

# Dimension of Self-Similar Sets and Measures: A Survey of Recent Results

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## Self-similar measures - motivation via random walks

- ▶  $\Phi = \{f_1, \dots, f_k\}$  similarity maps of  $\mathbb{R}^d$ , no common fixed point.
- ▶  $p = (p_1, \dots, p_k)$  a positive probability vector (a measure on  $\Phi$ ).
- ▶ Define a **random walk** on  $\mathbb{R}^d$  by fixing a point  $x_0 \in \mathbb{R}^d$  and setting

$$x_{n+1} = \xi_{n+1}x_n$$

where  $\xi_1, \xi_2, \xi_3, \xi_4, \dots$  are independent similarities with distribution  $p$ .

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$f_i$  contract  $\implies$   $\text{distribution}(x_n) \rightarrow \mu$  (**no universal behavior**).

$f_i$  expand  $\implies$   $x_n \rightarrow \infty$ , Boundary theory (**no universal behavior**)

## Here we focus mainly on the contracting case

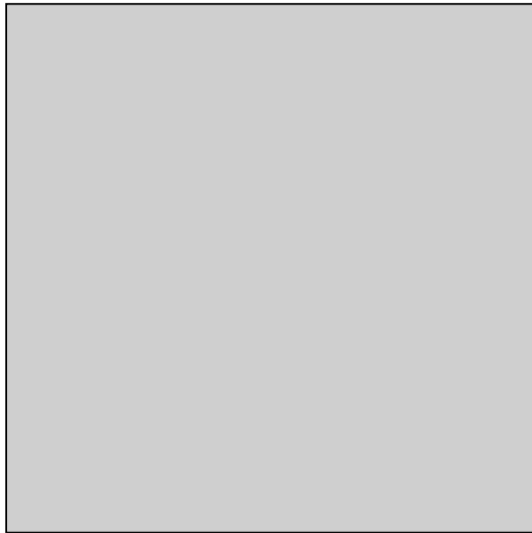
The limit distribution  $\mu$  is called a **self-similar measure**:

$$\mu = \sum_{i=1}^k p_i \cdot f_i \mu$$

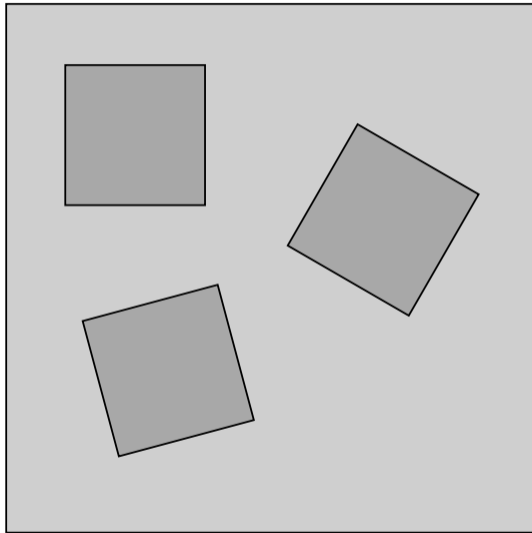
( $f_i \mu = \mu \circ f_i^{-1}$  is the push-forward of  $\mu$ ).

The support  $X$  of  $\mu$  a **self-similar set**: the unique non-empty compact set satisfying

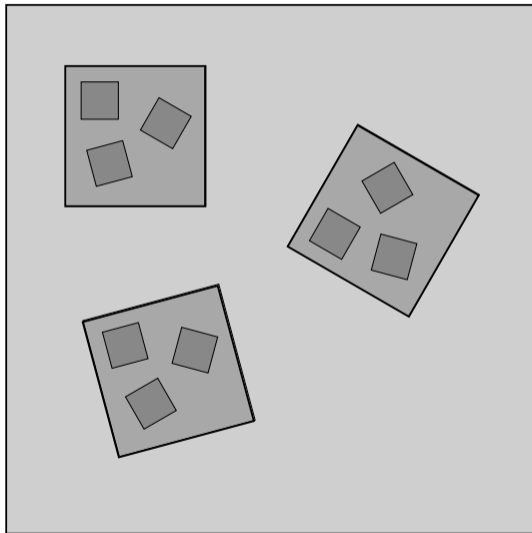
$$X = \bigcup_{i=1}^k f_i(X)$$



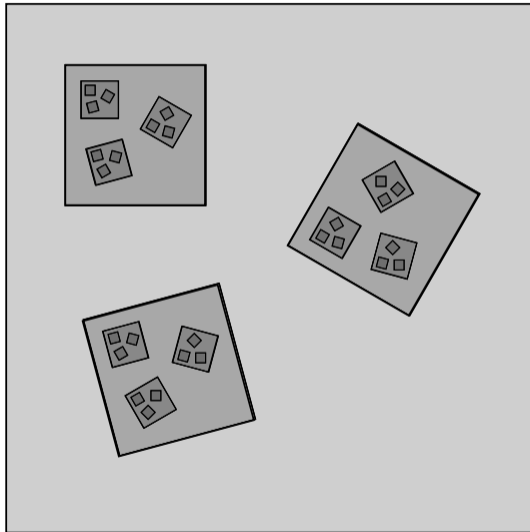




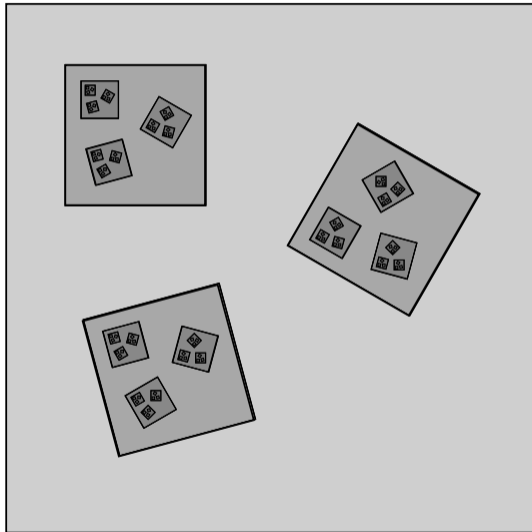
# Iterative construction



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## Main problem

What is the Hausdorff dimension of  $X$ ?

What is the Hausdorff dimension of  $\mu$ , defined as

$$\dim \mu = \alpha \iff \mu(B_r(x)) = r^{\alpha+o(1)} \text{ for } \mu\text{-a.e. } x$$

When is  $\mu$  smooth? (and how smooth is it?)

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## “Equidistribution conjecture”

“The random walk should spread out as much as possible ( $\mu$  should be as smooth as possible), unless algebraic obstructions occur.”

Classical answer [Hutchinson, Moran,...]:

Let  $r_i$  = contraction ratio of  $f_i$ . The **similarity dimension** is the solution  $s$  to

$$\sum r_i^s = 1$$

**Theorem [Hutchinson]**. One always has

$$\dim(X) \leq s$$

And, assuming the union  $X = \bigcup_{i=1}^k f_i(X)$  is disjoint (“**strong separation**”),

$$\dim(X) = s$$

An analogous statement holds for measures.



## The upper bound

By Hutchinson's theorem:

$$\dim X \leq s$$

Also:  $X \subseteq \mathbb{R}^d$ , therefore

$$\dim X \leq d$$

So we always have

$$\dim(X) \leq \min\{s, d\}$$

We call this **the trivial upper bound**.

If the inequality is strict we say there is **dimension drop**.

## Where does $s$ come from?

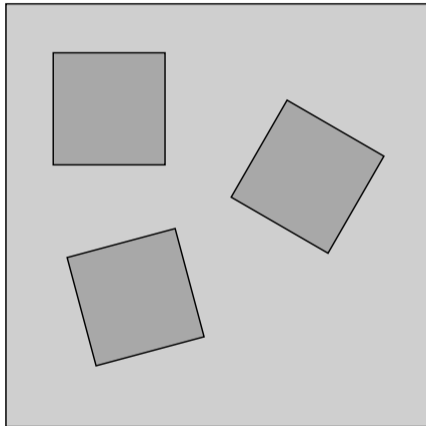
Assume 3 maps with contraction  $1/4 \implies s = \frac{\log 3}{\log 4}$ .



1 cube of side length 1

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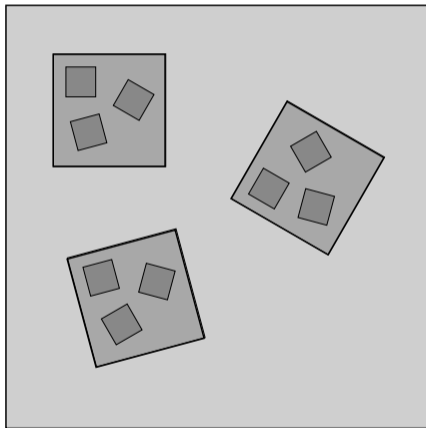
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3 cubes of side length  $\frac{1}{4}$

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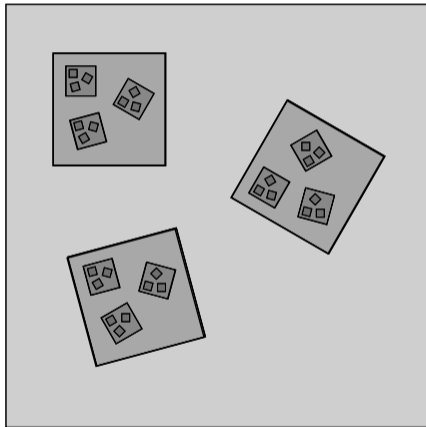
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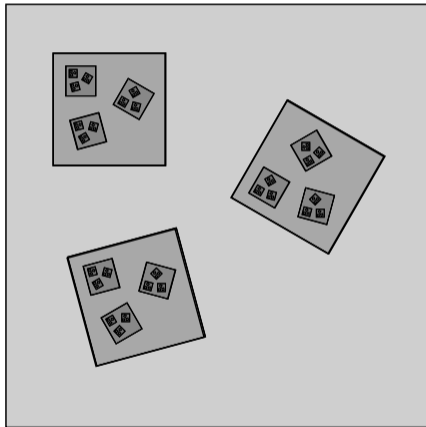
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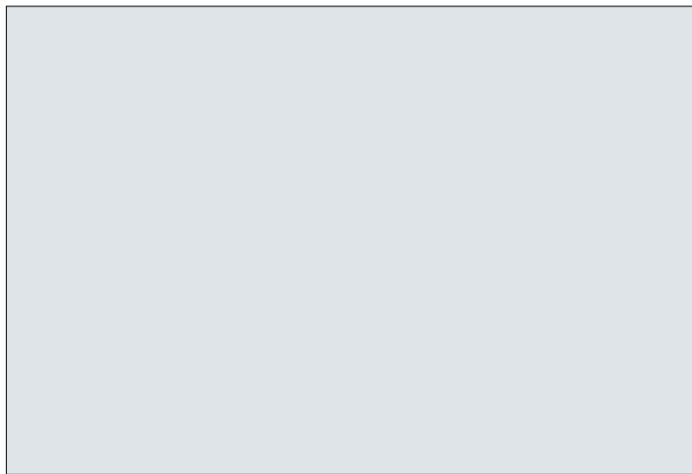
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Need  $3^n$  cubes of side length  $\frac{1}{4^n}$  to cover  $n$ -th iterate  $\implies \dim X = \frac{\log 3}{\log 4} = s$

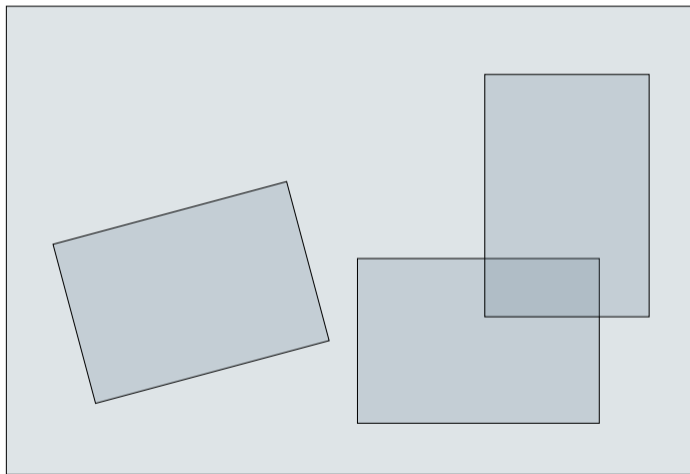
Why is it only an upper bound?



Overlapping case

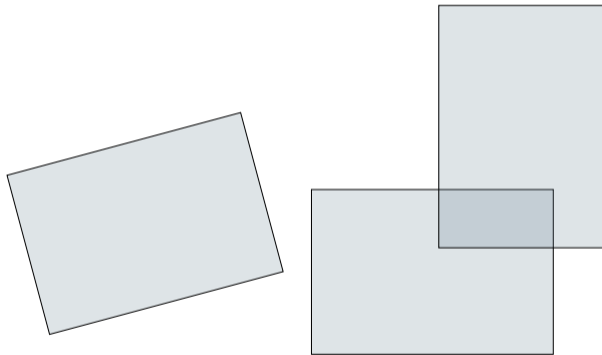


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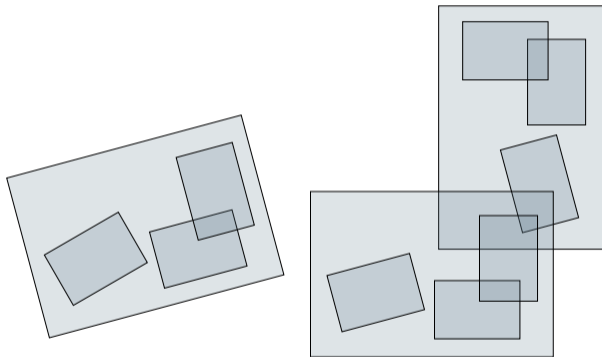
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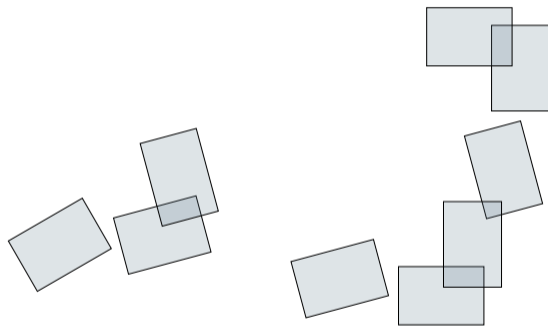
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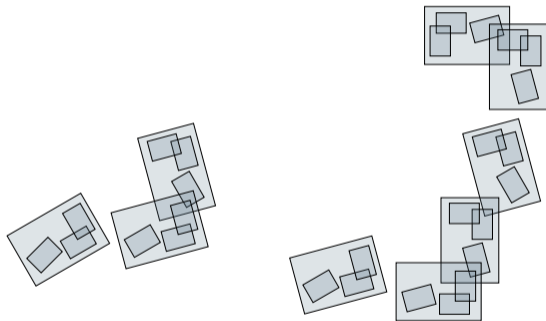
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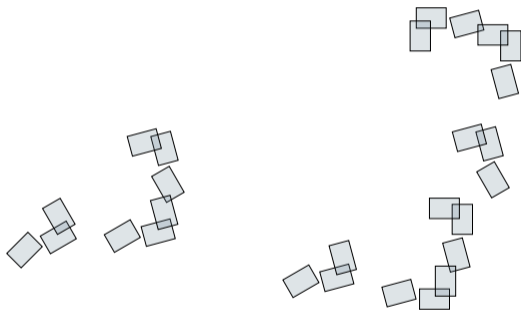
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## Why is it only an upper bound?



Where there are overlaps, more efficient covers may be possible.

## One reason for dimension drop

For  $\mathbf{i} = i_1 \dots i_n \in \{1, \dots, k\}^n$ ,

$$f_{\mathbf{i}} = f_{i_1} \circ \dots \circ f_{i_n}$$

**Exact overlaps** occur if there are  $\mathbf{i} \neq \mathbf{j}$  with  $f_{\mathbf{i}} = f_{\mathbf{j}}$ .

$\iff \{f_i\}_{i=1}^k$  do not freely generate the semigroup  $\{f_{\mathbf{i}}\}_{\mathbf{i} \in \{1, \dots, k\}^n}$ .

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## Conjecture [Erdős, Furstenberg, Simon, ...]

In dimension  $d = 1$ , exact overlaps are the **only** cause for dimension drop.

Some support from analysis of parametric families (Pollicott, Simon, Solomyak, ...)

## Measuring separation

Choose a left invariant Riemannian metric  $d(\cdot, \cdot)$  on the **similarity group** (many other metrics are be equally good).

Define

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1.  $\Delta_n$  is decreasing.
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Say that  $\{f_1, \dots, f_k\}$  are **exponentially separated** if there exists  $\rho > 0$  such that  $\Delta_n \geq \rho^n$ .  
(This property does not depend very much on the metric we choose)

## Theorem (H. 2014)

In dimension  $d = 1$ , (at least) one of the following holds:

- ▶  $\dim X = \min\{1, s\}$
- ▶  $\Delta_n \rightarrow 0$  super-exponentially.

**Equivalently:** exponential separation  $\implies$  no dimension drop.

An analogous statement holds for measures.

**Corollary.** In dimension  $d = 1$ , for  $f_i$  with algebraic coefficients, dimension drop implies exact overlaps.

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For suitable choice of the metric, the distance

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$\implies$  By the theorem, there is no dimension drop.

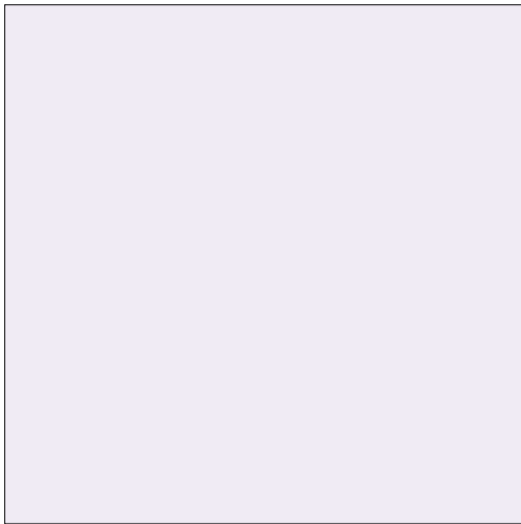
## Higher dimensions

The analogous statements are **false for  $d > 1$** : we can have

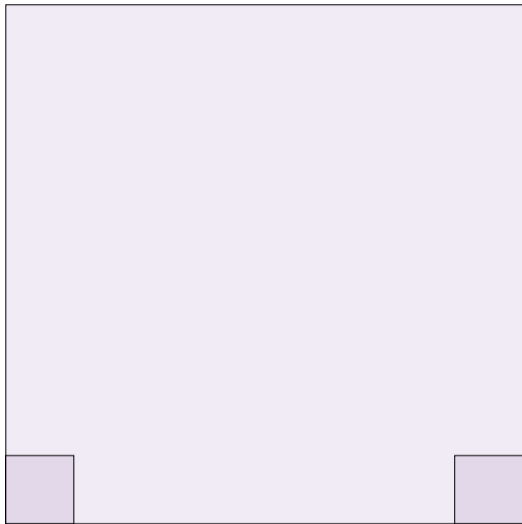
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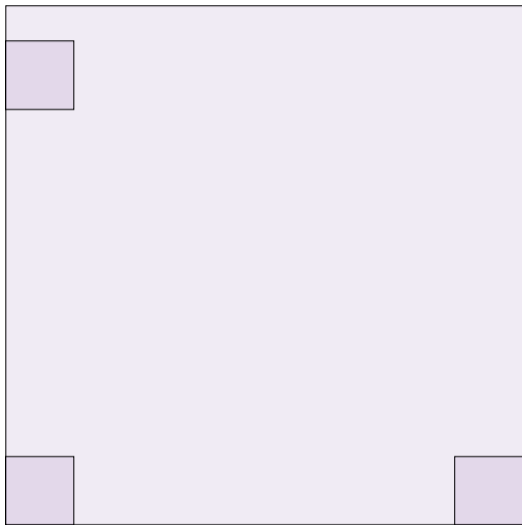
but no exact overlaps (and even exponential separation).

The “excess dimension” is absorbed on vertical lines, which are **invariant** (under the orthogonal parts of the  $f_i$ )



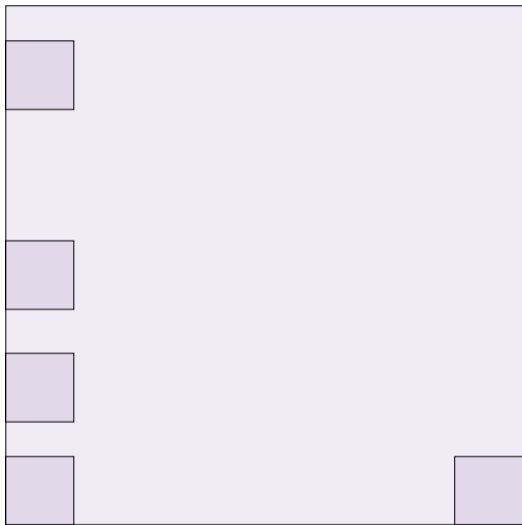
Contraction  $r \ll 1$





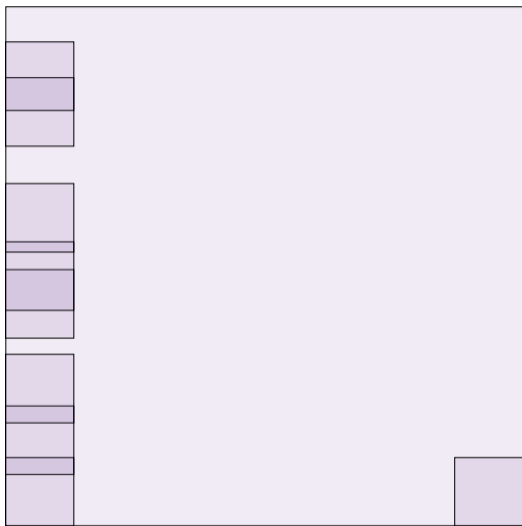
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$N \gg 1/r$  maps



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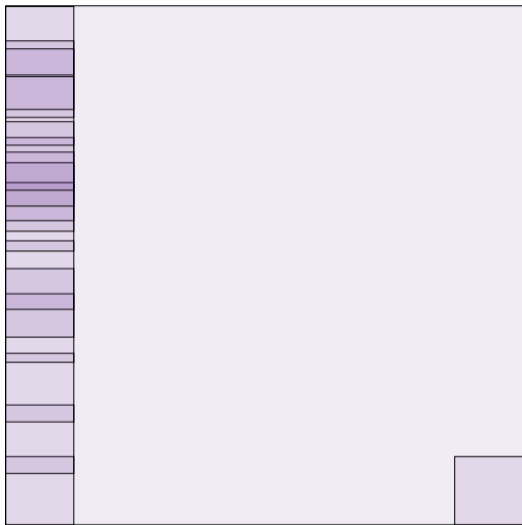
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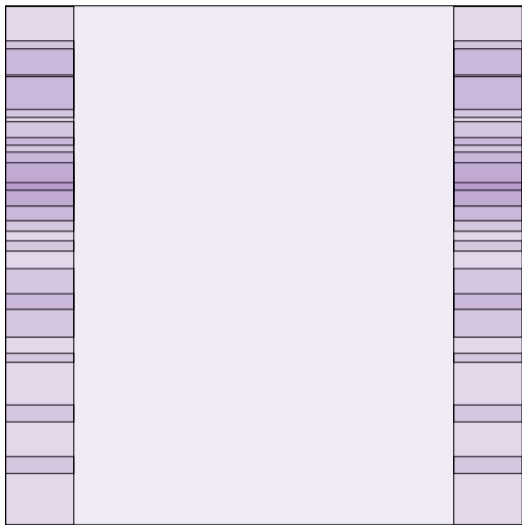
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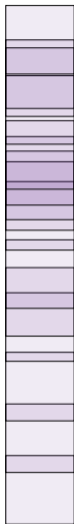
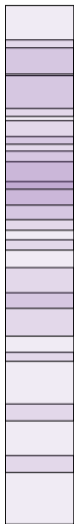
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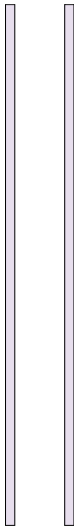
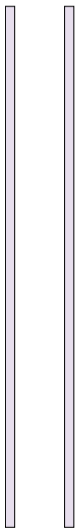
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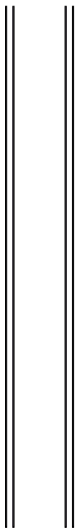
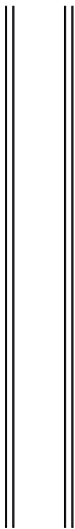
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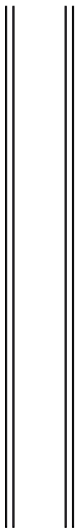
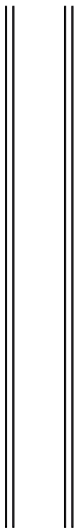
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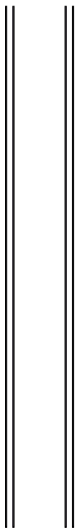
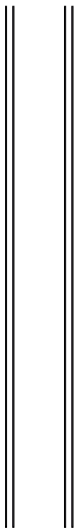
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$$\begin{aligned} \dim X_1 &= \frac{\log 2}{\log(1/r)} \\ &\ll 1 \end{aligned}$$



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$$\begin{aligned} \dim X &= \dim X_1 + 1 \\ &\ll \min\{2, s\} \end{aligned}$$

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### Conjecture for $d > 1$

At least one of the following holds:

- ▶  $\dim X = \min\{s, d\}$ .
- ▶ Exact overlaps occur.
- ▶  $\exists \{U_i\}$ -invariant subspace  $0 \neq V < \mathbb{R}^d$  and  $x \in X$  s.t.

$$\dim((V+x) \cap X) = \dim V$$

## Theorem (H. 2014/2019?)

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(**Corollary:** if  $\{U_i\}$  acts irreducibly, exponential separation implies no dimension drop).

There is an analog for measures.

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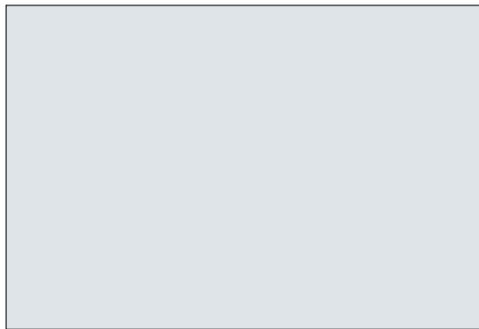
$$\dim((V+x) \cap X) = \dim V$$

**(Corollary:** if  $\{U_i\}$  acts irreducibly, exponential separation implies no dimension drop).

There is an analog for measures.

Compare with work of Lindenstrauss-Varjú: If  $\{U_i\}$  have spectral gap and  $f_i$  have weak enough contraction, and  $p$  has high enough entropy, then  $\mu$  is absolutely continuous.

## One proof ingredient: Additive combinatorics

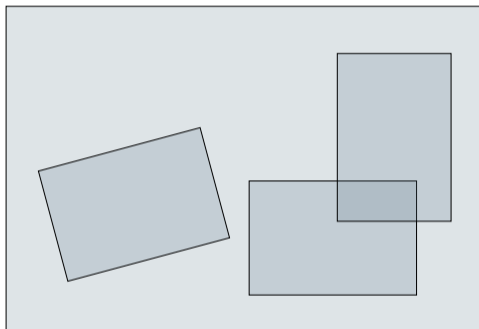


Assume dimension drop and go to a small scale.

Locally, we see exponentially many copies - a convolution of the original measure with a “high entropy” discrete measure (this assumes exp. separation!).

Use results on entropy growth of convolutions.

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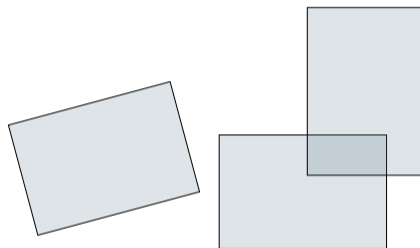


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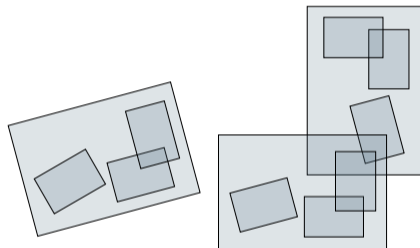


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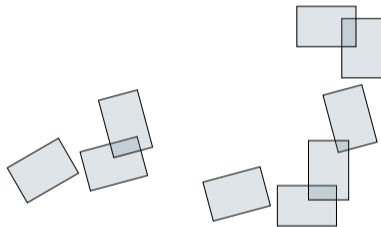


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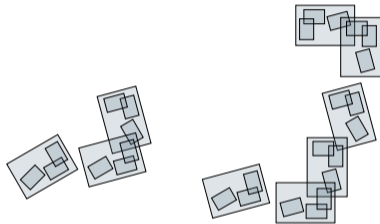
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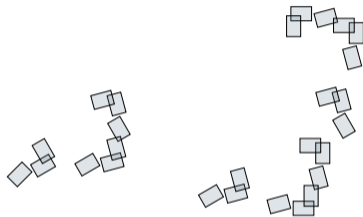


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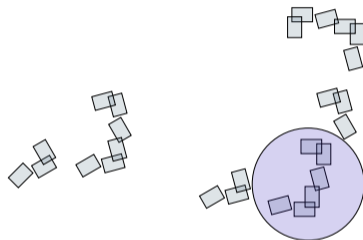


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## Application: Bernoulli convolutions

Fix  $0 < \lambda < 1$ .

Let  $\nu_\lambda$  = the distribution of the random real number

$$\sum_{k=0}^{\infty} \pm \lambda^k \quad (\text{signs i.i.d. and uniform})$$

Then

$$\sum_{k=0}^{\infty} \pm \lambda^k = \pm 1 + \lambda \cdot \sum_{k=0}^{\infty} \pm \lambda^k$$

The inner sum has the same distribution as  $\nu_\lambda$ , so, conditioning on the first sign, we just have  $\nu_\lambda$  translated by  $\pm 1$  and scaled by  $\lambda$ .

This shows that  $\nu_\lambda$  is self-similar.

The **trivial upper bound** on the dimension (analogous to that for sets) is

$$\dim v_\lambda \leq \min\left\{1, \frac{\log 2}{\log(1/\lambda)}\right\} = 1$$

when  $1/2 \leq \lambda < 1$ . So potentially there is equality, and perhaps smoothness.

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### Problem

For which  $\lambda$  is  $\nu_\lambda$  **absolutely continuous**?

For which  $\lambda$  is  **$\dim \nu_\lambda = 1$** ?

(the former implies the latter).

## A very brief history:

- ▶ Jessen and Wintner 1935: Laws of pure type.
- ▶ Erdős 1939: If  $\lambda^{-1}$  is Pisot, then  $\nu_\lambda \perp \text{Leb}$  (and  $\dim \nu_\lambda < 1$  [Garsia 1963]).
- ▶ Salem 1963:  $\widehat{\nu}_\lambda(k) \xrightarrow[k \rightarrow \infty]{} 0 \iff \lambda^{-1}$  is Pisot.
- ▶ Solomyak 1995:  $\nu_\lambda \ll \text{Leb}$  for a.e.  $\lambda \in (1/2, 1)$ .
- ▶ Peres-Schlag 2000:  $\dim\{1 - t < \lambda < 1 : \nu_\lambda \perp \text{Leb}\} \rightarrow 0$  as  $t \rightarrow 1$ .

Theorem (H. 2014)

$$\dim\{\lambda \in [\frac{1}{2}, 1) : \dim v_\lambda < 1\} = 0$$



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Theorem (Shmerkin 2014)

$$\dim\{\lambda \in [\frac{1}{2}, 1) : v_\lambda \ll \text{Leb}\} = 0$$

The proofs use that outside a dimension 0 set of  $\lambda$ , there is exponential separation.  
The second theorem also involves a Fourier-theoretic argument.

### Theorem (Varjú 2019?)

For every  $\varepsilon > 0$  there exists a  $c > 0$ , with the following property: If  $\lambda$  is an algebraic number with Mahler measure  $M_\lambda$  and satisfying

$$\lambda > 1 - c \min\{\log M_\lambda, (\log M_\lambda)^{-1-\varepsilon}\}$$

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### Theorem (Breuillard-Varjú 2019?)

$$\{\lambda \in [\frac{1}{2}, 1) : \dim \nu_\lambda < 1\} = \overline{\{\lambda \in [\frac{1}{2}, 1) : \dim \nu_\lambda < 1 \text{ and } \lambda \text{ is algebraic}\}}$$

The proofs rely partly on more quantitative estimates of what exponential separation.

## Related results using similar philosophy:

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5. H.-Rapaport (in progress): Replace separation with exponential separation for **self-affine** sets in  $\mathbb{R}^2$ . New phenomenon: In reducible case, must exclude set supported on quadratic curves! (Examples exist by Bandt-Kravchenko).



The main conjecture is still open...