

Algorithmic Fractal Dimensions

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Lectures

1. Information and Dimensions, Classical and Algorithmic
2. Algorithmic Dimensions in Fractal Geometry
3. **Mutual Dimensions and Finite-State Dimensions**

Lecture 3. Mutual Dimensions and Finite-State Dimensions

Today's topics

Mutual dimensions

Data processing inequalities

Borel Normality

Finite-state dimension

Zeta-dimension

Copeland-Erdős sequences

Preserving finite-state dimension

Mutual Dimensions

(Case and J. Lutz 2015)

In both Shannon and algorithmic information theories, applications to communications and computation typically involve the mutual (shared) information between data objects. The following definition, which goes back to Kolmogorov, is analogous to that of Shannon mutual information.

Definition

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$$I(p : q) = K(p) - K(p|q).$$

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Symmetry of information:

$$\begin{aligned} I(p : q) &= K(p) + K(q) - K(p, q) + O(1) \\ &= I(q : p) + O(1). \end{aligned}$$

Definition

The **mutual information** between sets $E \subseteq \mathbb{R}^m$ and $F \subseteq \mathbb{R}^n$ is

$$I(E : F) = \min\{I(p : q) \mid p \in \mathbb{Q}^m \cap E \text{ and } q \in \mathbb{Q}^n \cap F\}.$$

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Definition

The **mutual information** between $x \in \mathbb{R}^m$ and $y \in \mathbb{R}^n$ at **precision** $r \in \mathbb{N}$ is

$$I_r(x : y) = I(B_{2^{-r}}(x) : B_{2^{-r}}(y)).$$

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The **mutual dimension** between $x \in \mathbb{R}^m$ and $y \in \mathbb{R}^n$ is

$$\text{mdim}(x : y) = \liminf_{r \rightarrow \infty} \frac{I_r(x : y)}{r}.$$

Data Processing Inequalities

- In Shannon information theory: If X , Y , and Z are ensembles and $f : X \rightarrow Y$, then

$$I(f(X); Z) \leq I(X; Z).$$

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$$I(f(x) : z) \leq I(x : z) + c_f.$$

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- Today: If $f : \mathbb{R}^m \rightarrow \mathbb{R}^n$ is computable and Lipschitz, then, for all $x \in \mathbb{R}^m$ and $z \in \mathbb{R}^t$,

$$\text{mdim}(f(x) : z) \leq \text{mdim}(x : z).$$

Why/what Lipschitz??

Why/what Lipschitz??

Example

Let $f : \mathbb{R} \rightarrow \mathbb{R}^2$ be computable and **space-filling**, in the sense that $[0, 1]^2 \subseteq \text{range}(f)$. (Examples are well known.) Choose $x \in \mathbb{R}$ such that $\dim(f(x)) = 2$, and let $z = f(x)$. Then

$$\begin{aligned} \text{mdim}(f(x) : z) &= \text{mdim}(f(x) : f(x)) \\ &= \dim(f(x)) \\ &= 2 \\ &> \dim(x) \\ &\geq \text{mdim}(x : z). \end{aligned}$$

Definition

$f : \mathbb{R}^m \rightarrow \mathbb{R}^n$ is **Lipschitz** if there is a real number $c > 0$ such that, for all $x, x' \in \mathbb{R}^m$,

$$|f(x) - f(x')| \leq c|x - x'|.$$

Intuition: f is not so sensitive to its input that it can compress a great deal of “sparse” high-precision information about its input into “dense” lower-precision information about its output $f(x)$.

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To repeat, the **data-processing inequality**

$$\text{mdim}(f(x) : z) \leq \text{mdim}(x : z)$$

holds for all computable, Lipschitz $f : \mathbb{R}^m \rightarrow \mathbb{R}^n$.

Dai, Lathrop, J. Lutz, Mayordomo 2004

- A finite-state version of classical Hausdorff (fractal) dimension.
- For a sequence $S \in \Sigma^\infty$ (where $\Sigma = \{0, 1, \dots, k-1\}$), $\dim_{\text{FS}}(S) =$ “asymptotic density of finite-state information in S ” $\in [0, 1]$.
- First defined using finite-state gamblers.

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- Equivalent definitions:
 - Information-lossless finite-state compressors (DLMM 2004)
 - Block-entropy rates (Bourke, Hitchcock, Vinodchandran 2006)
 - Finite-state log-loss predictors (Hitchcock 2003)

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Robust!

Normal Sequences

$$\Sigma = \{0, 1, \dots, k-1\}$$

For $S \in \Sigma^\infty$, $w \in \Sigma^+$, $n \in \mathbb{Z}^+$,

$$\begin{aligned} \text{freq}_n(w, S) &= \frac{|\{i < n \mid S[i..i + |w| - 1] = w\}|}{n} \\ &= n^{\text{th}} \text{ frequency of } w \text{ in } S. \end{aligned}$$

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Definition (Borel 1909)

A sequence $S \in \Sigma^\infty$ is **normal** if

$$(\forall w \in \Sigma^+) \lim_{n \rightarrow \infty} \text{freq}_n(w, S) = k^{-|w|}.$$

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Fact (Schnorr, Stimm 1972; BHV 2006)

S is normal $\Leftrightarrow \dim_{\text{FS}}(S) = 1$.

Copeland-Erdős Sequences

For $n \in \mathbb{Z}^+$, $\sigma_k(n) = k$ -ary expansion of n .

Definition

The k -ary **Copeland-Erdős sequence** of an infinite set

$$A = \{a_1 < a_2 < \dots\} \subseteq \mathbb{Z}^+$$

is the sequence $\text{CE}_k(A) = \sigma_k(a_1)\sigma_k(a_2)\sigma_k(a_3)\dots$

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Theorem (Champernowne 1933)

The decimal **Champernowne sequence**

$$\text{CE}_{10}(\mathbb{Z}^+) = 12345678910111213\dots$$

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Theorem (Champernowne 1933)

The sequence $\text{CE}_{10}(\text{PRIMES}) = 23571113171923\dots$ *is also normal.*

Theorem (Copeland & Erdős 1946)

For all $k \geq 2$, $CE_k(\text{PRIMES})$ is normal.

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Outline of proof

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Outline of proof

1. For all sufficiently dense $A \subseteq \mathbb{Z}^+$, $CE_k(A)$ is normal.
2. PRIMES is sufficiently dense. □

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OBJECTIVE

Extend this to a quantitative lower-bound criterion for the finite-state dimensions of Copeland-Erdős sequences.

The Four Dimensions

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3. Zeta-dimension

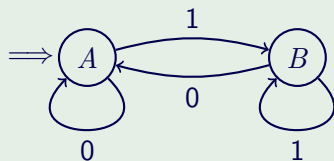
The Four Dimensions

1. Finite-state dimension
2. Finite-state strong dimension
3. Zeta-dimension
4. Lower zeta-dimension

Dai, Lathrop, J. Lutz, Mayordomo 2004

Example

A 2-state gambler on the alphabet $\Sigma = \{0, 1\}$:



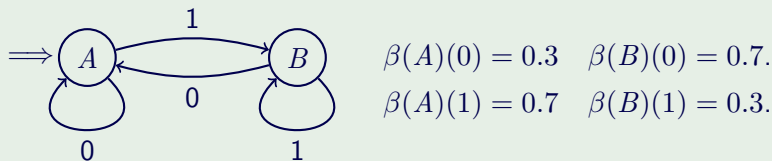
$$\beta(A)(0) = 0.3 \quad \beta(B)(0) = 0.7.$$

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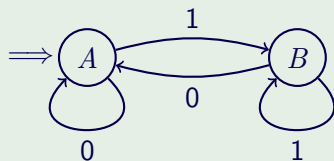


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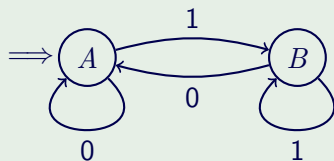
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$$d_G(\lambda) = 1 \text{ always}$$

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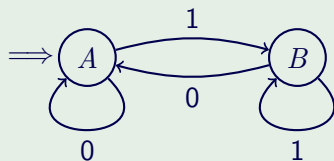
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$$d_G(1) = 2(0.7)d_G(\lambda) = 1.4$$

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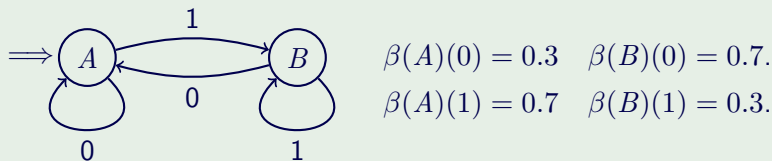
$$d_G(1) = 2(0.7)d_G(\lambda) = 1.4$$

$$d_G(11) = 2(0.3)d_G(1) = 0.84$$

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$$d_G(11) = 2(0.3)d_G(1) = 0.84$$

$$d_G(110) = 2(0.7)d_G(11) = 1.176$$

\vdots

Definition

Let G be a finite-state gambler (FSG) over $\Sigma = \{0, 1, \dots, k-1\}$, and let $s \in [0, \infty)$ be a “fairness parameter.” The s -gale of G is the function $d_G^{(s)} : \Sigma^* \rightarrow [0, \infty)$ given by

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$$d_G^{(s)}(wa) = k^s d_G^{(s)}(w) \beta(\delta(w))(a)$$

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Definition

1. G s -succeeds on $S \in \Sigma^\infty$ if $\limsup_{n \rightarrow \infty} d_G^{(s)}(S \upharpoonright n) = \infty$.
2. G strongly s -succeeds on $S \in \Sigma^\infty$ if $\liminf_{n \rightarrow \infty} d_G^{(s)}(S \upharpoonright n) = \infty$.

Definition

The **finite-state dimension** of a sequence $S \in \Sigma^\infty$ is

$$\dim_{\text{FS}}(S) = \inf\{s \mid \exists \text{ an FSG that } s\text{-succeeds on } S\}.$$

Athreya, Hitchcock, J. Lutz, Mayordomo 2007

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The **finite-state strong dimension** of a sequence $S \in \Sigma^\infty$ is

$$\text{Dim}_{\text{FS}}(S) = \inf\{s \mid \exists \text{ an FSG that strongly } s\text{-succeeds on } S\}.$$

In general, $0 \leq \dim_{\text{FS}}(S) \leq \text{Dim}_{\text{FS}}(S) \leq 1$.

Invented many times! “Discrete fractal dimension”

Definition

Let $A \subseteq \mathbb{Z}^+$.

- The **A-zeta function** $\zeta_A : [0, \infty) \rightarrow [0, \infty]$ is defined by

$$\zeta_A(s) = \sum_{n \in A} n^{-s}.$$

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Entropy characterization (Cahen 1894)

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Definition

The **lower zeta-dimension** of $A \subseteq \mathbb{Z}^+$ is

$$\dim_\zeta(A) = \liminf_{n \rightarrow \infty} \frac{\log |A \cap \{1, \dots, n\}|}{\log n}.$$

Entropy characterization (Cahen 1894)

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Definition

The **lower zeta-dimension** of $A \subseteq \mathbb{Z}^+$ is

$$\dim_\zeta(A) = \liminf_{n \rightarrow \infty} \frac{\log |A \cap \{1, \dots, n\}|}{\log n}.$$

Clearly, $0 \leq \dim_\zeta(A) \leq \text{Dim}_\zeta(A) \leq 1$.

Theorem (Gu, J. Lutz, and Moser 2007)

- For every infinite $A \subseteq \mathbb{Z}^+$,
 $\dim_{\text{FS}}(\text{CE}_k(A)) \geq \dim_{\zeta}(A)$ and
 $\text{Dim}_{\text{FS}}(\text{CE}_k(A)) \geq \text{Dim}_{\zeta}(A)$.

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- For *any* four real numbers

$$\begin{array}{ccccccc} 0 & \leq & \alpha & \leq & \beta & & \\ & & \wedge & & \wedge & & \\ & & \gamma & \leq & \delta & \leq & 1, \end{array}$$

there exists an infinite $A \subseteq \mathbb{Z}^+$ with

$$\begin{array}{ll} \dim_{\zeta}(A) = \alpha & \text{Dim}_{\zeta}(A) = \beta \\ \dim_{\text{FS}}(\text{CE}_k(A)) = \gamma & \text{Dim}_{\text{FS}}(\text{CE}_k(A)) = \delta. \end{array}$$

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 $\dim_{\text{FS}}(\text{CE}_k(A)) \geq \dim_{\zeta}(A)$ and $\text{Dim}_{\text{FS}}(\text{CE}_k(A)) \geq \text{Dim}_{\zeta}(A)$. (*)
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$$\begin{array}{ll} \dim_{\zeta}(A) = \alpha & \text{Dim}_{\zeta}(A) = \beta \\ \dim_{\text{FS}}(\text{CE}_k(A)) = \gamma & \text{Dim}_{\text{FS}}(\text{CE}_k(A)) = \delta. \end{array}$$

(*) implies the Copeland-Erdős theorem.

QUESTION

Which operations on sequences preserve normality?

Preserving Normality I: Subsequence Selection

Theorem (Wall 1949)

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If S is normal and S' is a subsequence chosen using a regular language, then S' is normal.

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If S is normal and S' is a subsequence chosen using a regular language, then S' is normal.

Theorem (Merkle, Reimann 2003)

*Subsequence selection using a context-free language — even a one-counter language — does **not** preserve normality.*

Definition (Borel 1909)

A real number α is **normal in base k** if its base- k expansion is a normal sequence.

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Theorem (Cassels 1959, Schmidt 1960)

A real number may be normal in one base, but not in another.

Preserving Normality II: Real Arithmetic

Definition (Borel 1909)

A real number α is **normal in base k** if its base- k expansion is a normal sequence.

Theorem (Cassels 1959, Schmidt 1960)

A real number may be normal in one base, but not in another.

Theorem (Wall 1949)

If q is a non-zero rational, then, for every real number α , α is normal in base $k \Rightarrow q + \alpha$ and $q\alpha$ are normal base k .

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Which operations on sequences preserve finite-state dimension?

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Observation: Every operation that preserves finite-state dimension preserves normality.

Preserving FSD I: Subsequence Selection

Observation: Let

$$S = b_0 0 b_1 0 b_2 0 b_3 \dots ,$$

where $b_0 b_1 b_2 b_3 \dots \in \{0, 1\}^\infty$ is normal, and consider

$$S' = b_0 b_1 b_2 b_3 \dots ,$$

$$S'' = 0000 \dots .$$

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Then

$$\dim_{\text{FS}}(S) = \text{Dim}_{\text{FS}}(S) = 1/2$$

$$\dim_{\text{FS}}(S') = \text{Dim}_{\text{FS}}(S') = 1$$

$$\dim_{\text{FS}}(S'') = \text{Dim}_{\text{FS}}(S'') = 0 .$$

Preserving FSD I: Subsequence Selection

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Finite state dimension is not preserved by even the simplest subsequence selections.

Theorem (Doty, Lutz, and Nandakumar 2007)

For every base $k \geq 2$, every nonzero rational q , and every real number α , the base- k expansions of α , $q + \alpha$, and $q\alpha$ all have the same finite dimension and the same finite-state strong dimension.

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Gives a new proof of Wall's 1949 theorem.

Ingredients of Proof: Block-Entropy Rates

Notation:

- For $w, x \in \Sigma^+$,

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Ingredients of Proof: Block-Entropy Rates

- For $S \in \Sigma^\infty$ and $\ell \in \mathbb{Z}^+$, the ℓ^{th} **normalized lower and upper block entropy rates** of S are

$$H_\ell^-(S) = \frac{1}{\ell \log k} \liminf_{n \rightarrow \infty} H \left(\pi_{S,n}^{(\ell)} \right),$$

$$H_\ell^+(S) = \frac{1}{\ell \log k} \limsup_{n \rightarrow \infty} H \left(\pi_{S,n}^{(\ell)} \right),$$

where

$$\begin{aligned} H(\pi) &= \text{Shannon entropy of } \pi \\ &= \sum_w \pi(w) \log \frac{1}{\pi(w)}. \end{aligned}$$

Theorem (Bourke, Hitchcock, Vinodchandran 2005)

For all $S \in \Sigma^\infty$,

$$\dim_{\text{FS}}(S) = \inf_{\ell \in \mathbb{Z}^+} H_\ell^-(S),$$

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where m is the least positive integer for which there is an $n \times n$ non-negative real matrix $A = (a_{ij})$ satisfying:

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- $A\pi = \mu$, i.e., $\sum_{j=1}^n a_{ij}\pi(j) = \mu(i)$ for all $1 \leq i \leq n$.
- No row or column of A contains more than m non-zero entries. (“Dispersion is limited by m .”)

Definition

The **normalized upper log-dispersion** between sequences $S, T \in \Sigma^\infty$ is

$$\delta^+(S, T) = \limsup_{\ell \rightarrow \infty} \frac{1}{\ell \log k} \limsup_{n \rightarrow \infty} \delta \left(\pi_{S,n}^{(\ell)}, \pi_{T,n}^{(\ell)} \right).$$

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1. $\delta^+(S, T) \geq 0$, with equality **if (not iff)** $S = T$.
2. $\delta^+(S, T) = \delta^+(T, S)$.
3. $\delta^+(S, U) \leq \delta^+(S, T) + \delta^+(T, U)$.

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Theorem (Doty, Lutz, and Nandadumar 2007)

\dim_{FS} and Dim_{FS} are δ^+ -contractive:

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- Proof uses Schur concavity of Shannon entropy.

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Conjecture 2

Many of these more general theorems will drive the development of useful new methods.

Thank you!