

Algorithmic randomness for non-uniform probability measures

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Introduction

In algorithmic randomness, a sub-discipline of computability theory, one major research focus is to study the relationships between various formal definitions of randomness.

In this talk, I will focus primarily on two equivalent definitions of random infinite sequence:

- ▶ Kolmogorov incompressible sequences, and
- ▶ Martin-Löf random sequences.

The equivalence of these two definitions, known as the Levin-Schnorr theorem, is one of the central results in the theory of algorithmic randomness.

Introduction (continued)

The goals of today's talk are to:

- ▶ motivate and precisely define these two notions of randomness;
- ▶ outline the proof of their equivalence;
- ▶ extend these definitions to computable probability measures on 2^ω ; and
- ▶ to discuss some recent work on the interplay between
 - (i) the growth rates of the initial segment complexity of sequences random with respect to some computable probability measure, and
 - (ii) certain properties of this underlying measure (such as continuity vs. discontinuity).

Outline

1. Definitions of algorithmic randomness
2. The Levin-Schnorr theorem
3. Randomness with respect to a computable measure
4. The initial segment complexity of proper sequences

1. Definitions of algorithmic randomness

A motivating question

What does it mean for a sequence of 0s and 1s to be random?

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(3) 10100010110101000110101101000111110000111110100011

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(4) 00100100001111110110101010001000100001011010001100

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(5) 01001001011010111111110101010011110011111111110010

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(3) List names of American states alphabetically: 0 = even # of letters, 1 = odd # of letters.

(4) First fifty digits of the binary expansion of π .

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(5) 0100100101101011111111010101001111001111111110010

(3) List names of American states alphabetically: 0 = even # of letters, 1 = odd # of letters.

(4) First fifty digits of the binary expansion of π .

(5) Fifty digits obtained from random.org (atmospheric noise?).

Two rough definitions of algorithmic randomness

Intuitively, a sequence is algorithmically random if it contains no “effectively definable regularities.”

“effectively definable regularities” \approx patterns definable in some computable way

Suppose $X \in 2^\omega$ contains no such regularities. Then:

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Suppose $X \in 2^\omega$ contains no such regularities. Then:

1. Initial segments of X cannot be compressed by an effective procedure.
2. X cannot be detected as non-random by any effective test for randomness.

Kolmogorov Complexity (relative to a prefix-free machine M)

Let $M : 2^{<\omega} \rightarrow 2^{<\omega}$ be a Turing machine that is *prefix-free*, which means that if $M(\sigma)\downarrow$ and $\sigma \prec \tau$, then $M(\tau)\uparrow$.

Definition

The *prefix-free Kolmogorov complexity* of $\sigma \in 2^{<\omega}$ relative to M is

$$K_M(\sigma) = \min\{|\tau| : M(\tau)\downarrow = \sigma\}.$$

(We set $K_M(\sigma) = \infty$ if σ is not in the range of M .)

Some remarks

Given a prefix-free machine M such that $M(\tau) = \sigma$, τ is called an *M -description* of σ .

$K_M(\sigma)$ is thus the length of the shortest M -description of σ .

We might say that σ is random relative to M if $K_M(\sigma) \approx |\sigma|$, but we want a definition of randomness that is not dependent upon our choice of M .

Question: In terms of which machine should we define randomness?

Answer: We restrict to a *universal*, prefix-free Turing machine.

Universal Prefix-Free Turing Machines

We can effectively enumerate the collection of all prefix-free Turing machines $\{M_i\}_{i \in \omega}$.

Then the function U defined by

$$U(1^e 0 \sigma) \simeq M_e(\sigma)$$

for every $e \in \omega$ and every $\sigma \in 2^{<\omega}$ is a *universal prefix-free Turing machine*.

Kolmogorov complexity

Let $U : 2^{<\omega} \rightarrow 2^{<\omega}$ be a universal, prefix-free Turing machine.

For each $\sigma \in 2^{<\omega}$, the *prefix-free Kolmogorov complexity* of σ is defined to be

$$K(\sigma) := \min\{|\tau| : U(\tau)\downarrow = \sigma\}.$$

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Question: Has our worry about the choice of Turing machine been addressed?

Optimality and Invariance

Theorem (The Optimality Theorem)

Let U be a universal prefix-free Turing machine. Then for every prefix-free Turing machine M , there is some $c \in \omega$ such that

$$K_U(\sigma) \leq K_M(\sigma) + c$$

for every $\sigma \in 2^{<\omega}$.

Optimality and Invariance

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for every $\sigma \in 2^{<\omega}$.

Consequently, we have:

Theorem (The Invariance Theorem)

For every two universal Turing machines U_1 and U_2 , there is some $c_{U_1, U_2} \in \omega$ such that for every $\sigma \in 2^{<\omega}$,

$$|K_{U_1}(\sigma) - K_{U_2}(\sigma)| \leq c_{U_1, U_2}.$$

Incompressible Strings

Let $c \in \omega$. If σ satisfies

$$K(\sigma) \geq |\sigma| - c,$$

then we say that σ is *c-incompressible*.

Can this be extended to infinite sequences?

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Definition

We say that $X \in 2^\omega$ is *Kolmogorov incompressible* if

$$(\exists c)(\forall n) K(X \upharpoonright n) \geq n - c.$$

Lebesgue measure one many sequences are Kolmogorov incompressible.

The statistical definition of randomness (for $2^{<\omega}$)

Given a finite string $\sigma \in 2^{<\omega}$, we'd like to test whether it is random.

Null hypothesis: σ is random.

How do we test this hypothesis?

We employ a statistical test \mathcal{T} that has a critical region U corresponding to the significance level α .

If our string is contained in the critical region U , we reject the hypothesis of randomness at level α (say, $\alpha = 0.05$ or $\alpha = 0.01$).

The statistical definition of randomness (for 2^ω)

Given an infinite sequence $X \in 2^\omega$, we'd like to test whether it is random.

Null hypothesis: X is random.

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The statistical definition of randomness (for 2^ω)

Given an infinite sequence $X \in 2^\omega$, we'd like to test whether it is random.

Null hypothesis: X is random.

How do we test this hypothesis?

We test initial segments of X at *every level of significance*:

$$\alpha = \frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \dots, \frac{1}{2^n}, \dots$$

A test for 2^ω is now given by an infinite collection $(\mathcal{T}_i)_{i \in \omega}$ of tests for $2^{<\omega}$, where the critical region U_i of \mathcal{T}_i corresponds to the significance level $\alpha = 2^{-i}$.

Formally...

A *Martin-Löf test* is a sequence $(U_i)_{i \in \omega}$ of uniformly computably enumerable sets of strings such that for each i ,

$$\sum_{\sigma \in U_i} 2^{-|\sigma|} \leq 2^{-i}.$$

(Think of each U_i as the critical region for a statistical test \mathcal{T}_i at significance level $\alpha = 2^{-i}$.)

A sequence $X \in 2^\omega$ *passes a Martin-Löf test* $(U_i)_{i \in \omega}$ if there is some i such that for every k , $X \upharpoonright k \notin U_i$.

$X \in 2^\omega$ is *Martin-Löf random*, denoted $X \in \text{MLR}$, if X passes every Martin-Löf test.

The measure-theoretic formulation

Given $\sigma \in 2^{<\omega}$,

$$[\![\sigma]\!] := \{X \in 2^\omega : \sigma \prec X\}.$$

These are the basic open subsets of 2^ω .

The Lebesgue measure on 2^ω is defined by

$$\lambda([\![\sigma]\!]) = 2^{-|\sigma|}.$$

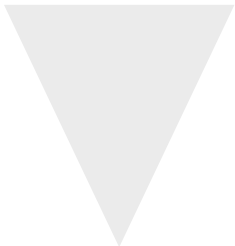
Thus we can consider a Martin-Löf test to be a collection $(\mathcal{U}_i)_{i \in \omega}$ of uniformly effectively open subsets of 2^ω such that

$$\lambda(\mathcal{U}_i) \leq 2^{-i}$$

for every i .

Moreover, X passes the test $(\mathcal{U}_i)_{i \in \omega}$ if $X \notin \bigcap_i \mathcal{U}_i$.

\mathcal{U}_1

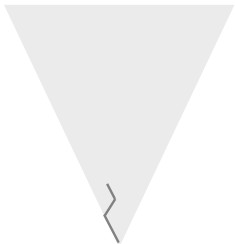


\mathcal{U}_2

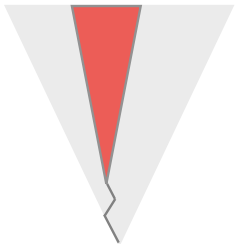


\mathcal{U}_3

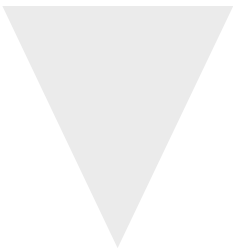


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\mathcal{U}_1

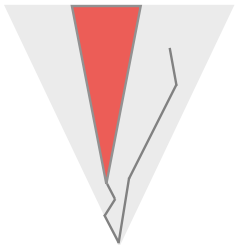


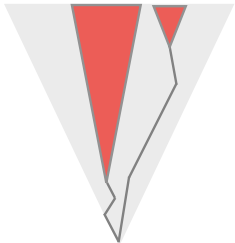
\mathcal{U}_2

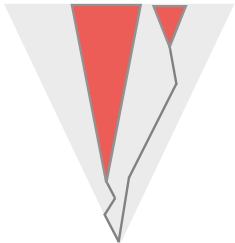
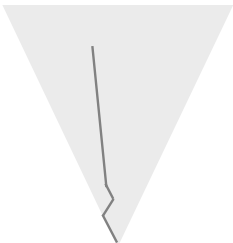


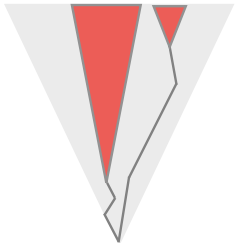
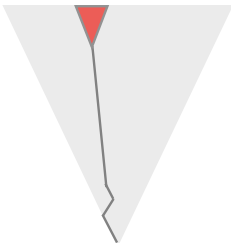
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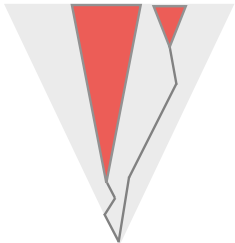
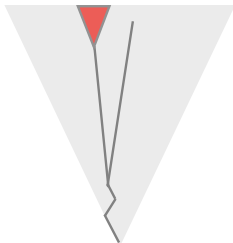


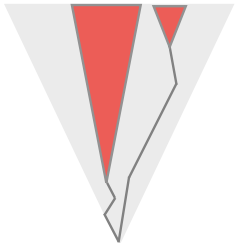
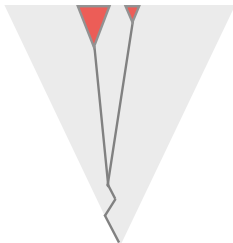
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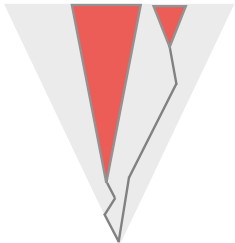
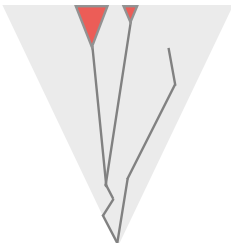
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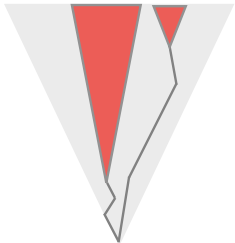
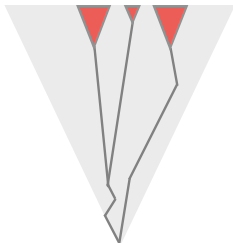
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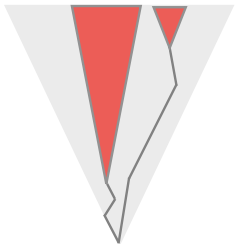
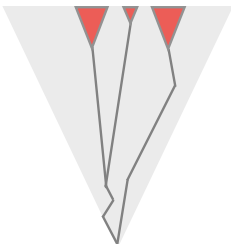
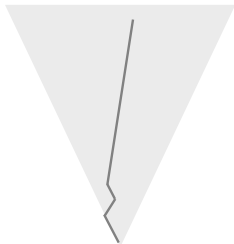
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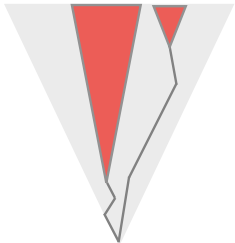
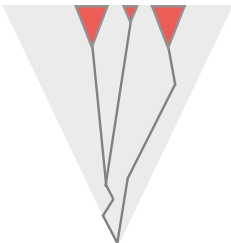
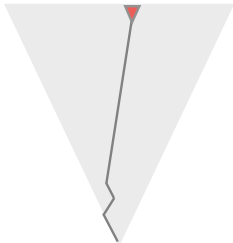
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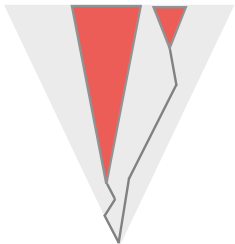
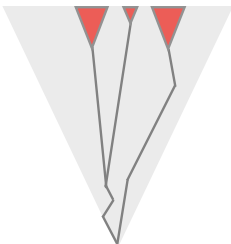
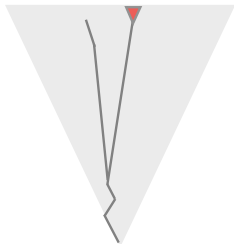
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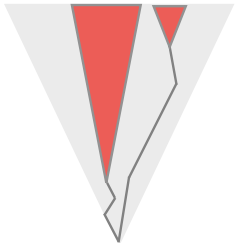
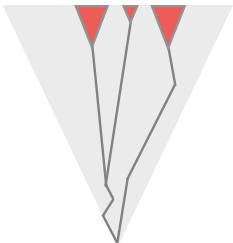
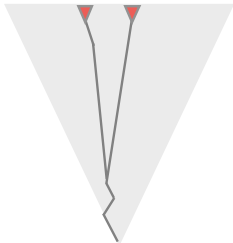
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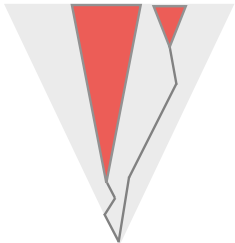
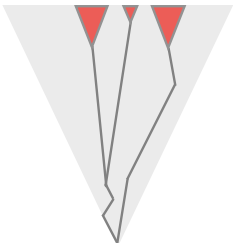
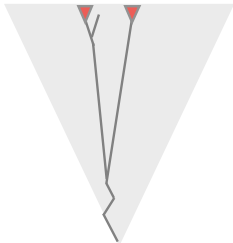
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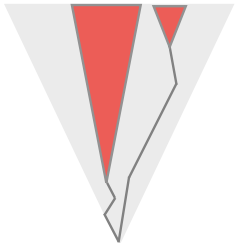
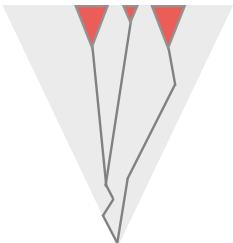
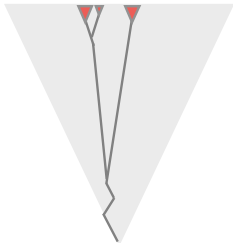
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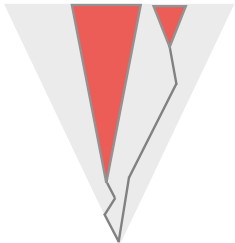
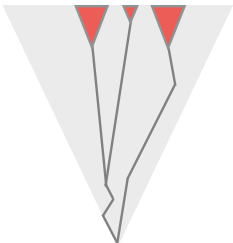
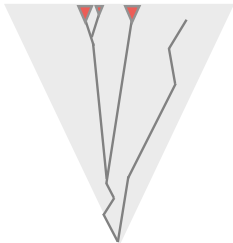
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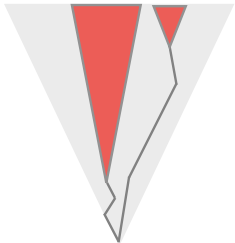
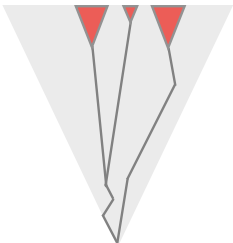
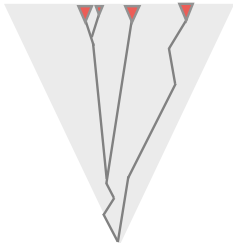
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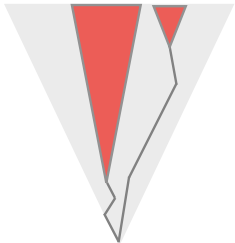
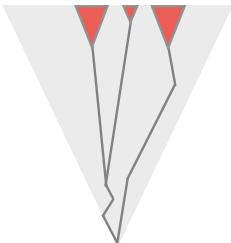
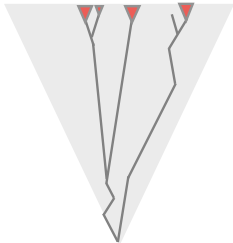
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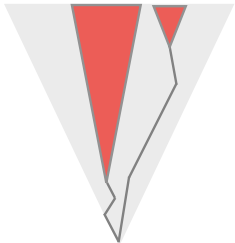
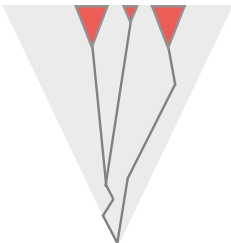
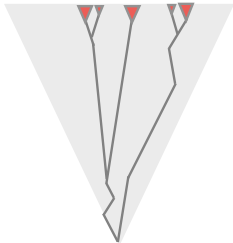
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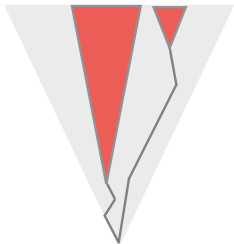
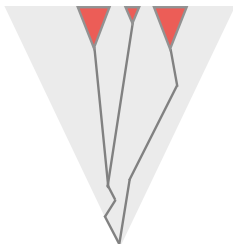
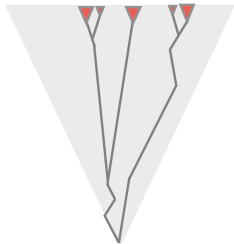
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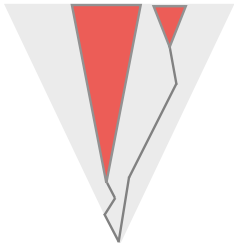
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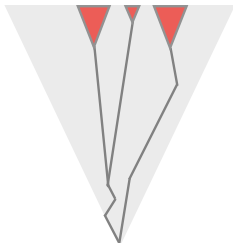
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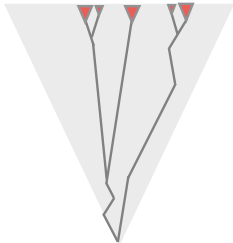
$$\sum_{\sigma \in \mathcal{U}_1} 2^{-|\sigma|} \leq \frac{1}{2}$$

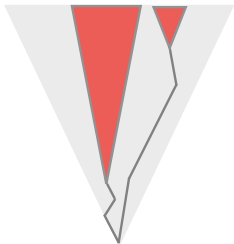
\mathcal{U}_1 

$$\sum_{\sigma \in U_1} 2^{-|\sigma|} \leq \frac{1}{2}$$

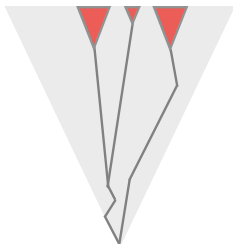
 \mathcal{U}_2 

$$\sum_{\sigma \in U_2} 2^{-|\sigma|} \leq \frac{1}{4}$$

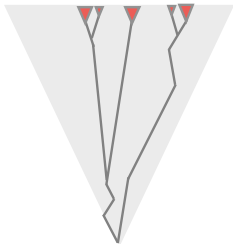
 \mathcal{U}_3 

\mathcal{U}_1 

$$\sum_{\sigma \in U_1} 2^{-|\sigma|} \leq \frac{1}{2}$$

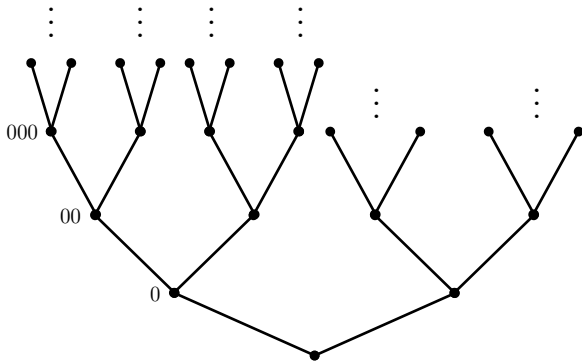
 \mathcal{U}_2 

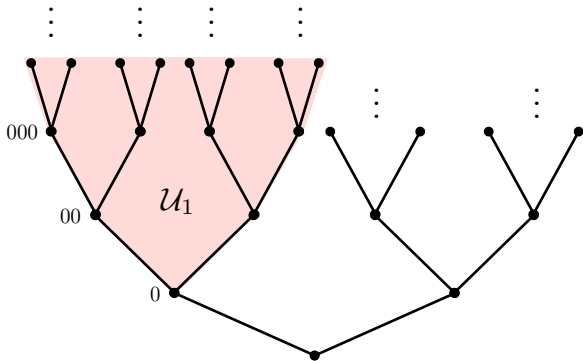
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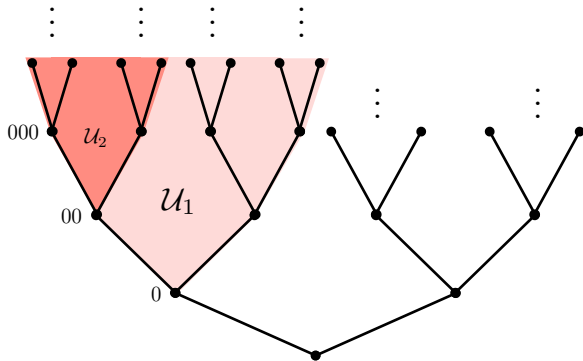
 \mathcal{U}_3 

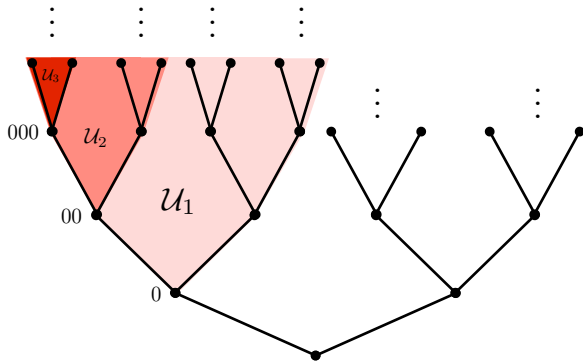
$$\sum_{\sigma \in U_3} 2^{-|\sigma|} \leq \frac{1}{8}$$

...









2. The Levin-Schnorr theorem

Theorem (Levin, Schnorr)

$X \in 2^\omega$ is Martin-Löf random if and only if

$$\forall n K(X \upharpoonright n) \geq n - O(1).$$

Proof idea

For one direction, the strategy is to show that the compressible sequences c -compressible strings for various $c \in \mathbb{N}$ can be used to define a Martin-Löf test.

For the other direction, the strategy is to show that for each Martin-Löf test, there is some machine that compresses those sequences that do not pass the test.

Martin-Löf random \Rightarrow Kolmogorov incompressible

Suppose that X is not Kolmogorov incompressible; that is, for every i , there is some n_i such that

$$K(X \upharpoonright n_i) < n_i - i.$$

Let $U_i = \{\sigma : K(\sigma) < |\sigma| - i\}$. Then

$$\sum_{\sigma \in U_i} 2^{-|\sigma|} \leq \sum_{\sigma \in U_i} 2^{-K(\sigma)-i} \leq 2^{-i}.$$

Setting $\mathcal{U}_i = \bigcup_{\sigma \in U_i} \llbracket \sigma \rrbracket$, it follows that $(\mathcal{U}_i)_{i \in \omega}$ is a Martin-Löf test containing X .

Kolmogorov incompressible \Rightarrow Martin-Löf random

Suppose that $X \in \bigcap_{i \in \omega} \mathcal{U}_i$ for some Martin-Löf test $(\mathcal{U}_i)_{i \in \omega}$.

Idea: Build a prefix-free machine M such that if σ determines an open subset of \mathcal{U}_{2^i} , then we set $M(\tau) = \sigma$ for some τ with $|\tau| \leq |\sigma| - i$.

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Kraft's inequality: If $\sum_{i \in \omega} 2^{-n_i} \leq 1$, then there is an instantaneous code consisting of codewords with lengths in $(n_i)_{i \in \omega}$.

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Effective version of Kraft's inequality: Given an effective list of pairs (σ_i, n_i) such that $\sum_{i \in \omega} 2^{-n_i} \leq 1$, there is a prefix-free machine M such that $K_M(\sigma_i) \leq n_i$.

3. Randomness with respect to a computable measure

Computable measures

We can also define Martin-Löf randomness with respect to any computable measure on 2^ω .

Definition

A measure μ on 2^ω is *computable* if $\sigma \mapsto \mu(\llbracket \sigma \rrbracket)$ is computable as a real-valued function.

In other words, μ is computable if there is a computable function $\hat{\mu} : 2^{<\omega} \times \omega \rightarrow \mathbb{Q}_2 \cap [0, 1]$ such that

$$|\mu(\llbracket \sigma \rrbracket) - \hat{\mu}(\sigma, i)| \leq 2^{-i}$$

for every $\sigma \in 2^{<\omega}$ and $i \in \omega$. (Here $\mathbb{Q}_2 = \{\frac{m}{2^n} : m, n \in \omega\}$.)

From now on we will write $\mu(\sigma)$ instead of $\mu(\llbracket \sigma \rrbracket)$.

MLR with respect to a computable measure

Definition

Let μ be a computable measure.

- ▶ A μ -*Martin-Löf test* is a sequence $(\mathcal{U}_i)_{i \in \omega}$ of uniformly effectively open subsets of 2^ω such that for each i ,

$$\mu(\mathcal{U}_i) \leq 2^{-i}.$$

- ▶ $X \in 2^\omega$ is μ -*Martin-Löf random*, denoted $X \in \text{MLR}_\mu$, if X passes every μ -Martin-Löf test.

Hereafter, we will refer to a sequence as *proper* if it is random with respect to some computable measure.

Atomic computable measures

A measure μ is *atomic* if there is some $X \in 2^\omega$ such that $\mu(\{X\}) > 0$; otherwise μ is *continuous*.

Note that if X is an atom of a computable measure μ , then $X \in \text{MLR}_\mu$.

Every computable sequence is the atom of some computable measure, namely the Dirac measure δ_X that concentrates all of its measure on X .

In fact, the converse holds: if X is the atom of a computable measure, then X is a computable sequence.

Generalizing the Levin-Schnorr Theorem

Theorem (Levin, Schnorr)

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$$\forall n \ K(X \upharpoonright n) \geq n - O(1).$$

Generalizing the Levin-Schnorr Theorem

Theorem (Levin, Schnorr)

$X \in 2^\omega$ is Martin-Löf random if and only if

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Theorem

Let μ be a computable measure on 2^ω . Then $X \in 2^\omega$ is μ -Martin-Löf random if and only if

$$\forall n K(X \upharpoonright n) \geq -\log(\mu(X \upharpoonright n)) - O(1).$$

4. The initial segment complexity of proper sequences

Complex sequences

An *order function* $h : \omega \rightarrow \omega$ is an unbounded, non-decreasing function.

Definition

$X \in 2^\omega$ is *complex* if there is a computable order function $h : \omega \rightarrow \omega$ such that

$$\forall n K(X \upharpoonright n) \geq h(n).$$

Proper sequences and complexity

Suppose that X is Martin-Löf random with respect to a computable measure μ .

Then by the generalized version of the Levin-Schnorr theorem,

$$\forall n K(X \upharpoonright n) \geq -\log(\mu(X \upharpoonright n)) - O(1).$$

Note that this does not imply that X is complex, since the function $n \mapsto -\log(\mu(X \upharpoonright n))$ is in most cases not computable but only X -computable.

Are there conditions that guarantee that a proper sequence is complex?

A priori complexity

Definition

- ▶ A *semi-measure* is a function $\rho : 2^{<\omega} \rightarrow [0, 1]$ satisfying
 - $\rho(\epsilon) = 1$ and
 - $\rho(\sigma) \geq \rho(\sigma 0) + \rho(\sigma 1)$.
- ▶ A semi-measure ρ is *left-c.e.* if ρ is computably approximable from below.

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Fact: There exists a *universal* left-c.e. semi-measure M . That is, for every left-c.e. semi-measure ρ there is some c such that

$$c \cdot M(\sigma) \geq \rho(\sigma)$$

for every σ .

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We define the *a priori complexity* of $\sigma \in 2^{<\omega}$ to be

$$KA(\sigma) := -\log M(\sigma).$$

A sufficient condition for complexity

Theorem (Hölzl, Merkle, Porter)

If $X \in 2^\omega$ is Martin-Löf random with respect to a computable, continuous measure μ , then X is complex.

A sufficient condition for complexity

Theorem (Hölzl, Merkle, Porter)

If $X \in 2^\omega$ is Martin-Löf random with respect to a computable, continuous measure μ , then X is complex.

This follows from the following two results.

- ▶ Let μ be a computable, continuous measure and let $X \in \text{MLR}_\mu$. Then X computes some $Y \in \text{MLR}$ by an effective procedure that is total on all oracles.
- ▶ If Y is complex and X computes Y by an effective procedure that is total on all oracles, then X is complex.

What about the converse?

The converse of the previous theorem doesn't hold, as there are complex sequences that are not proper.

However, we do have a partial converse.

Theorem (Hölzl, Merkle, Porter)

Let $X \in 2^\omega$ be proper. If X is complex, then $X \in \text{MLR}_\mu$ for some computable, continuous measure μ .

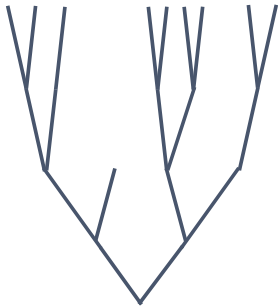
A useful lemma

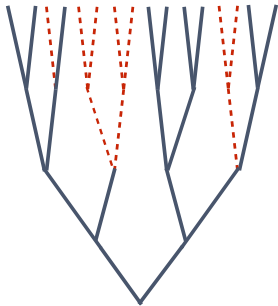
Lemma

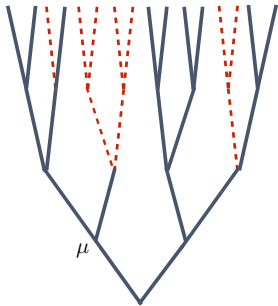
Suppose that

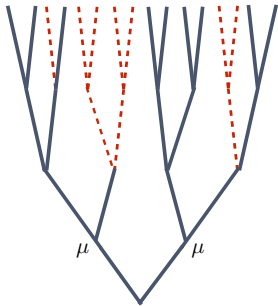
- ▶ μ is a computable measure,
- ▶ $X \in \text{MLR}_\mu$ is non-computable,
- ▶ \mathcal{P} is a Π_1^0 class with no computable members, and
- ▶ $X \in \mathcal{P}$.

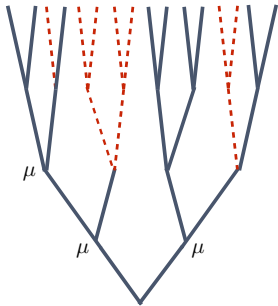
Then there is some computable, continuous measure ν such that $X \in \text{MLR}_\nu$.

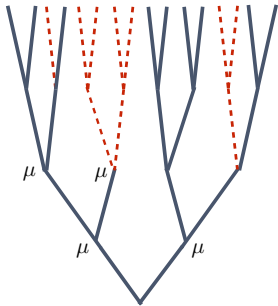


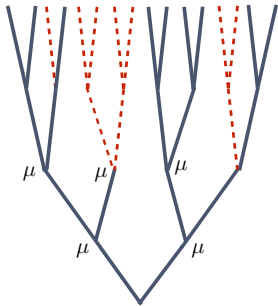


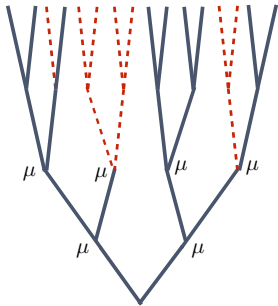


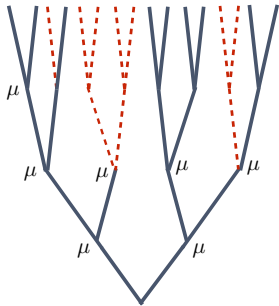


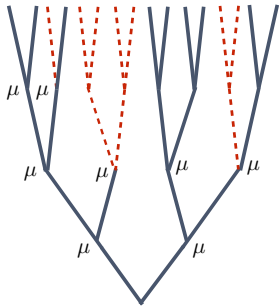


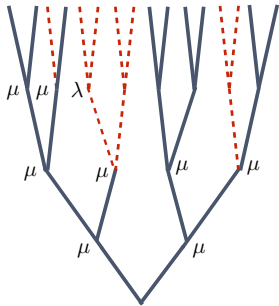


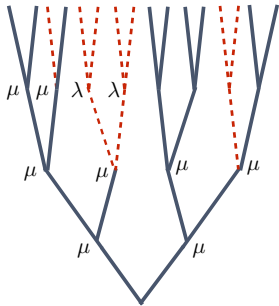


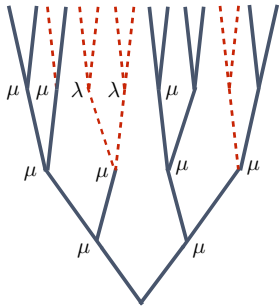


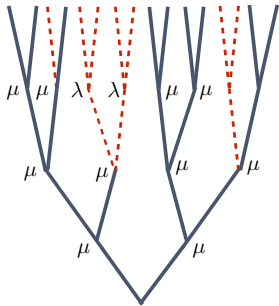


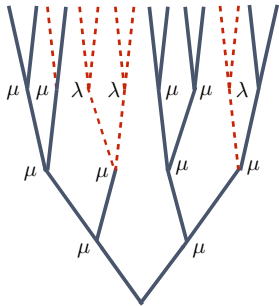


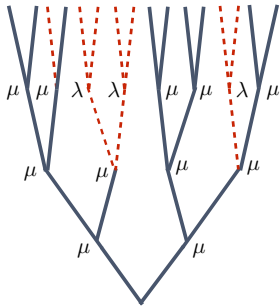


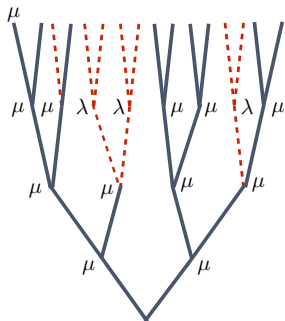


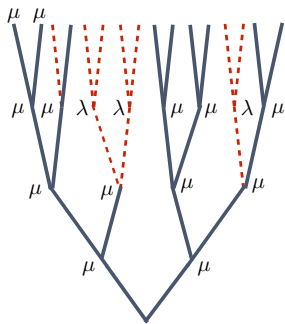


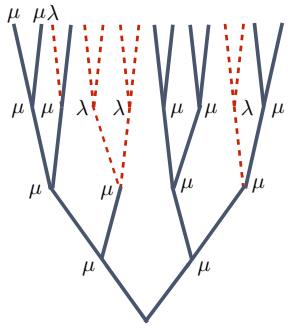


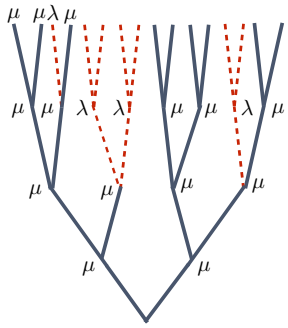


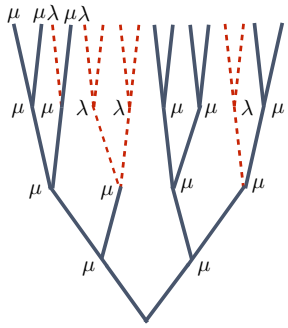


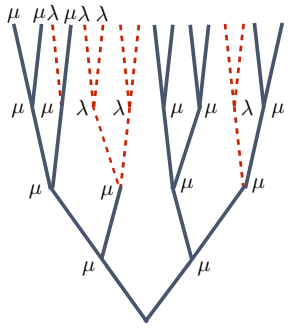


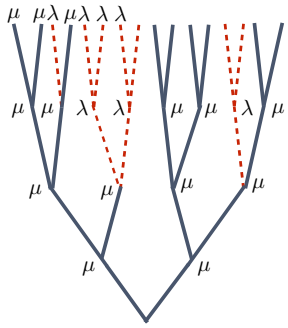


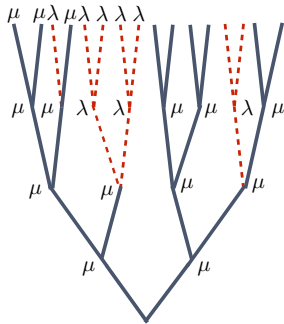


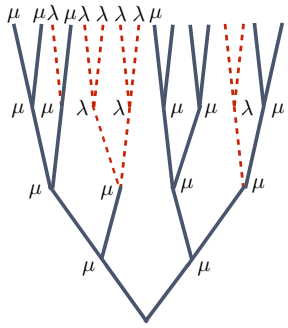


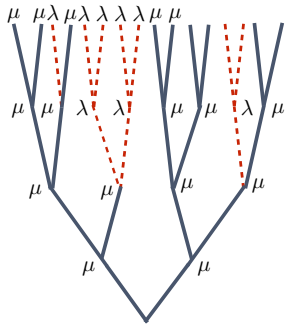


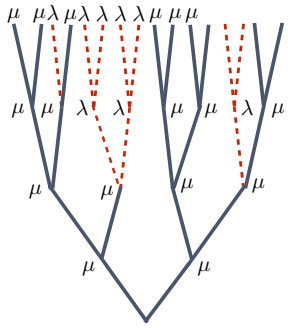


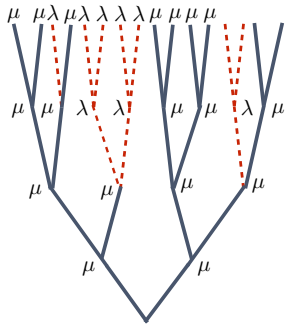


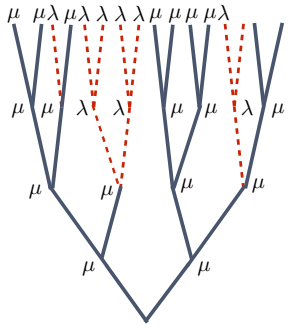


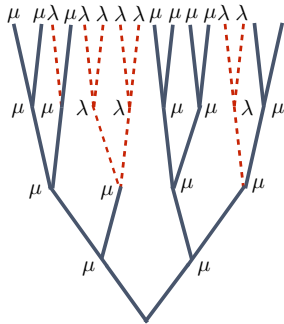


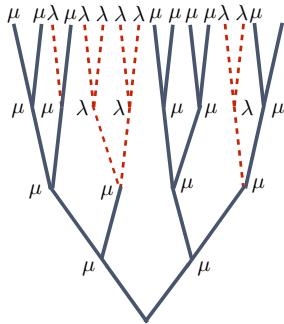


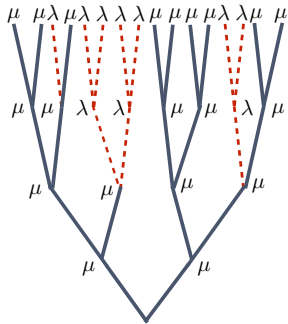












Establishing the partial converse

Theorem

Let $X \in 2^\omega$ be proper. If X is complex, then $X \in \text{MLR}_\mu$ for some computable, continuous measure μ .

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Let $X \in 2^\omega$ be proper. If X is complex, then $X \in \text{MLR}_\mu$ for some computable, continuous measure μ .

To prove this theorem, let h be the computable order function that witnesses that X is complex.

Then we apply the previous lemma to the Π_1^0 class

$$\{A \in 2^\omega : K(A \upharpoonright n) \geq h(n)\},$$

which contains X but no computable sequences.

Connection to semigenericity

Definition

$X \in 2^\omega$ is *semigeneric* if X is non-computable and for every Π_1^0 class \mathcal{P} with $X \in \mathcal{P}$, \mathcal{P} contains some computable member.

Theorem (Hölzl, Merkle, Porter)

Let $X \in 2^\omega$ be proper. The following are equivalent:

1. $X \in \text{MLR}_\mu$ for some computable, continuous μ .
2. X is complex.
3. X is not semigeneric.

A follow-up question

Let μ be a computable, continuous measure.

Since every sequence that is random with respect μ is complex, is there a single computable order function that witnesses the complexity of μ -random sequences?

Is there a least such function (up to an additive constant)?

A follow-up result

Definition

Let μ be a continuous measure. Then the *granularity function of μ* , denoted g_μ , is the order function mapping n to the least ℓ such that $\mu(\sigma) < 2^{-n}$ for every σ of length ℓ .

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Theorem (Hölzl, Merkle, Porter)

Let μ be a computable, continuous measure and let $X \in \text{MLR}_\mu$. Then we have

$$\forall n \text{ KA}(X \upharpoonright n) \geq g_\mu^{-1}(n) - O(1).$$

Some facts about the granularity of a computable measure

- ▶ If μ is exactly computable, that is, μ is \mathbb{Q}_2 -valued and the function $\sigma \mapsto \mu(\sigma)$ is a computable function, then g_μ is computable.

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- ▶ If μ is exactly computable, that is, μ is \mathbb{Q}_2 -valued and the function $\sigma \mapsto \mu(\sigma)$ is a computable function, then g_μ is computable.
- ▶ However, there is a computable, continuous measure μ such that the granularity function g_μ of μ is not computable.
- ▶ For every computable, continuous measure μ , there is a computable order function $f : \omega \rightarrow \omega$ such that

$$|f(n) - g_\mu(n)^{-1}| \leq O(1).$$

Such a function f provides as a global computable lower bound for the initial segment complexity of every μ -random sequence.

A question about uniformity

Question

If we have a computable, atomic measure μ such that

$$\forall X \in 2^\omega (X \in \text{MLR}_\mu \setminus \text{Atoms}_\mu \Rightarrow X \text{ is complex}),$$

is there a computable, continuous measure ν such that

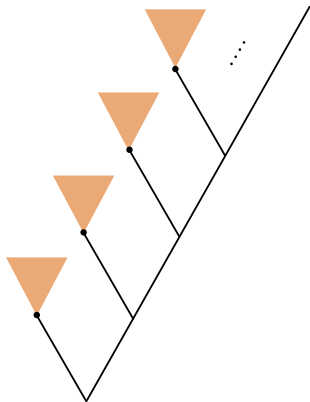
$$\text{MLR}_\mu \setminus \text{Atoms}_\mu \subseteq \text{MLR}_\nu?$$

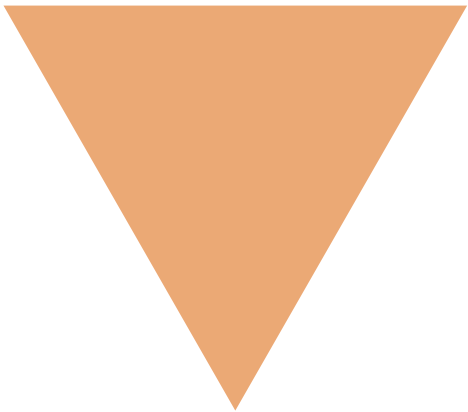
An answer

Theorem (Hölzl, Merkle, Porter)

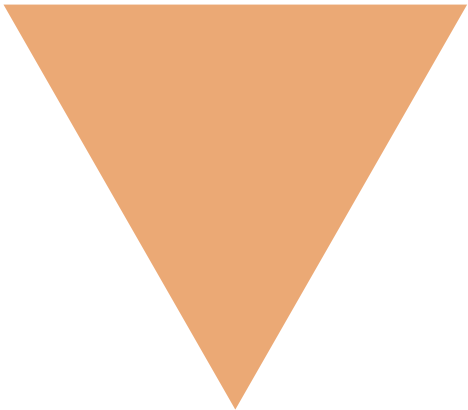
There is a computable, atomic measure μ such that

- ▶ *every $X \in \text{MLR}_\mu \setminus \text{Atoms}_\mu$ is complex but*
- ▶ *there is no computable, continuous measure ν such that $\text{MLR}_\mu \setminus \text{Atoms}_\mu \subseteq \text{MLR}_\nu$.*



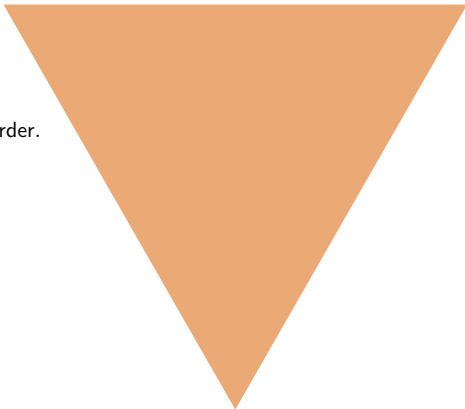


the i^{th} neighborhood



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Suppose that ϕ_i is an order.



the i^{th} neighborhood

Suppose that ϕ_i is an order.

We define the measure μ so that for any complex μ -random X in this neighborhood, we have

$$KA(X \upharpoonright n) < \phi_i^{-1}(n)$$

for almost every n .

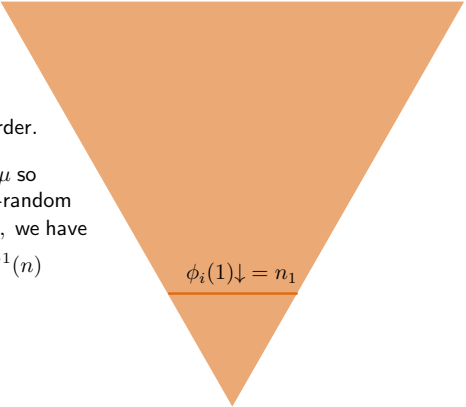
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$$\phi_i(1) \downarrow = n_1$$

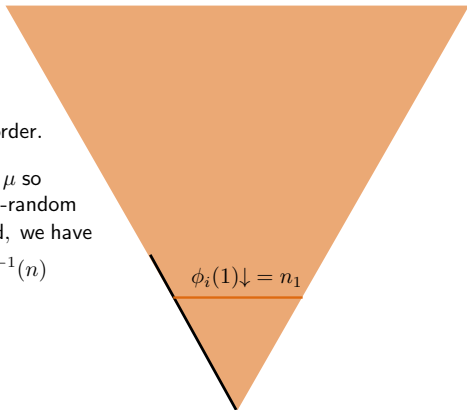
the i^{th} neighborhood

Suppose that ϕ_i is an order.

We define the measure μ so that for any complex μ -random X in this neighborhood, we have

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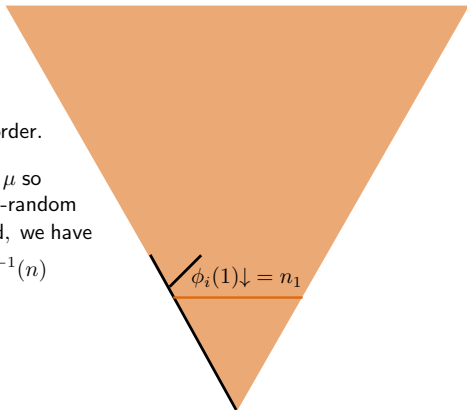
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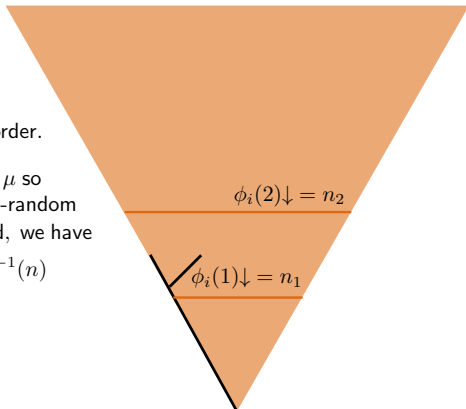
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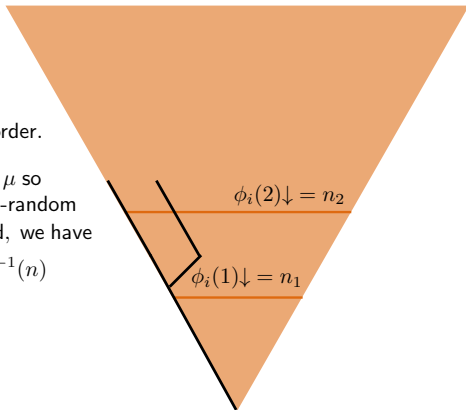
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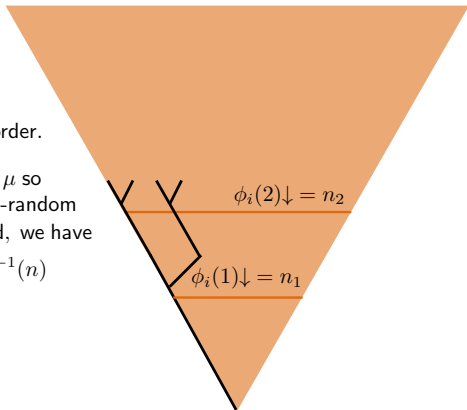
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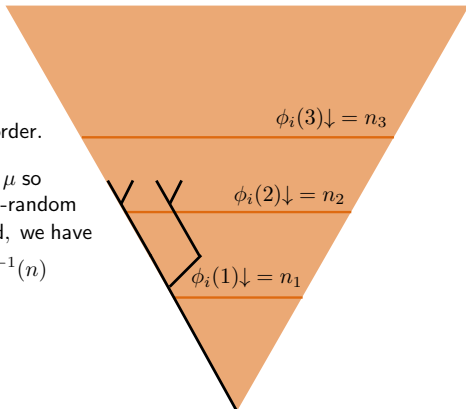
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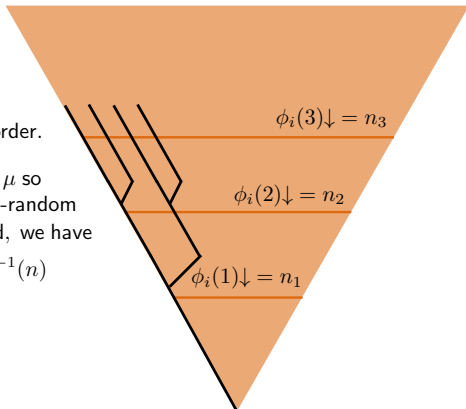
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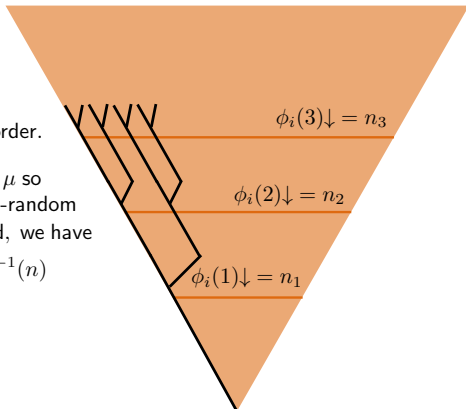
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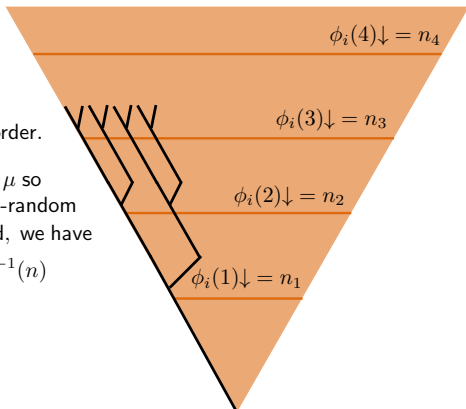
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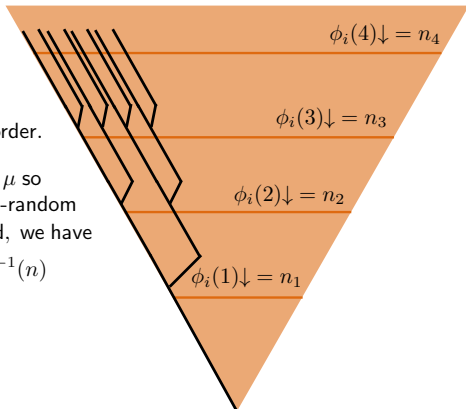
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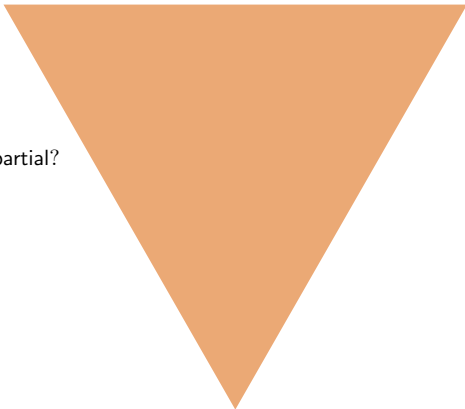
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What happens if ϕ_i is partial?



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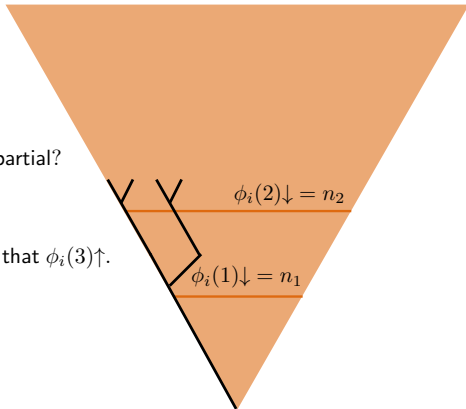
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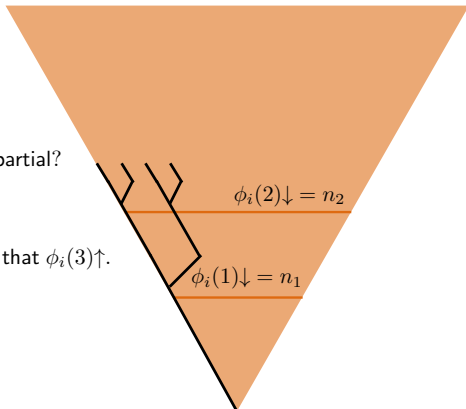
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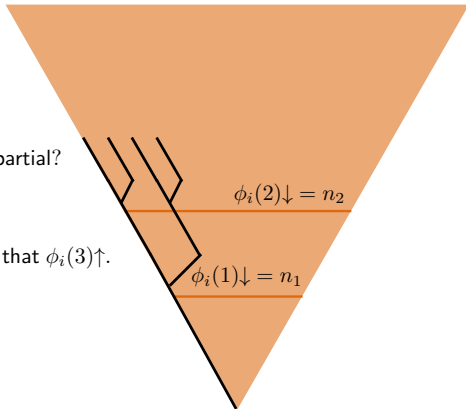
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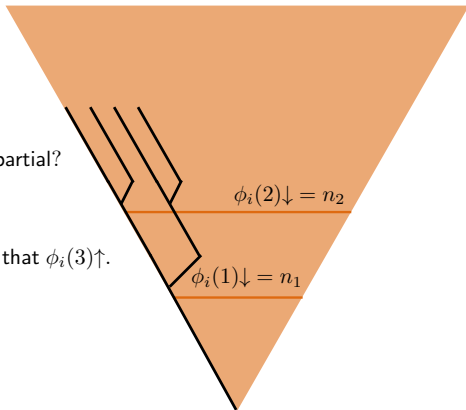
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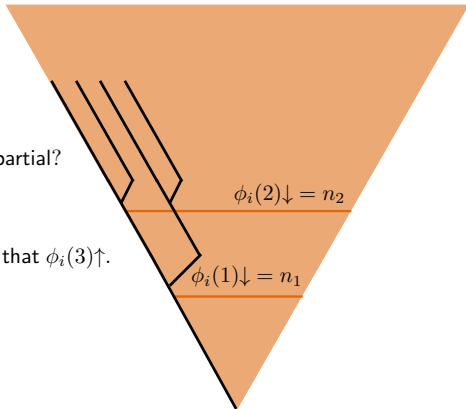
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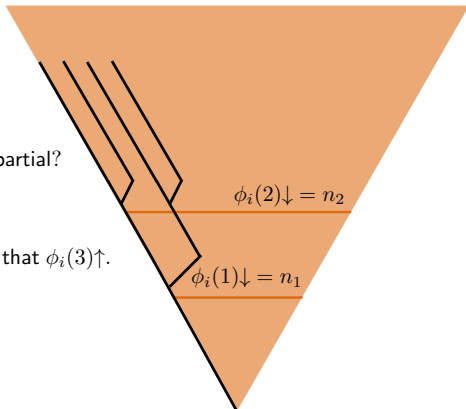
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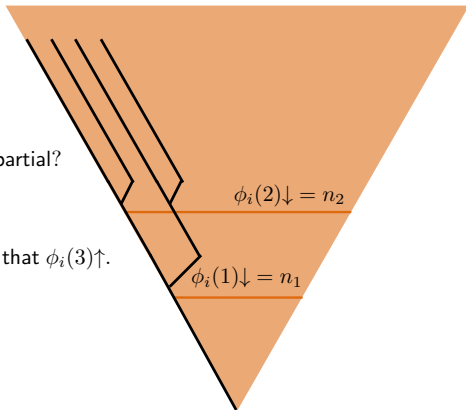
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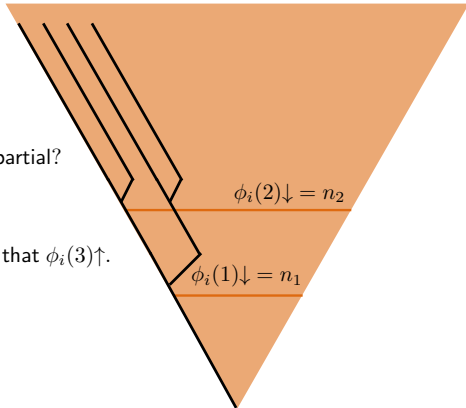
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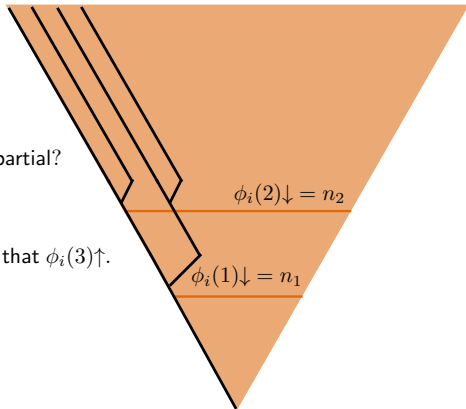
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Let $[[\sigma_i]]$ be the i^{th} neighborhood.

One can verify that

- ▶ if ϕ_i is partial, then $[[\sigma_i]] \cap \text{MLR}_\mu \subseteq \text{Atoms}_\mu$;
- ▶ if ϕ_i is total, then $[[\sigma_i]] \cap \text{Atoms}_\mu = \emptyset$ and every $X \in \text{MLR}_\mu \cap [[\sigma_i]]$ is complex.

Lastly, if there is some computable, continuous ν such that $\text{MLR}_\mu \setminus \text{Atoms}_\mu \subseteq \text{MLR}_\nu$, then there is a computable order $f = \phi_i$ such that for every $X \in \text{MLR}_\mu \setminus \text{Atoms}_\mu$,

$$KA(X \upharpoonright n) \geq f^{-1}(n) - O(1)$$

for every n , which yields a contradiction.

Thank you!