

# Effective fractal dimension theory: exploring the extreme cases (II)

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# Left out Monday

- Open problems:
  - Partially complete problems
  - BPP sources
- References

# Today

0. Introduction of effective dimension
1. Resource-bounded Hausdorff dimension for Complexity Classes
2. **Compression and dimension for low resource bounds.**  
**Very effective construction of a normal sequence**
3. Looking back at fractal geometry, other metric spaces

# Compression characterizations of effective measure

- **Constructive Hausdorff dimension can be entirely defined using Kolmogorov complexity**

Theorem

*For every  $A \subseteq \{0, 1\}^\infty$ ,  $\text{cdim}(A) = \inf_{x \in A} \frac{K(x \upharpoonright n)}{n}$ .*

For a finite string  $w$ ,  $K(w)$  is the length of the shortest description from which  $w$  can be computably recovered

# Space-bounded Kolmogorov complexity characterizations

$$\text{KS}^f(w) = \min \{ |p| \mid U(p) = w \text{ in space } f(|w|) \}$$

Theorem

For every  $A \subseteq \{0, 1\}^\infty$ ,

$$\dim_{\text{pspace}}(A) = \inf_q \text{polynomial} \inf_{x \in A} \frac{\text{KS}^q(x \upharpoonright n)}{n}.$$

# What about time?

- Time-bounded Kolmogorov complexity is hard to work with due to invertibility issues
- $p$ -dimension (predictability) can be characterized in terms of a class of polynomial time reversible compressors: *compressors that do not start from scratch*
- I will leave out the technical definition, but for instance a compressor  $C$  for which  $C(w)$  and  $C(wu)$  have a common prefix of length at least  $|C(w)| - O(\log(|w|))$  does not start from scratch

## Theorem

*$p$ -dimension is exactly the best compression rate achievable through polynomial-time compressors that do not start from scratch*

# Pushdown dimension

We consider BPD the set of pushdown machines that work with a bounded number of  $\lambda$ -transitions per input symbol

Theorem

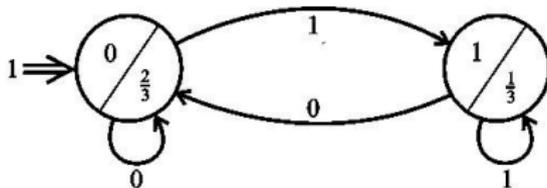
*BPD-dimension is exactly the best compression rate achievable through BPD-compressors*

**Still open for general PD-computation**

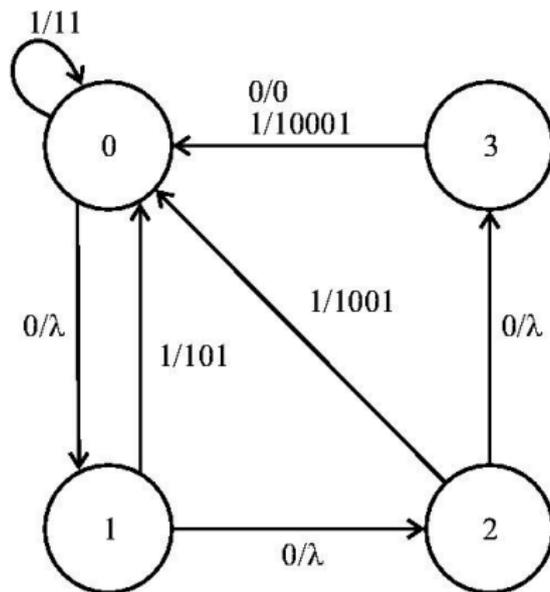
# Finite state dimension

We considered the case of Finite-State computation

$\dim_{\text{FS}}(A) = \inf \{s \mid \text{there is a Finite State } s\text{-gale that succeeds on } A\}$



# Finite state compression



The input can be recovered given the output and the final state

# Finite state dimension characterization

## Theorem

*Finite-state dimension is exactly the best compression rate achievable through finite-state compressors, that is,*

$$\dim_{\text{FS}}(x) = \inf_{C \text{ FS-comp}} \liminf_n \frac{|C(x \upharpoonright n)|}{n}$$

# FS-compressors and Lempel-Ziv algorithm

- **Lempel-Ziv algorithm** subsumes FS-compressors:

$$\rho_{LZ}(x) = \liminf \liminf_n \frac{|LZ(x \upharpoonright n)|}{n}$$

Theorem

For every  $x \in \{0, 1\}^\infty$

$$\rho_{LZ}(x) \leq \dim_{\text{FS}}(x)$$

- Lempel-Ziv algorithm is universal for FS dimension/compression
- It is known that there are sequences for which  $\rho_{LZ}(x) < \dim_{\text{FS}}(x)$

# Comparison among different levels

## Theorem

*PD-compression is incomparable with the Lempel-Ziv compression algorithm:*

- *There are sequences for which PD-compression is better than LZ.*
  - *There are sequences for which Lempel-Ziv compression is better than PD.*
- 
- There is a FS-random sequence that is not PD-random (note: FS-random is equivalent to FS-dimension 1)
  - There is a sequence such that  $\dim_{PD}(x) < \dim_{FS}(x) < 1$

# Open question

- Is PD-dimension 1 different from FS-dimension 1?
- Can PD-dimension be characterized in terms of compression?

# Open questions

- There are characterizations of effective fractal dimension in terms of Kolmogorov complexity/compressibility at the most and least restricted computation levels
- They happen for completely different reasons
- Understanding what happens at intermediate levels can have useful applications for learning/compression
- Understanding what happens with FS-dimension/randomness may be useful for number theory

## References for compression and dimension

- E. Mayordomo. A Kolmogorov complexity characterization of constructive Hausdorff dimension. *Information Processing Letters*, 84(1):1-3, 2002.
- M. López-Valdés and E. Mayordomo. Dimension is compression. In *Proceedings of the 30th International Symposium on Mathematical Foundations of Computer Science*, pages 676-685. Springer-Verlag, 2005.
- P. Albert, E. Mayordomo, and P. Moser. Bounded Pushdown dimension vs Lempel Ziv information density. *Computability and Complexity* pp. 95-114, *Essays Dedicated to Rodney G. Downey on the Occasion of His 60th Birthday* (Day, A., Fellows, M., Greenberg, N., Khossainov, B., Melnikov, A., Rosamond, F. (Eds.)) *Lecture Notes in Computer Science* book series (LNCS, volume 10010), 2017.

## References for compression and dimension

- J. J. Dai, J. I. Lathrop, J. H. Lutz, and E. Mayordomo. Finite-state dimension. *Theoretical Computer Science*, 310(1-3):1-33, 2004.
- D. Doty and J. Nichols. Pushdown dimension. *Theoretical Computer Science*, 381(1-3):105-123, 2007.
- W. Merkle, J. Reimann. On selection functions that do not preserve normality. *Theory of Computing Systems*, 39(5):685-697, 2006.

# Very effective construction of an absolutely normal sequence

- At the lowest resource-bounded level, FS, dimension meets number theory
- Sequences with FS-dimension 1 are exactly Borel normal sequences
- FS-dimension is not closed under base change
- Can we use a constructive probabilistic method to construct an absolutely normal sequence?

# Normal numbers

Borel, 1909:

- A real number  $\alpha$  is **normal** in base  $b$  ( $b \geq 2$ ) if, for every finite sequence  $w$  of base- $b$  digits,

$$\lim_n \frac{N_\alpha(w, n)}{n} = \frac{1}{b^{|w|}}$$

the asymptotic, empirical frequency of  $w$  in the base- $b$  expansion of  $\alpha$  is  $b^{-|w|}$ .

- $\alpha$  is **absolutely normal** if it is normal in every base  $b \geq 2$ .

Theorem (Cassels 1959, Schmidt 1960)

*There exist a number that is normal in base 2 but not in base 3.*

# Examples of normal numbers

- Champernowne's sequence

0.123456...

- Copeland-Erdős sequence

0.235711...

Pretty far from natural

# Absolutely Normal numbers

## Theorem (Borel)

*Almost every real number (i.e., every real number outside a set of Lebesgue measure 0) is absolutely normal.*

- Computer analyses of the expansions of  $\pi$ ,  $e$ ,  $\sqrt{2}$ ,  $\ln 2$ , and other irrational numbers that arise in common mathematical practice **suggest** that these numbers are absolutely normal.
- No such “natural” example of a real number has been proven to be normal in *any* base, let alone absolutely normal.
- The **conjectures that every algebraic irrational is absolutely normal** and that  $\pi$  is absolutely normal are especially well known open problems.
- In cryptographic applications constants such as  $\pi$  and  $\sqrt{2}$  are used and expected to be “somehow random” (**nothing up my sleeve numbers**)

# Computing absolutely normal numbers

- We are interested in the **complexity of** explicitly **computing** an absolutely normal real number
- Sierpinski and Lebesgue gave explicit constructions of absolutely normal numbers in 1917 (intricate limiting processes, no complexity or insight into the nature of the numbers constructed)
- Turing (1936, unpublished) gave a **constructive proof** that almost all real numbers are absolutely normal and then *derived* constructions of absolutely normal numbers from this proof.

# Turing vision

- We believed that Schmidt (1960) was the first to construct absolutely normal numbers
- But the most surprising part was Turing's idea of effective measure and its application as an effective probabilistic method
- As analysed by Figueira, Becher and Picci (2007) Turing's unpublished note shows is that the set of non-normal numbers has computable measure 0
- The formalization of effective measure and randomness did not come until the sixties: Martin-Löf (paper 1966), Von-Mises, Solomonoff (1960), Kolmogorov, ...
- We now know that normality is a type of randomness

# Computing absolutely normal numbers

- (Becher, Heiber, and Slaman 2013, simultaneous work from other authors) Algorithm that computes an absolutely normal number in polynomial time.
- Specifically, they compute the binary expansion of an absolutely normal number  $x$ , with the  $n$ th bit of  $x$  appearing after  $O(n^2 \text{polylog}(n))$  steps.
- Here we present a new algorithm that computes an absolutely normal in **nearly linear time**. Our algorithm computes the binary expansion of an absolutely normal number  $x$ , with the  $n$ th bit of  $x$  appearing after  $O(n \text{polylog}(n))$  steps.

Note: The term “nearly linear time” was introduced by Gurevich and Shelah (1989). While linear time computability is very model-dependent, nearly linear time is very robust.

# Gales and martingales in base $b$

- $\Sigma_b = \{0, \dots, b-1\}$  the base  $b$  alphabet
- $\Sigma_b^*$  are finite sequences,  $\Sigma_b^\infty$  infinite sequences
- For  $s \in [0, \infty)$ , an **s-gale** is a function  $\Sigma_b^* \rightarrow [0, \infty)$  such that for  $w \in \Sigma_b^*$

$$d(w) = \frac{d(w0) + d(w1)}{b^s}$$

- A **martingale** is a function  $d : \Sigma_b^* \rightarrow [0, \infty)$  with the fairness property, for every finite sequence  $w$ ,

$$d(w) = \frac{\sum_{i \in \Sigma_b} d(wi)}{b}$$

- The **success set** of an  $s$ -gale  $d$  is

$$S^\infty[d] = \left\{ x \in \Sigma_b^\infty \mid \limsup_n d(x \upharpoonright n) = \infty \right\}$$

- **Notice that if  $d$  is an  $s$ -gale then  $d'(w) = b^{(1-s)|w|}d(w)$  is a martingale**

# Finite-state randomness

## Definition

$x$  is **FS random** if no finite automata computable martingale succeeds on  $x$

**Notice that if  $\dim_{\text{FS}}(x) < 1$  then  $x$  is not FS-random**

# Normality and Finite-state randomness

- If  $x$  is the base  $b$  representation of a non-normal number,  $w$  is a finite string that is “unbalanced” in  $x$ , for instance i.o.  $w$  appears more often than it should, a finite automata can bet a bit more than its fair share and make infinite money ...
- Clearly FS random sequences are representations of base  $b$  normal numbers
- Even better **FS-random = normal** –Schnorr and Stimm (1972)

# Finite-State dimension

Schnorr and Stimm (1972) implicitly defined **finite-state martingales** and proved that every sequence  $S \in \Sigma_b^\infty$  obeys this dichotomy:

- 1 If  $S$  is  $b$ -normal, then no finite-state base- $b$  martingale succeeds on  $S$ . (In fact, every finite-state base- $b$  martingale decays exponentially on  $S$ .)
- 2 If  $S$  is not  $b$ -normal, then some finite-state base- $b$  martingale **succeeds exponentially** on  $S$ .

Using dimension terminology

- 1 If  $S$  is  $b$ -normal, then  $S$  is FS-random.
- 2 If  $S$  is not  $b$ -normal, then  $\dim_{\text{FS}}(S) < 1$ .

Therefore **FS-dimension 1 = normal**

## Remember ...

- **Objective** Compute a (provably) absolutely normal number  $x \in (0, 1)$  **fast**.
- Absolutely normal number means that is normal in every base
- We need to construct a single real number that is  $b$ -normal for every base  $b$
- We will use Lempel-Ziv algorithm that is universal for FS-compressors **in a single base**

# Lempel-Ziv martingales

Feder (1991) implicitly defined the **base- $b$  Lempel-Ziv martingale**  $d_{LZ(b)}$  and proved that it is at least as successful **on every sequence** as every finite-state martingale.

$\therefore$  if  $S \in \Sigma_b^\infty$  is not normal, then  $\dim_{d_{LZ(b)}}(S) < 1$ .

$\therefore x \in (0, 1)$  is absolutely normal if none of the martingales  $d_{LZ(b)}$  succeed **exponentially** on the base- $b$  expansion of  $x$ .

Moreover,  $d_{LZ(b)}$  has a fast and beautiful theory.

Celebrated Lempel-Ziv compression algorithm and martingale can be both computed very efficiently (time very close to linear)

# Lempel-Ziv martingales

How  $d_{LZ(b)}$  works:

Parse  $w \in \Sigma_b^*$  into distinct **phrases**, using a growing tree whose leaves are all of the previous phrases.

At each step, bet on the next digit in proportion to the number of leaves below each of the  $b$  options.

## Base change notation

- For a real  $x$ ,  $\text{seq}_b(x) \in \Sigma_b^\infty$  is the base- $b$  representation of  $x$
- For a sequence  $S \in \Sigma_b^\infty$ ,  $\text{real}_b(S) \in [0, 1]$  is the real number represented by  $S$

# How to construct an absolutely normal number

- For each base  $b$ , we need to construct  $x$  such that  $b$ -Lempel-Ziv martingale does not succeed on  $x$
- We need to construct a single real number that is  $b$ -normal for every base  $b$
- It suffices to translate  $b$ -Lempel-Ziv martingale into base 2 (very efficiently)
- We need a martingale  $d : \Sigma_2^* \rightarrow [0, \infty)$  that succeeds on base 2 representations of the numbers for which  $b$ -Lempel-Ziv martingale succeeds
- For this translation to be possible (**and efficient**) the martingale must be quite well behaving ...

# How to construct an absolutely normal number

- ① Transform  $b$ -Lempel-Ziv martingale into a better behaving and still efficient martingale that still succeeds on not  $b$ -normal sequences
- ② Efficiently change base for the resulting martingale
- ③ Efficiently combine all resulting martingales into one
- ④ Diagonalize resulting martingale

## Savings Accounts, strong success

- The value of Lempel-Ziv martingale  $d_{LZ(b)}$  on a certain infinite string  $S$  can fluctuate a lot
- This makes base change more complicated (and time consuming)
- We use the notion of “savings account” here, we are looking at an alternative martingale that **keeps money aside for the bad times to come**

The **strong success set** of an  $s$ -supergale  $d$  is

$$S_{\text{str}}^{\infty}[d] = \left\{ x \in \{0, 1\}^{\infty} \mid \lim_n d(x \upharpoonright n) = \infty \right\}$$

# Savings Accounts, strong success

- We construct a new martingale  $d'_b$  that is a conservative version of  $d_{LZ(b)}$
- $d'_b$  strongly succeeds at least on non- $b$ -normal sequences

$$\{S \mid \dim_{LZ}(S) < 1\} \subseteq S_{\text{str}}^{\infty}[d'_b]$$

- $d'_b$  can be computed in nearly linear time
- If  $S \notin S_{\text{str}}^{\infty}[d'_b]$  then  $S$  is  $b$ -normal

# Base Change

- We want an absolutely normal real number  $x$ , that is, the base  $b$  representation  $\text{seq}_b(x)$  is not in  $S^\infty[d'_b]$
- For this we convert  $d'_b$  into a base-2 martingale  $d_b^{(2)}$  succeeding on the **base-2 representations of the reals with base- $b$  representation in  $S_{\text{str}}^\infty[d'_b]$**
- Again,  $d_b^{(2)}$  succeeds on  $\text{seq}_2(\text{real}_b(S_{\text{str}}^\infty[d'_b]))$

$$\text{real}_b(S_{\text{str}}^\infty[d'_b]) \subseteq \text{real}_2(S_{\text{str}}^\infty[d_b^{(2)}])$$

- We use Carathéodory construction to define measures
- Computing in nearly linear time is also delicate
- In fact our computation  $\widehat{d_b^{(2)}}$  approximates slowly  $d_b^{(2)}$

$$|\widehat{d_b^{(2)}}(y) - d_b^{(2)}(y)| \leq \frac{1}{|y|^3}$$

# Absolutely Normal Numbers

- From previous steps we have a family of martingales  $(d_b^{(2)})_b$  so that  $d_b^{(2)}$  **succeeds on base-2 representations of non- $b$ -normal sequences**
- For each  $b$  we have a nearly linear time computation  $\widehat{d_b^{(2)}}$
- We want to construct  $S \notin S^\infty[d_b^{(2)}]$  for every  $b$
- Nearly linear time makes it painful to construct a martingale  $d$  for the union of  $S^\infty[d_b^{(2)}]$
- Then we diagonalize over  $d$  to construct  $S$

# Martingale diagonalization

- For a martingale  $d$ , how to construct  $x$  such that  $d$  martingale does not succeed on  $x$  (with time similar to the computation time for  $d$ )?
- Recursive construction, if we have the prefix  $x \upharpoonright n$  choose the next symbol  $i$  such that

$$d(x \upharpoonright ni)$$

is the minimum over all possible symbols

- By the fairness condition of a martingale

$$d(w) = \frac{\sum_{i \in \Sigma_b} d(wi)}{b}$$

$d$  does not succeed on the resulting  $x$

- Time is  $n \cdot t(n)$  if  $d$  is computable in time  $t(n)$

## Time bounds ...

- All the steps were performed in nearly linear time on a common **time bound independent of base  $b$**
- Many technical details were simplified in this presentation ... please read paper

# Base invariance

- Normality corresponds exactly to the lowest level of algorithmic randomness, Finite-State randomness
- Finite-State randomness and Finite-State dimension are not closed under base change
- $p$ -dimension and  $p$ -randomness are closed under base change
- What about intermediate levels, PD, LZ, nearly linear time?

# Conclusions

- Lots of remaining questions,
  - can we substitute “suspected” absolute normal numbers by proven absolutely normal numbers in Cryptography?
  - “biased-normality”? (based on FS-dimension)
  - Tight complexity for the operation of base change
  - The algorithm of Becher, Heiber, and Slaman’s has nearly quadratic time but (apparently) a much lower discrepancy. Can we improve our discrepancy while maintaining nearly linear time?

## References for construction of absolutely normal numbers

- J. H. Lutz and E. Mayordomo, Computing absolutely normal numbers in nearly linear time, submitted. (arxiv 1611.05911)
- V. Becher, P.A. Heiber, and T. Slaman, A polynomial-time algorithm for computing absolutely normal numbers, Information and Computation 232: 1–9, 2013.
- C. Aistleitner, V. Becher, A.-M. Scheerer, and T. Slaman, On the construction of absolutely normal numbers, 2017, to appear in Acta Arithmetica. (arXiv 1707.02628)
- V. Becher, S.Figueira, and R. Picchi, Turing's unpublished algorithm for normal numbers, Theoretical Computer Science 377: 126-138, 2007.

# Next lecture

0. Introduction of effective dimension
1. Resource-bounded Hausdorff dimension for Complexity Classes
2. Compression and dimension for low resource bounds. Very effective construction of a normal sequence
3. **Looking back at fractal geometry, other metric spaces**