

# A multi-scale approach to the Erdős-Falconer type single distance problems.

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May 22, 2013

## Background

Problems

A definition

## Multi-scale approach

A convoluted definition

Results

# Discrete single distance problem

- ▶ Conjecture[Erdős, 1946]: If  $E \subset \mathbb{R}^2$  is a set of  $n$  points, then no distance may occur more than  $\lesssim n\sqrt{\log n}$  times.

# Discrete single distance problem

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- ▶ Theorem,[Spencer, Szemerédi, Trotter, 1984]: For  $d = 2$ , no distance may occur more than  $\lesssim n^{\frac{4}{3}}$  times.

# Discrete single distance problem

- ▶ Lenz (Private Communication to Erdős): Discrete, Euclidean,  $d \geq 4$ .  
Arrange half of the points on a unit circle in two dimensions, and the other half on a unit circle in two other dimensions. A single distance will occur  $n^2$  times.

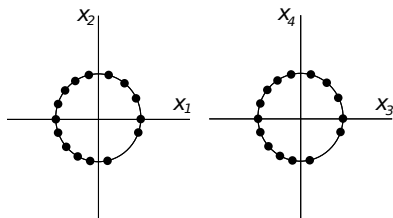


Figure: Lenz's example

# Falconer distance problem

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  - ▶ Theorem, [Erdős 2006]: For  $d \geq 3$ ,  $s > \frac{d}{2} + \frac{1}{3}$ , suffices.

# Continuous single distance problem

- ▶ Main estimate: If  $\mu$  is a Borel probability measure, supported on  $E \subset [0, 1]^d$ , with Hausdorff dimension  $s > \frac{d+1}{2}$ , and satisfying an energy estimate,

$$I_s = \int \int |x - y|^{-s} d\mu(x) d\mu(y) < \infty, \text{ then}$$

$$(\mu \times \mu)\{(x, y) \in E \times E : 1 \leq |x - y| \leq 1 + \epsilon\} \lesssim \epsilon.$$

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- ▶ False! Mattila 1985: Continuous, Euclidean,  $d = 2$ .  
Consider  $[0, 1] \times \mathcal{C}_\alpha$ , where  $0 < \alpha < \frac{1}{2}$ . We have bounded energy, but we don't get the "Main estimate."  
Can be adapted for  $d = 3$ , but not higher dimensions.

# $s$ -adaptability

## ► Definition

We say that a set  $P$  of  $n$  points in  $[0, 1]^d$  is  $s$ -adaptable, for  $0 \leq s \leq d$ , if it satisfies the following two conditions:

$$i) \frac{1}{\binom{n}{2}} \sum_{x \neq y \in P} \frac{1}{|x - y|^s} \lesssim 1.$$

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- Any subset is 0-adaptable
- Any  $d$ -adaptable subset is basically a perturbed lattice.



# Conversion mechanism

- ▶ Take a set in  $E \subset [0, 1]^d$  of  $n$ , which is “ $s$ -adaptable” (basically a discrete energy condition), and thicken each point by  $\epsilon = n^{-\frac{1}{s}}$ . The same continuous analysis techniques now apply directly to the thickened set.

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- ▶  $\Rightarrow n^{-2} \#(\text{single distance occurs}) \lesssim n^{-\frac{1}{s}}.$
- ▶ Theorems, [Iosevich, Jorati, Łaba, 2007]: For  $d \geq 2, s > \frac{d+1}{2}$ ,  $E \subset \mathbb{R}^d$  of  $n$  points, “homogeneous”, with “ $s$ -well-behaved” metrics  $\Rightarrow$  no single distance occurs more than  $n^{2-\frac{1}{s}}$  times.

# Where current $s$ -adaptability methods fail

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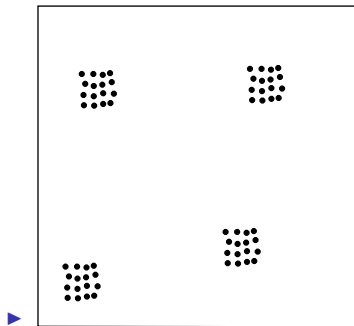


Figure: Concentrated clusters of points

# $(u, v; \alpha)$ -adaptability

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- ▶ (ii) Let the center of each  $Q_j$  be denoted  $q_j$ . The set of points,  $F := \{q_j : Q_j \in \mathcal{E}\}$  forms a  $u$ -adaptable point set in  $[0, 1]^d$ .

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- ▶ (iii) The points of  $E$  within each  $Q_j$  are distributed to form a  $v$ -adaptable set *within* the  $Q_j$ .

# An example of a $(u, v; \alpha)$ -adaptable set

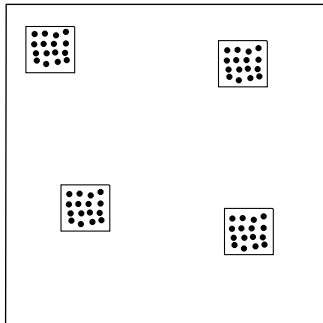
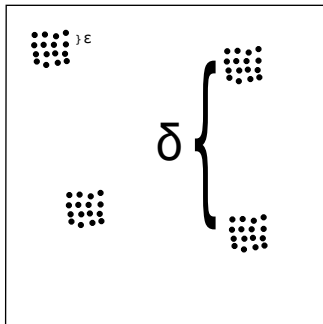


Figure: Cover of disjoint cubes (i)

# An example of a $(u, v; \alpha)$ -adaptable set



**Figure:** The centers of the clusters are  $u$ -adaptable on scale  $\delta$  (ii), and each cluster is  $v$ -adaptable on scale  $\epsilon$  (iii).

# Main results

## ► Theorem

Let  $E$  be a  $(u, v; \alpha)$ -adaptable set of  $N$  points, where  $u \geq \frac{d-1}{2}$ , and  $t = \min\{1, u - \frac{d-1}{2}\}$  then for  $\epsilon = N^{-\frac{\alpha u + (1-\alpha)v}{uv}}$ , we have

$$|\{(x, y) \in E \times E : 1 \leq |x - y| \leq 1 + \epsilon\}| \lesssim N^{2 - (2\alpha + \frac{t-\alpha}{u} - \frac{d-1}{v}\alpha)}$$

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## ► Corollary (one illustrative example)

Many new non-trivial estimates for the range  $s < \frac{uv}{\alpha u + (1-\alpha)v}$ .

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- In particular, we now have non-trivial estimates for a wide class of sets which are only  $s$ -adaptable for  $s < \frac{d-1}{2}$ .

# A word on the proof

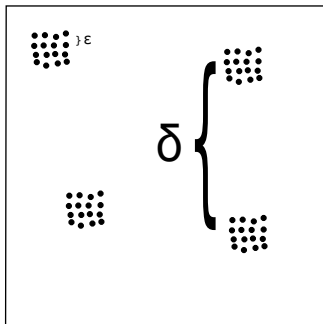


Figure: Simple combinatorics on scale  $\epsilon$ , Falconer's estimate on scale  $\delta$ .



# Thanks

# Thank You!