

Weak 2-randomness

Daniel Osherson and Scott Weinstein, *Recognizing Strong Random Reals*, 2008

Greg Langmead, November 23, 2020

Summary

- A random real should be impossible for us to **compute**
 - Not just directly, but also with machines that have the right bits as **limiting values** ("**computably approximable**")
- or to **computably recognize** as it streams in bit by bit
 - with a machine that maps $2^{<\omega} \rightarrow \{\text{Yes, No}\}$
- These operations motivate "strong M-L" tests
 - These are M-L tests but where the decreasing measure is not bounded by 2^{-n} (hence the name "strong 1-randomness")
 - These are exactly the Π_2^0 sets of measure 0 (hence the name "weak 2-randomness")

Weak 2-random \hookrightarrow ML random \hookrightarrow Computably random \hookrightarrow Schnorr random \hookrightarrow Weak 1-random

Review: Borel hierarchy

- Σ_1^0 : effectively open; unions of prefix-free cylinders
- Π_1^0 : effectively closed; complement of Σ_1^0
- Σ_2^0 : countable union of uniformly Π_1^0 sets (WLOG: nested)
- Π_2^0 : countable intersection of uniformly Σ_1^0 sets (WLOG: nested)

Computably approximable

aka *limiting recursive*

- Computable sequence $P : \mathbb{N} \rightarrow \{0,1\}$. It emits bit j , marked final, and terminates.
- The *limiting* version converges to a bit: $P : \mathbb{N} \rightarrow 2^\omega$, s.t. $\lim_{n \rightarrow \infty} P(j)_n$ exists for all j .
- Epistemic Note: as observers at finite time n we don't get to know if the limit is achieved

\exists a computably approximable ML random

- Chaitin's $\Omega = \sum_{\sigma \in \text{dom} \mathcal{U}} 2^{-|\sigma|}$ is ML-random number
- approximable from below by $\Omega_s = \sum_{\mathcal{U}(\sigma)[s] \downarrow} 2^{-|\sigma|}$
- \mathcal{U} is a universal prefix-free compression machine implementing Kolmogorov complexity.
- So Ω is a left-c.e. real
- Hence computably approximable (each digit can be computed in finite steps)
- Such computability should be non-random, so let's tighten the definition.

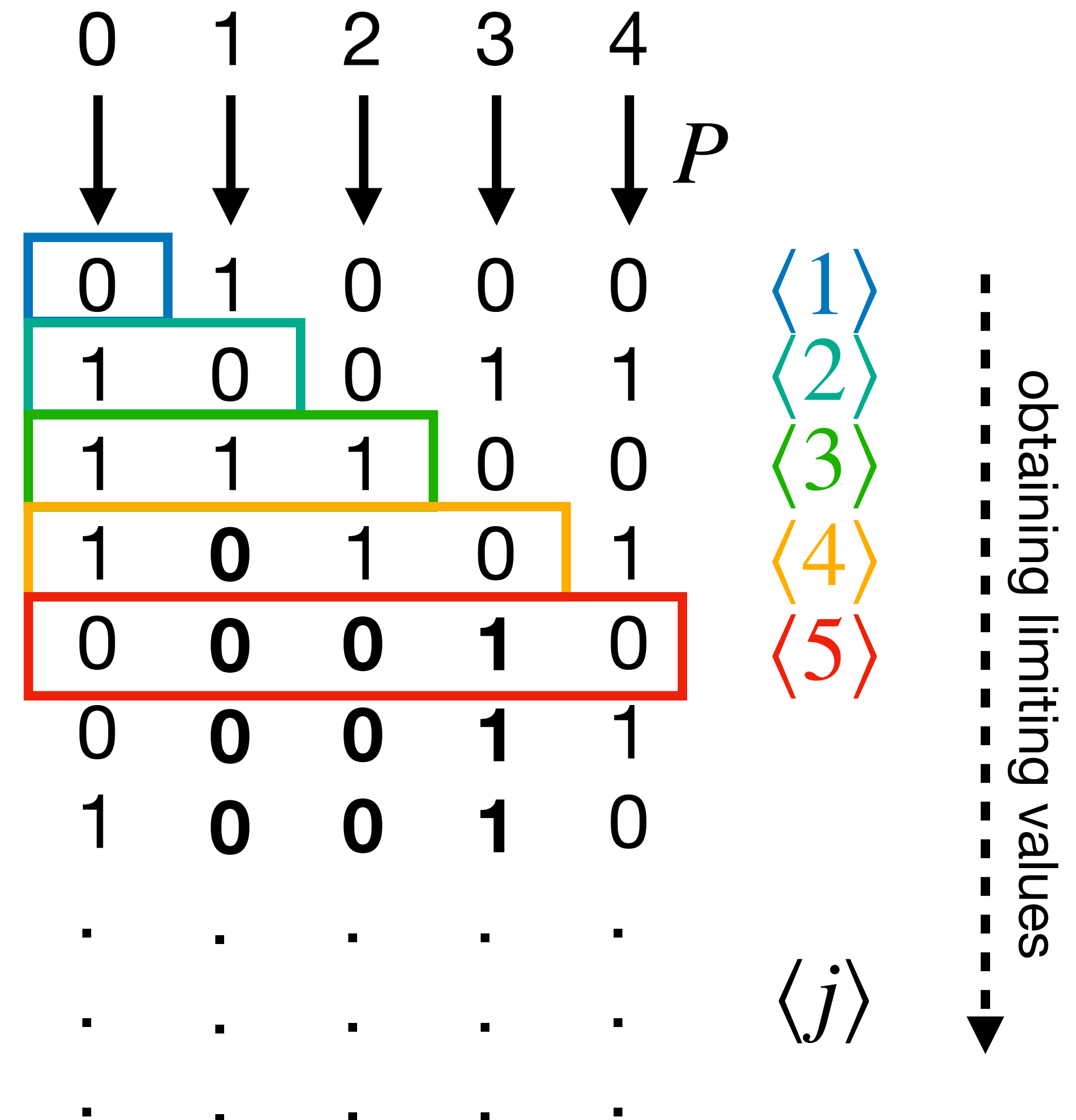
Generalized ML tests

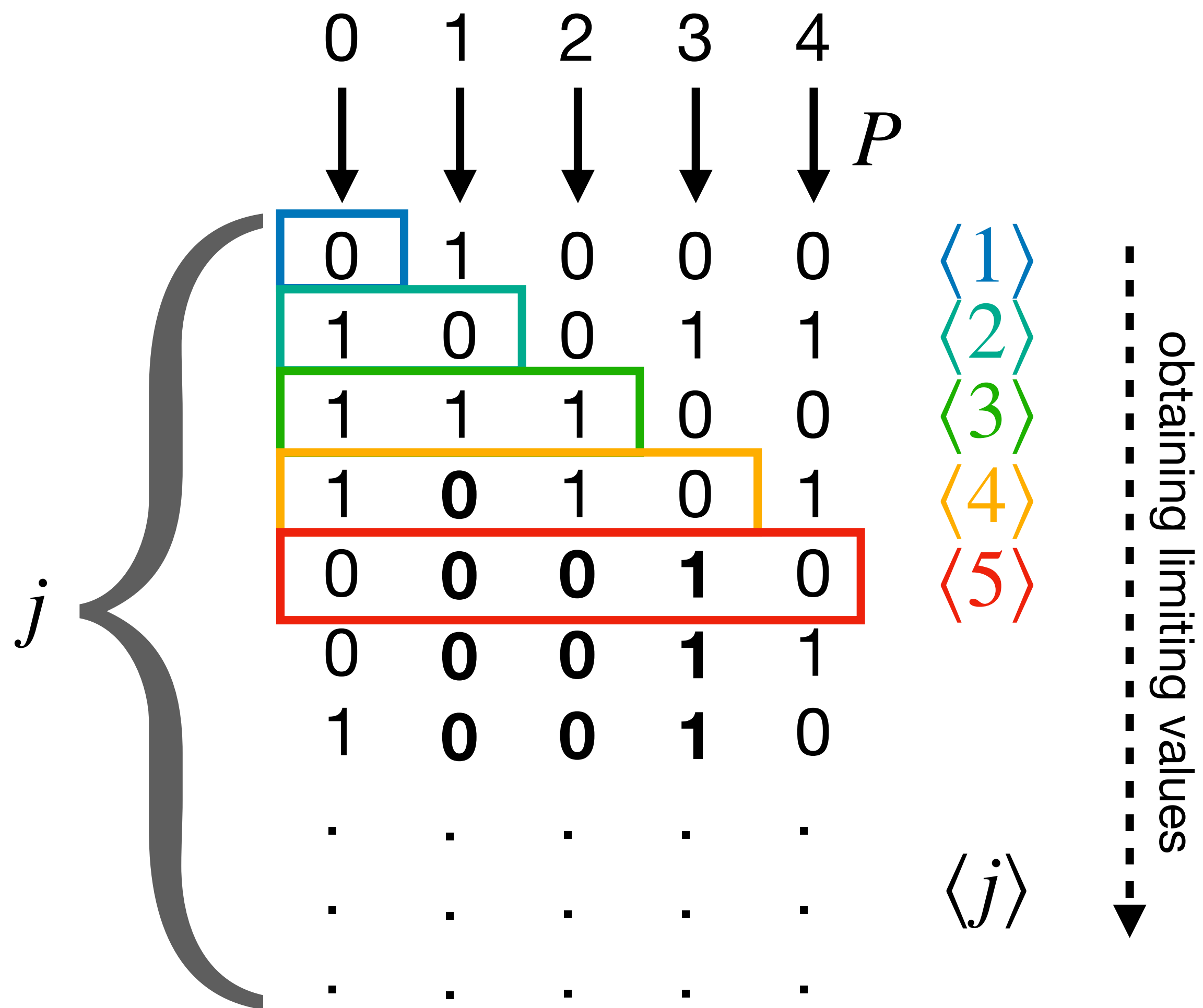
- Uniformly Σ_1^0 sets $\{U_n\}$ with $\mu\left(\bigcap_n U_n\right) = 0$
 - drops the condition $\mu(U_n) \leq 2^{-n}$ from ML randomness
 - WLOG: U_n are nested, and each is a union of cylinders $[W_n]$ for some c.e. collection of prefix-free strings $W_n \subset 2^{<\omega}$
 - O&W name the uniform enumeration f , so f_i is an enumeration of W_i
 - equivalently $\lim_{n \rightarrow \infty} \mu(U_n) = 0$
 - **a Π_2^0 set of measure 0**
- hence: there are *more* such tests than ML-randomness, and *fewer* randoms
- also called: strong 1-randomness, weak 2-randomness

Weak 2-randoms are not computably approximable

- weak 2-random \implies no computable approximation
- contrapositive: if x is c.a., i.e.

$$\exists P \lim_{n \rightarrow \infty} P(i)_n = x_i \implies x \in \bigcap_i [W_{f(i)}]$$
- Given P ,
 - Define $\langle j \rangle$, a sequence of length j , by $\langle j \rangle(i) = P(i)_j$
 - call this a " P -output": we have run P for j steps and j is also the length
 - $W_{f(n)} = \{ \sigma \in 2^{<\omega} : (|\sigma| = n) \text{ and } \exists j > n . \sigma \subset \langle j \rangle \}$
 - sequences of length n that are prefixes of P -outputs





$$[W_{f(n)}] \supseteq [W_{f(n+1)}]$$

Being a prefix of some $\langle j \rangle$ means your prefixes are as well.

If P limit-computes x then

$$\forall n \exists j . x[n] = \langle j \rangle[n].$$

Eventually P gets the first n bits of x right.

If $y \neq x$ then

$$\forall n \exists j . \forall k \geq j . y[n] \neq \langle k \rangle[n]$$

if you differ from x at some bit, then eventually so does $\langle k \rangle$.

$\therefore \bigcap_n [W_{f(n)}] = \{x\}$ and so f is a
GML test

Weak 2-tests = computable learners

- Computable learner: $L : 2^{<\omega} \rightarrow \{\text{Yes}, \text{No}\}$
- L **recognizes** $x \in 2^\omega$ if $\exists S . \mu(S) = 0, x \in S$, and s.t. $y \in S \iff L(y[n]) = \text{Yes}$ infinitely often
 - Note: this means $\{L(y[n])\}$ does not converge to No (might or might not converge to Yes)
 - It's like saying "I never stop resonating with x and its friends in S "
 - Note: later we'll consider learners that converge to Yes
 - Note: having a whole set S that the learner recognizes instead of just x is confusing!
- Claim: strong ML test $\iff L$

Given a learner L for a set $X \ni x$

$$W_{f(n)} = \{b \in 2^{<\omega} . \exists c \subset b, |c| \geq n, L(c) = \text{Yes}\}$$

descending chain because such c works for level $n - 1$ as well.

$$\bigcap_n [W_{f(n)}] = S \text{ so } f \text{ is a GML test.}$$

Given a GML test f

Enumerate the elements of

$$W_{f(n)} : W_{f(n),1}, W_{f(n),2}, \dots$$

these are each single strings w/ two parameters

Define $g : 2^{<\omega} \rightarrow \mathbb{N}$ by

$$g(b) = \max(\{j . \exists \sigma \subset b . \sigma \in \text{some } W_{f(j), \leq |b|}\})$$

length of longest prefix seen in an expanding set

L will detect jumps in g :

For $\beta \in \{0,1\}$ define $L(b\beta) = \text{Yes}$ if $g(b\beta) > g(b)$, else No.

oh look, I see a longer string in one of the GML test sets I'm visiting

Strong recognition

- The learner L strongly recognizes x if it converges to Yes (is Yes cofinitely often in O&W's terminology).
- We will prove this is equivalent to weak 1-randomness, a.k.a. Kurtz randomness.
- A number is Kurtz random iff it is in every measure-1 Σ_1^0 set.
- This is the largest set of randoms in the zoo.

Given a strong learner L for a set
 $Y \ni x \implies x$ is not Kurtz random

$$Y_m = \{b \in 2^\omega . \forall n > m, L(b[n]) = \text{Yes}\}$$

← recognized by L starting at bit m

$\bigcup_m Y_m$ is everything recognized by L

and $x \in$ some Y_m , call it Y_k .

← Y, Y_m measure 0 by hypothesis

$$S_m = \{b \in 2^\omega . |b| > m \text{ and } L(b) = \text{No}\}$$

$$[S_m] = 2^\omega - Y_m.$$

← not recognized by L at bit m

S_k is a Kurtz test and $x \notin S_k$.

Not Kurtz random \implies strongly
recognized

Given S with $x \notin [S]$, $\mu([S]) = 1$.

Enumerate the elements of S :

S_1, S_2, \dots

$$L(b) = \begin{cases} \text{No} & \exists \sigma \subset b . \exists i . \sigma \in S_{\leq i} \\ \text{Yes} & \text{otherwise} \end{cases}$$

\leftarrow No means "in $[S]$ " because to be
in S means being in some S_n

$\{n : L(y[n]) = \text{Yes}\}$ is cofinite iff
 $y \notin [S]$, hence includes x .

Here's the Deal

We have finite minds and computing machines are good models of this.

"Random" should mean "numbers we cannot identify with our minds."

If we strongly recognize a number, it is definitely non-random. But we can weaken this and say that even more numbers are non-random.

To weakly recognize a number you have to answer "Yes" infinitely many times.

This is "minimally infinite" and so is the right demarcation line.

A couple counterpoints

- Computable learners might spend 10 million years between Yeses.
- Do we really recognize such a number in practical terms?
- Maybe it's OK for these to be called "random" since they are not super-accessible to us and our computers.