## Higher randomness and triviality

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1. Higher randomness: the basics

## $\Delta_{1}^{1}$ randomness

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In his seminal work on randomness, Martin-Löf did not only define the notion we now know as Martin-Löf randomness.

Indeed, he also introduced a higher notion of randomness:
$\Delta_{1}^{1}$-randomness, where $X$ is $\Delta_{1}^{1}$ random if and only if it does not belong to any $\Delta_{1}^{1}$ set of measure 0 .

## $\Delta_{1}^{1}$-ML-randomness

Another way to define randomness via $\Delta_{1}^{1}$ objects would be to mimic Martin-Löf's definition for the classical case:

## Definition

A $\Delta_{1}^{1}$-Martin-Löf test is a sequence $\left(\mathcal{U}_{n}\right)$ of uniformly $\Delta_{1}^{1}$ open sets such that $\mu\left(\mathcal{U}_{n}\right) \leq 2^{-n}$. A sequence $X$ is $\Delta_{1}^{1}$-Martin-Löf random if $X \notin \bigcap_{n} \mathcal{U}_{n}$ for all $\Delta_{1}^{1}$-Martin-Löf tests.

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As it turns out, these two concepts are equivalent:
Theorem (Sacks)
$\Delta_{1}^{1}$-randomness and $\Delta_{1}^{1}$-Martin-Löf randomness coincide.

## $\Pi_{1}^{1} / \Sigma_{1}^{1}$ versions of randomness

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- For $\Sigma_{1}^{1}$, everything collapses (Sacks):

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- The situation is a lot more interesting for $\Pi_{1}^{1}$ randomness...


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Theorem (Kechris)
There exists a $\Pi_{1}^{1}$ nullset which contains all others.
Thus a sequence $X$ is $\prod_{1}^{1}$-random iff it avoids this maximal $\prod_{1}^{1}$-nullset.

## $\Pi_{1}^{1}$ ML-randomness

## Definition

A $\Pi_{1}^{1}$ Martin-Löf test is a sequence $\left(\mathcal{U}_{n}\right)$ of uniformly $\Pi_{1}^{1}$ open sets such that $\mu\left(\mathcal{U}_{n}\right) \leq 2^{-n}$. A sequence $X$ is $\prod_{1}^{1}$-Martin-Löf random if $X \notin \bigcap_{n} \mathcal{U}_{n}$ for all $\Pi_{1}^{1}$-Martin-Löf tests.

## $\Pi_{1}^{1}$ ML-randomness

## Definition

A $\Pi_{1}^{1}$ Martin-Löf test is a sequence $\left(\mathcal{U}_{n}\right)$ of uniformly $\prod_{1}^{1}$ open sets such that $\mu\left(\mathcal{U}_{n}\right) \leq 2^{-n}$. A sequence $X$ is $\prod_{1}^{1}$-Martin-Löf random if $X \notin \bigcap_{n} \mathcal{U}_{n}$ for all $\Pi_{1}^{1}$-Martin-Löf tests.

It is easy to see that if $\left(\mathcal{U}_{n}\right)$ is a $\Pi_{1}^{1}-\mathrm{ML}$ test, then $\bigcap_{n} \mathcal{U}_{n}$ is a $\Pi_{1}^{1}$ set. Thus $\Pi_{1}^{1}$-randomness implies $\Pi_{1}^{1}-\mathrm{ML}$ randomness.

## A digression

In higher recursion theory, the analog of the class of c.e. sets of integers (or strings, or...) is the class of $\Pi_{1}^{1}$ sets of integers. Indeed, by the Gandy-Spector theorem, one can think of a $\Pi_{1}^{1}$ set of integers as being given by an enumeration with stages $\left\{s \mid s<\omega_{1}^{c k}\right\}$.

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| Bottom setting | Higher analogue |
| :---: | :---: |
| c.e. | $\Pi_{1}^{1}$ |
| finite c.e. | $\Delta_{1}^{1}$ |
| computable | $\Delta_{1}^{1}$ |
| $\emptyset^{\prime}$ | $\mathcal{O}$ |
| $\leq_{T}$ | $? ? ?$ |

Thus, $\Pi_{1}^{1} \mathrm{ML}$-randomness really is the analogue of Martin-Löf randomness in the higher setting.

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For example, we can state: it is possible to enumerate all
$\Pi_{1}^{1}$-Martin-Löf tests (or Martin-Löf tests!) and thus there exists a universal one.

## $\Delta_{1}^{1}$-randomness vs $\prod_{1}^{1}$-ML randomness

With this correspondence in mind, we see that $\Delta_{1}^{1}$-randomness is defined in terms of computable/finite objects, thus it should be related to computable randomness or Schnorr randomness....

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... and indeed it coincides with both.
Using the usual techniques, one can thus show that $\prod_{1}^{1}-\mathrm{ML}$ randomness is strictly stronger than $\Delta_{1}^{1}$-randomness.

## $\Pi_{1}^{1}$-randomness vs $\Pi_{1}^{1}$-ML randomness

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Theorem (Hjorth-Nies / Chong-Nies-Yu)
The following are equivalent:

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The following are equivalent:

- $X$ is $\Pi_{1}^{1}$ random
- $X$ is $\Pi_{1}^{1}-M L$ random and $\omega_{1}^{X}=\omega_{1}^{c k}$.
- $X$ is $\Delta_{1}^{1}-M L$ random and $\omega_{1}^{X}=\omega_{1}^{c k}$.


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And thus it suffices to separate the first two notions to show that there exists a $\prod_{1}^{1}$-ML-random such that $\omega_{1}^{X}>\omega_{1}^{c k}$.

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And thus it suffices to separate the first two notions to show that there exists a $\Pi_{1}^{1}$-ML-random such that $\omega_{1}^{X}>\omega_{1}^{c k}$. In fact, $\Omega$ is such a real (although $\Omega \not ¥_{T} \mathcal{O}$ ).

## Summing up



And the implications are strict.

## weak-2-randomness

With the same intuition, the analog of weak-2-randomness is the following

## Definition

A weak-2-test is a sequence $\left(\mathcal{U}_{n}\right)$ of uniformly c.e. open sets such that $\mu\left(\mathcal{U}_{n}\right) \rightarrow 0$. A sequence $X$ is weak-2-random if $X \notin \bigcap_{n} \mathcal{U}_{n}$ for all weak-2-tests.

## weak-2-randomness

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The second implication is strict, as we will see.
A seemingly difficult open question: are weak-2-randomness and $\Pi_{1}^{1}$-randomness equivalent?

## Kolmogorov complexity

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Just like in the classical setting, one can define Kolmogorov complexity, denoted $K$, via a universal prefix-free machine, or via a universal left-c.e. semimeasure.

The Levin-Schnorr theorem still holds: $X$ is $\mathbf{M L}$ random if and only if $\mathrm{K}(X \upharpoonright n) \geq n-O(1)$.
2. Higher Turing reductions

## Higher reductions

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Turing degrees, we need to first find the correct analog of Turing reduction.

What does it mean for $X$ be to be computable in $Y$ ?

The most obvious definition: $X$ is $\Delta_{1}^{1}$ in $A$, meaning that there is a $\Pi_{1}^{1}$-set $P$ and a $\Sigma_{1}^{1}$ set $S$ such that

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n \in X \Leftrightarrow(A, n) \in P \Leftrightarrow(A, n) \in S
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$$
n \in X \Leftrightarrow(A, n) \in P \Leftrightarrow(A, n) \in S
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We also write $X \leq_{h} A$ as by a result of Kleene, this is equivalent for $X$ to be hyperarithmetic in $A$ (i.e. $X \leq_{T} A^{(\gamma)}$ for some $\gamma<\omega_{1}^{A}$ ).

## Higher reductions

The problem with this reduction is of topological nature. When studying the interactions between randomness and Turing degrees, we make great use of the fact that Turing reductions are continuous, i.e., that when we have $\Phi^{Y}=X$, only a finite prefix of $Y$ is used in the computation of a given prefix of $X$.

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The solution: in the classical setting, a Turing reduction $\Phi$ can be viewed as a c.e. set of pairs of strings

## Higher reductions

## Definition (BGM)

A Turing reduction $\Phi$ is a c.e. set of pairs of strings. We write $\Phi^{Y}=X$ if

- $(\forall n)(\exists k)\langle Y \upharpoonright k, X \upharpoonright n\rangle \in \Phi$
- $(\forall k)[(\exists \tau)\langle Y \upharpoonright k, \tau\rangle \in \Phi \Rightarrow \tau \preceq X]$


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- $(\forall k)[(\exists \tau)\langle Y \upharpoonright k, \tau\rangle \in \Phi \Rightarrow \tau \preceq X]$

We do not require the domain of $\Phi$ to be closed under prefixes, as Hjorth and Nies do with the notion of fin-h reducibility.

## Higher reductions

We (of course) denote higher Turing reducibility by $\leq_{T}$.

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Although this may not be clear from the definition, $\leq_{T}$ is a refinement of $\leq_{n}$ :

$$
X \leq_{T} Y \Rightarrow X \leq_{n} Y
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## First results... for free!

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Theorem (Kučera-Gács / Hjorth-Nies)

- For every $X$, there exists $Y$ which is $\prod_{1}^{1}-M L$ random and $X \leq_{T} Y$ (and thus $X \leq_{h} Y$ ).
- For every $X \geq_{T} \mathcal{O}$, there exists a $\Pi_{1}^{1}-M L$ random $Y$ such that $X \equiv{ }_{T} Y$


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- For every $X \geq_{T} \mathcal{O}$, there exists a $\Pi_{1}^{1}-M L$ random $Y$ such that $X \equiv{ }_{T} Y$

Theorem (Chaitin, adapted)
There exists a left-c.e. $\Pi_{1}^{1}-M a r t i n-L o ̈ f ~ r a n d o m ~ r e a l ; ~ c a l l ~ i t ~ \Omega . ~$
Any such real computes $\mathcal{O}$.

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One can similarly define A-c.e. open set as an open set generated by a A-c.e. set of strings and thus define $A$-MLR.

Theorem (van Lambalgen, adapted)
$X \oplus Y$ is Martin-Löf random if and only if $X$ is Martin-Löf random and $Y$ is $X$-Martin-Löf random.

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- It is not true any more that for a c.e. open set $\mathcal{U}$ and cylinder $[\sigma]$, the set $[\sigma] \backslash \mathcal{U}[s]$ clopen, because $\mathcal{U}[s]$ may no longer be clopen for $s \geq \omega$.


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- "Time tricks" don't work. There are several theorems in algorithmic randomness that exploit the length of a string as an enumeration time (e.g. $\mathrm{K}_{|\sigma|}^{\sigma}$ ).


## 2-MLR and $\mathcal{O}-$ MLR

A well-known theorem of Miller/Nies-Stephan-Terwijn: 2-MLR reals are characterized by the condition:

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C(X \upharpoonright n) \geq n-c \text { for some } c \text { and infinitely many } n(\diamond)
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The proof of $(\diamond) \Rightarrow 2-M L R$ involves a time trick. This does not translate... and indeed, the condition

$$
C(X \upharpoonright n) \geq n-c \text { for some } c \text { and infinitely many } n(\diamond>)
$$

is not equivalent to being $\mathcal{O}$-MLR; it is somewhere between MLR and $\prod_{1}^{1}$-random [A recent result of Greenberg and Slaman: $\mathcal{O}$-ML randomness implies (strictly) $\prod_{1}^{1}$-randomness].

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Theorem (Hirschfeldt-Miller)
A real is weakly-2-random if and only if it is Martin-Löf random and forms a minimal pair with $\emptyset^{\prime}$.

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A real is weakly-2-random if and only if it is Martin-Löf random and forms a minimal pair with $\emptyset^{\prime}$.

It is not the case that a set is weakly-2-random iff it forms a (Turing) minimal pair with $\mathcal{O}$ [indeed, by the Gandy basis theorem, there exists an $\mathcal{O}$-computable $\prod_{1}^{1}$-random, hence weakly-2-random].

## W2R and $\prod_{1}^{1}$-RAND: separation attempts

$\Pi_{1}^{1}$-randoms are Martin-Löf randoms $X$ such that $\omega_{1}^{X}=\omega_{1}^{c k}$. This is equivalent to $X \not ¥_{h} \mathcal{O}$.

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So asking whether weak-2-randomness equals $\Pi_{1}^{1}$-randomness amounts to asking whether there is a weak-2-random $X$ such that $X \geq{ }_{h} \mathcal{O}$.

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An weaker question: is there a weak-2-random $X$ such that $X \geq{ }_{T} \mathcal{O}$ ?

Proposition (BGM)
No weak-2-random $X$ is such that $X \geq_{T} \mathcal{O}$.

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Theorem (BGM)
$\Omega_{0}$ is not weak-2-random. In fact, no $X \leq_{t t} \mathcal{O}$ is.

## A conjecture

One way to separate weak-2-randomness from $\prod_{1}^{1}$-randomness would be to evaluate the Borel rank of the class of $\Pi_{1}^{1}$-randomness.

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The Borel rank of the set of weak-2-randoms is $\Pi_{3}^{0}$. The set of $\prod_{1}^{1}$-randoms must have much higher rank, but we don't know how to prove this.
3. Higher lowness and triviality

## Complexity and semi-measures

Recall that a (discrete) semimeasure is a function $m: \omega \rightarrow \mathbb{R}^{+}$such that

$$
\sum_{i} m(i) \leq 1
$$

we say that it is (left-)c.e. if its lower graph is c.e.

## Proposition

There exists a universal c.e. semimeasure, i.e. a c.e. semimeasure $\tilde{m}$
such that for any other c.e. semimeasure $\mu$ one has

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To prove Levin's theorem, one can assume that $m$ is dyadic and whenever a new amount $2^{-k}$ is added to some $i$, a new description of $i$ is issued in $M$. The new description is carefully chosen to allow (potentially short) future descriptions. This is done by keeping track of the binary expansion of $\sum_{i} m(i)[s]$ at each stage $s$.

## Levin's coding theorem

In the higher setting, a bit more care is needed as the binary expansion of $\sum_{i} m(i)[s]$ can now be an infinite object, but it turns out that the only case where this could cause an issue is when the binary expansion is of the form

$$
0 . * * * * 011111111111111 \ldots
$$

which is equal
0. $* * * * 100000000000000 \ldots$
and thus is finite.

## Levin's coding theorem

This observation was made by Nies and Hjorth, who thus obtained:

Theorem (Nies-Hjorth)
Given a c.e. semimeasure m, one can uniformly build a prefix-free machine $M$ such that $K_{M}=-\log m \pm 1$.

## K-triviality

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## Definition

A real $X$ is $\mathbf{K}$-trivial if

$$
K(A \upharpoonright n) \leq^{+} K(n)
$$

These are the reals that are as far as random as possible from the point of view of K. Computable reals are K-trivial but Solovay was able to construct a non-computable c.e. K-trivial.

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The following are equivalent:

- $A$ is K-trivial
- $A$ is low for MLR: $M L R^{A}=M L R$
- $A$ is low for $\mathrm{K}: \mathrm{K}^{A}={ }^{+} \mathrm{K}$ (or $\tilde{m}^{A}={ }^{\times} \tilde{m}$ )


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The following are equivalent:

- $A$ is $K$-trivial
- $A$ is low for MLR: $M L R^{A}=M L R$
- $A$ is low for $\mathrm{K}: \mathrm{K}^{A}={ }^{+} \mathrm{K}$ (or $\tilde{m}^{A}={ }^{\times} \tilde{m}$ )
- $A$ is a base for ML randomness: there exists an $A-M L$ random real $X$ such that $X \geq_{T} A$.


## Relativizing Kolmogorov complexity

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In the classical setting, $\tilde{m}^{A}$ is defined in terms of a uniformly universal c.e. semimeasure. By this, we mean a function

$$
\tilde{m}_{2}: 2^{<\omega} \times 2^{\omega} \rightarrow \mathbb{R}^{+}
$$

- $\tilde{m}_{2}(.,$.$) is left-c.e. in both arguments, i.e. \tilde{m}_{2}(x, A)>q$ is a $\Sigma_{1}^{0}$-statement
- For all $A, \sum_{i} \tilde{m}_{2}(x, A) \leq 1$
- For all $A$ and every $A$-c.e. semimeasure $\mu, \tilde{m}_{2}(., A)>^{\times} \mu$


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Theorem (BGM)
There exists an A such that there is no A-c.e. universal semimeasure.

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[Note: we showed that it does make sense in some particular cases: when $A$ is $\mathbf{M L}$ random, when $A \leq_{t t} \mathcal{O}$, when $A$ is 1 -generic....]

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[Note: we showed that it does make sense in some particular cases: when $A$ is ML random, when $A \leq_{t t} \mathcal{O}$, when $A$ is 1 -generic....]

So one more quantifier is needed:
Definition
$A$ is low for K if for every $A$-c.e. semimeasure $\mu$ one has $\tilde{m}>^{\times} \mu$.

## K-trivials are well behaved

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[and there are some non-computable ones: Solovay's construction still works]


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- low for MLR implies base for ML randomness: this is a direct consequence of the higher Kučera-Gács theorem.
- Base for ML randomness implies K-trivial: this is done via the hungry sets constructions, with some careful adaptations.


## Caveat

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$$

This is not a mistake. This is because Nies means something different: he calls $A$-Martin-Löf random a real which passes all the Martin-Löf tests which are $\Pi_{1}^{1}[A]$ (equivalently, $\Sigma_{1}$-definable in $\left.\mathbb{L}_{\omega_{1}^{\mathrm{A}}}[A]\right)$.

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- K-trivials are jump traceable.


## Open questions

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Separate weak-2-randomness from $\Pi_{1}^{1}$-randomness.

Characterize the set of reals $X$ such that $\mathrm{C}(X \upharpoonright n)>n-c$ i.o.

