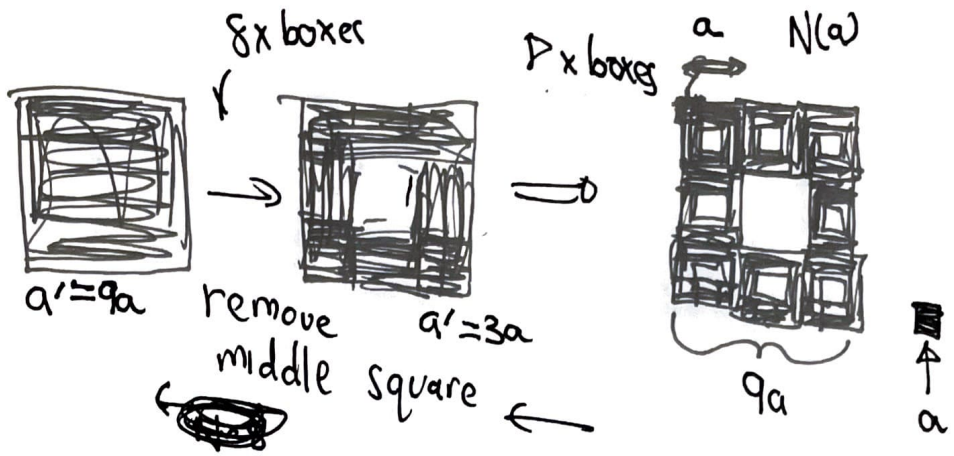
$$a^{-D} = 2(3a)^{-D}$$

$$\Rightarrow 1 = 2 \cdot 3^{-D}$$

$$D = \frac{\ln 2}{\ln 3}$$

This is a very typical form of an argument we will make...

Consider Sierpinski carpet



$$N(a) = 8 N(3a)$$

assuming $N(a) \sim a^{-D}$

$$a^{-D} = 8 (3a)^{-D}$$

$$\log 8 = -D \log 3$$

$$D = \frac{\log 8}{\log 3} = 1.8928 \dots$$

$$d_T \leq D \leq d \leftarrow \begin{matrix} \text{Embedded} \\ \text{in 2-dimensions} \end{matrix}$$

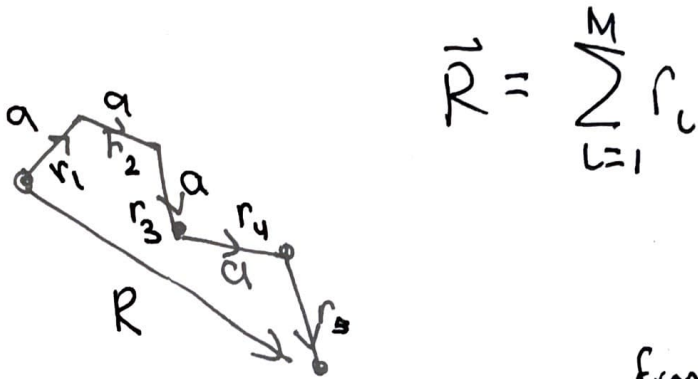
We will do this for class....

Perhaps the most famous and simple example of a self-similar object is a random walk (RW)

Show simulation from Mathematica..

Consider a RW in spatial dimension $d \geq 2$

Make M independent step of length r_c or length a



$$\vec{R} = \sum_{l=1}^M \vec{r}_l$$

from independence $\langle \vec{r}_i \cdot \vec{r}_j \rangle = 0$
if $i \neq j$

$$\langle |\vec{R}|^2 \rangle = \sum_{l=1}^M \sum_{j=1}^M \langle \vec{r}_l \cdot \vec{r}_j \rangle = \sum_{l=1}^M \langle r_l^2 \rangle = M a_0^2$$

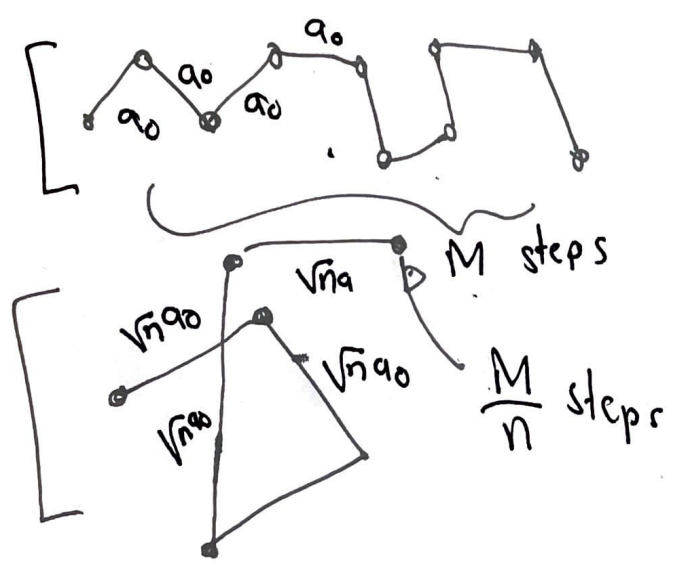
$$R = \sqrt{\langle |\vec{R}|^2 \rangle} \sim \sqrt{M} a_0$$

Now assume $M \gg 1$, we can divide random walk into n subwalks of M/n steps...

When $1 \ll n \ll M$, we can make identical argument

$$r(n) = \sqrt{n} a_0$$

So notice that R.W. of length M with steps a_0 is self similar to R.W. of length $\frac{M}{n}$ steps each of length $a = \sqrt{n} a_0$.



Change ruler to $a = \sqrt{n} a_0$

$$M \rightarrow \frac{M}{n}$$

Number of balls of size a_0

So now we have to think about $N(a_0) \sim M$

$$N(\sqrt{n} a_0) \sim \frac{M}{n}$$

$$N(a_0) = N(\sqrt{n} a_0)$$

for this to be true

$$N(a_0) \sim \frac{1}{a_0^2}$$

fractal dimension

$$D = 2$$

for any dimension $d \geq 2!$

Revisiting the anatomy of RG Transformation



Before constructing RG

Last time we said RG is a coarse graining procedure but that is not quite right

It actually has two steps

① Step 1: Decimation or coarse graining
=> "average out" or "integrate out"
or more properly "marginalize"
over ~~the~~ ^{short distance} degrees of freedom

② Step 2: Rescaling => Redefine unit of
. length => "Use bigger length"
=> Scale factor b => $X' = bX$

So that smallest distance is restored
" to original value...

So we have mapped original system
back to itself but with short distance
physics marginalized over...

This takes the form that the parameters
of the system $\{h_k\}$ $k=1, 2, \dots,$

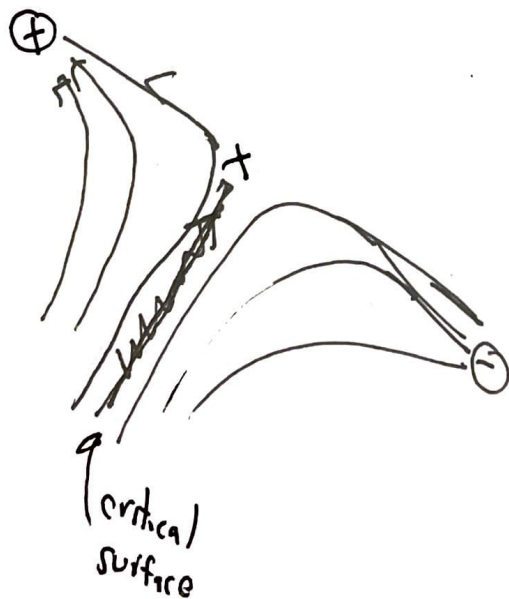
RG equations map to new parameters
 (important consider space of all possible couplings)
 to do this properly...

$$h'_k = R_k(\{h_j\})$$

Fixed point: $\lim_{n \rightarrow \infty} R_k(\dots n \text{ renormalizations } R_k(h_j^{(c)})) \rightarrow h_k^*$

This implies system is self similar...

The special set of values for which $h_j^{(c)}$ define
 "critical surface" \Rightarrow separator in flow space



Now consider

$$h_k = h_k^* + \epsilon_k \quad \text{with } |\epsilon_k| \ll 1$$

$$\epsilon'_k = \sum_j \frac{\partial h'_k}{\partial h_j} \epsilon_j \quad \text{Linearize}$$

$$\frac{\partial h'_k}{\partial h_j} = R_{kj} \quad \text{matrix ("Linear operator")}$$

Can of course find right eigenvectors

$$\sum_j R_{yj} \phi_j^{(n)} = \lambda^{(n)} \phi_c^{(n)}$$

and left Eigenvectors

$$\sum_j \tilde{\phi}_c^{(n)} R_{yj} = \lambda^{(n)} \tilde{\phi}_c^{(n)}$$

with

$$\sum_k \tilde{\phi}_k^{(n)} \phi_k^{(n)} = \delta_{nn'}$$

and

$$\sum_n \tilde{\phi}_j^{(n)} \phi_k^{(n)} = \delta_{jk}$$

So if we we write

$$E = \sum_c U_n \phi_c^{(n)}$$

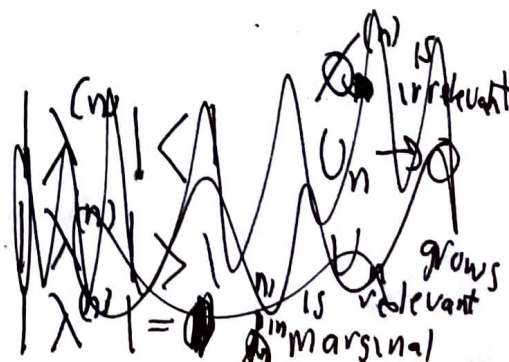
expand in right eigenvectors

Then under $R_{\mathcal{G}}$

$$E \rightarrow \lambda^{(n)} U_n \phi_c^{(n)}$$

Under repeated transformation $\phi_c^{(n)}$ coefficient grows $|\lambda^{(n)}| > 1$ shrinks $|\lambda^{(n)}| < 1$

or is marginal $|\lambda^{(n)}| = 1$



Directions that grow are called "relevant"

Directions that shrink are called "irrelevant"

Directions with $|\lambda^{(n)}| = 1$ are called "marginal"

(In practice sometimes one has to be a little more careful and we will return to this... maybe...)

RW via RG

So now lets return to RW... useful to consider slightly more general formulation...

$$p(\vec{r}) = \frac{1}{(2\pi\sigma_0^2)^{-d/2}} \exp\left(-\frac{(\vec{r}-\vec{r}_0)^2}{2\sigma_0^2}\right)$$

} step length is gaussian with mean \vec{r}_0 and width σ_0

Step 1: Coarse grain RW by considering n walks together

$$\vec{r}' = \sum_{l=1}^n \vec{r}_l$$

$$P(\vec{r}') = \int d\vec{r}_1 \dots d\vec{r}_n \delta(\vec{r}' - \sum_{l=1}^n \vec{r}_l) p(\vec{r}_1) \dots p(\vec{r}_n)$$

Fourier Transform

$$\int \frac{d^d k}{(2\pi)^d} e^{-i\vec{k}\cdot\vec{r}} \prod_{l=1}^n \left[e^{-i\vec{k}\cdot\vec{r}_l} p(\vec{r}_l) \right] d\vec{r}_l$$

Gaussian integral

$$\prod_{l=1}^n e^{-\frac{|\vec{k}|^2 \sigma_0^2}{2}} = e^{-\frac{n|\vec{k}|^2 \sigma_0^2}{2} + i\vec{k}\cdot\vec{r}_0}$$

$$P(r) = \int \frac{d^d k}{(2\pi)^d} e^{-\left[-n |k|^2 \frac{\sigma_0^2}{2} - i k \cdot r \right]}$$

(11)

$$e^{-\frac{a(x+2b)^2 + b^2}{a^2}} = e^{-\frac{ax^2 + 4bx + 4b^2 + b^2}{a^2}} = e^{-\frac{ax^2 + 4bx + 5b^2}{a^2}}$$

$$\prod_{\alpha=1}^d \int \frac{dk_\alpha}{(2\pi)} e^{-n \frac{k_\alpha^2 \sigma_0^2}{2} - i k_\alpha (r_\alpha - r_{0\alpha})}$$

Performing integral over k

$$\Rightarrow e^{-\frac{(r - nr_0)^2}{2n\sigma_0^2}}$$

$$P(r') = \frac{1}{(2\pi n \sigma_0^2)^{d/2}} \exp\left[-\frac{|r' - nr_0|^2}{2n\sigma_0^2}\right]$$

Unbiased Walk:

Consider first case where $r_0 = 0$ (Unbiased)

Same as original \Rightarrow Coarse grained σ'

$$\sigma' \rightarrow \sqrt{n} \sigma_0$$

Step 2 of RG

unit of length...

width

$$\vec{r}'' = \frac{\vec{r}'}{\sqrt{n}}$$

We want "rescale" our
Let's choose RG scheme preserve

~~width~~ Use bigger ruler

$$P(r'') = \frac{1}{(2\pi \sigma_0^2)^{d/2}} \exp\left[-\frac{(r'')^2}{2\sigma_0^2}\right]$$

Since $d^d r' = n^{d/2} d^d r''$

So we get

$$\sigma(r) = \sigma_0 \Rightarrow 0$$

σ is marginal variable...

Cannot distinguish Renormalized R.W.
from original R.W. \Rightarrow It is self similar..

(12)

Consider

$$R_{\sigma}(M) \sim \sigma M^{\nu}$$

distance covered by M steps

only dimension

We know that

$$R_{\sigma}(M) = R_{\sqrt{n}\sigma}\left(\frac{M}{n}\right)$$

$$\sigma M^{\nu} = \sqrt{n} \sigma \left(\frac{M}{n}\right)^{\nu} \Rightarrow \boxed{\nu = \frac{1}{2}}$$

So scaling exponent $\nu = \frac{1}{2}$

We see that $\nu = \frac{1}{D}$

Where D
is the fractal
dimension..

This RG equation

$\sigma^{(R)} = \sigma^0$ is typical of Gaussian models

However in many ways this is too simple..

Actually, one can really begin to get a feel (13)
for RG with just a slightly more difficult example...

~~Resistant~~ (Biased) R.W.

Imagine now the same process with preferred
direction \vec{r}_0 So that

$$p(\vec{r}) = \frac{1}{(2\pi\sigma^2)^{d/2}} e^{-\frac{(\vec{r}-\vec{r}_0)^2}{2\sigma^2}} \quad \vec{r}_0 \neq 0$$

Coarse graining this we did this work already

$$p(r') = \frac{1}{(2\pi n\sigma^2)^{d/2}} e^{-\frac{(r'-nr_0)^2}{2n\sigma^2}}$$

Let us coarse grain keep this invariant

$$\text{Coarse grained parameters} \begin{cases} r_0' = nr_0 \\ \sigma' = \sqrt{n}\sigma \end{cases}$$

Now let us rescale $\vec{r}' = \sqrt{n}\vec{r}'' \Leftrightarrow dr'' = \frac{dr'}{\sqrt{n}}$

$$P(r'') = \frac{1}{(2\pi\sigma^2)^{d/2}} e^{-\frac{(r''-r_0\sqrt{n})^2}{2\sigma^2}}$$

Then we have that

$$P(r'') = \frac{1}{(2\pi\sigma^{(R)})^2} e^{-\frac{(\vec{r}'' - \vec{r}_0^{(R)})^2}{2\sigma^{(R)2}}$$

where we have renormalized parameters

$$\sigma^{(R)} = \sigma_0 \quad] \quad \text{doesn't change as before}$$

$$r_0^{(R)} = \sqrt{n} r_0 \quad] \quad \text{gets bigger in magnitude ...}$$



Fixed points of this are

$$(\sigma, r_0 = 0) \quad \text{and} \quad (\sigma, r_0 = \infty)$$

The first fixed point is "Brownian" motion is pure unbiased RW

The second fixed point note that $R = \sum_{l=1}^M \vec{r}_l$

$$\begin{aligned} \langle |R|^2 \rangle &= \left\langle \sum_{l=1}^M \vec{r}_l \cdot \vec{r}_l \right\rangle \\ &= \sum_{j=1}^M \sum_{l=1}^M (\vec{r}_l - \vec{r}_0) \cdot (\vec{r}_j - \vec{r}_0) + 2M \sum_{l=1}^M \vec{r}_l \cdot \vec{r}_0 - M^2 |\vec{r}_0|^2 \\ &= M \langle (r_l - r_0)^2 \rangle + 2M^2 |\vec{r}_0|^2 - M^2 |\vec{r}_0|^2 \\ &= M(\sigma^2 + M r_0^2) = M\sigma^2 + M^2 r_0^2 \end{aligned}$$

At large M

$$\sqrt{\langle |R|^2 \rangle} \approx \sqrt{M r_0^2 + M \sigma_0^2}$$

$$\approx M r_0$$

So that # of spheres of size a needed to cover walk

$$N(r_0) \sim \frac{M r_0}{a} \sim \frac{l}{a} \text{ and } D=1$$

This is just ballistic motion

In other words the bias \vec{r}_0 is a "relevant" perturbation..

At short distances $\frac{|r|}{\sigma} \ll 1$ the walk looks unbiased (Brownian)

but as one examines the walk at long scale it looks ballistic

