Coin Tossing, Randomness Extraction, and Algorithmic Randomness

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Molivaling Question

Suppose you are given a biased coin, i.e. a coin such that

 $\mathbb{P}(H) = p$

and

 $\mathbb{P}(T) = 1 - p$

for some $p \neq 1/2$, and you are asked to use it to simulate a fair coin. Can this be done?

The Plan of Allack

1. Some technicalities

2. Von Neumann's Trick

3. Generalizing the problem

4. Addressing the general problem with algorithmic randomness

A Bil of Nolalion

Hereafter, we will represent the event H by 0 and the event T by 1.

Let $2^{<\omega}$ denote the set of all finite binary strings.

Let 2^w denote the set of all infinite binary sequences.

More Notation

Given $\sigma, \tau \in 2^{<\omega}$, $\sigma \preceq \tau$ means σ is an initial segment of τ .

Similarly, given $\sigma \in 2^{<\omega}$ and $X \in 2^{\omega}$, $\sigma \prec X$ means that σ is an initial segment of X.

Given $X \in 2^{\omega}$ and $n \in \omega$, $X \upharpoonright n$ denotes the initial segment of of length n.

A Few More Definitions 2^{ω} has a natural topology: the basic open sets are of the form: $\llbracket \sigma \rrbracket := \{ \overline{X \in 2^{\omega}} : \sigma \prec \overline{X} \}$ The Lebesgue measure λ on 2^{ω} is defined on basic open sets to be $\lambda(\llbracket \sigma \rrbracket) = 2^{-|\sigma|}$ Later we will consider other

probability measures on 2^{ω} .

Simulating a fair coin?

What does it mean to simulate a fair coin with a biased coin?

Roughly, we want to use our biased coin to generate a finite string (or even an infinite sequence!) that is indistinguishable from one produced by tossing a fair coin.

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This is not very helpful.

More precisely... (1) Suppose we produce the string $\sigma \in 2^{<\omega}$ using our biased coin.

We want some function $\phi: 2^{<\omega} \to 2^{<\omega}$ that will convert σ into an unbiased string $\tau \in 2^{<\omega}$.

For any $\xi \in 2^{<\omega}$, $\mathbb{P}(\phi(\xi) \cap 0 \mid \phi(\xi)) = \mathbb{P}(\phi(\xi) \cap 1 \mid \phi(\xi)) = \frac{1}{2}$.

More precisely... (2)

We also want ϕ to satisfy the following monotonicity property: $\sigma \preceq \sigma' \Rightarrow \phi(\sigma) \preceq \phi(\sigma')$

Such a function should also be effectively computable: there should be an algorithm for computing the values of ϕ .

Step 1: Split the string into blocks of length 2.

Von Neumann's Trick 01 00 00 01 00 10 01 01 00 00 01 01 00 10 00 00 00 11 01 00 00 00 00 01 10 00 10 00 01

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Von Neumann's Trick 01 20 20 01 20 10 01 01 20 20 01 01 00 10 00 00 00 20 01 00 DO DO DO DO X 10 DO 10 DO 01 01 01 00 01 01 01 00 10 00 00 <u>৯৫ ৯৫ 10 10 01 10 % ३৫ 10 10</u>

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01 01 10 01 01 01 01 10 01 10 10 10 01 01 01 01 01 01 10 10 10 01 10 10 10 10

0 01 10 01 01 01 01 10 01 10 10 01 01 01 01 01 01 10 10 10 01 10 10 10

0 0 10 01 01 01 01 10 01 10 10 01 01 01 01 01 01 10 10 10 01 10 10 10

0 0 1 0 01 01 01 10 01 10 10 01 01 01 01 01 01 10 10 10 10 10 10 10

0 0 1 0 0 01 01 10 01 10 10 01 01 01 01 01 01 10 10 10 10 10 10

0 0 1 0 0 0 0 0 00 0 10 01 10 10 01 01 01 01 01 01 10 10 10 10 10 10

0 0 1 0 0 0 0 1 0 10 10 01 01 01 01 01 10 10 10 01 10 10 10

<u>0 0 1 0 0 0 0 1 0 1 10 01</u> <u>01 01 01 01 10 10 10 10 10 10 10</u>

0 0 1 0 0 0 0 1 0 1 1 0 0 01 01 01 01 10 10 10 01 10 10 10

0 0 1 0 0 0 0 1 0 1 1 0 01 01 01 01 10 10 10 10 10 10 10

001000101100

001000010110000001110111

Formally...

Von Neumann's trick gives us a monotonic, computable function $\phi: 2^{<\omega} \to 2^{<\omega}$ satisfying:

(1) $\phi(\sigma \cap 00) = \phi(\sigma \cap 11) = \phi(\sigma)$, (2) $\phi(\sigma \cap 01) = \phi(\sigma) \cap 0$, and (3) $\phi(\sigma \cap 10) = \phi(\sigma) \cap 1$ for every $\sigma \in 2^{<\omega}$ of even length.

Why does this work? (1) Recall: $\mathbb{P}(\sigma^0 \mid \sigma) = p$, $\mathbb{P}(\sigma^1 \mid \sigma) = 1 - p$

Key observation: For every $\sigma \in 2^{<\omega}$, $\mathbb{P}(\sigma \frown 00 \mid \sigma) = p^2$, $\mathbb{P}(\sigma \frown 11 \mid \sigma) = (1-p)^2$ and $\mathbb{P}(\sigma \frown 01 \mid \sigma) = \mathbb{P}(\sigma \frown 10 \mid \sigma) = p(1-p)$.

Why does this work? (2) Key observation: For every $\sigma \in 2^{<\omega}$, $\mathbb{P}(\sigma^{\frown}00 \mid \sigma) = p^2$, $\mathbb{P}(\sigma^{\frown}11 \mid \sigma) = (1-p)^2$ and

 $\mathbb{P}(\overline{\sigma \cap 01 \mid \sigma}) = \mathbb{P}(\overline{\sigma \cap 10 \mid \sigma}) = p(1 - p)_{\bullet}$

The conditional probability that the next bit output by ϕ is a 0, given that it has read either 01 or 10, is 1/2.

Changing Chings up (1)

The probability measure on 2^{ω} induced by a coin with bias p is called a Bernoulli p-measure.

Suppose now we are given a sequence of biased coins, and we are asked to simulate a fair coin by tossing each biased coin consecutively.

Changing things up (2)

The probability measure on 2^{ω} induced by such a sequence of coins is called a generalized Bernoulli measure, denoted $\mu_{\vec{p}}$, where $\vec{p} = (p_0, p_1, ...)$ and $p_i \in [0, 1]$ for every $i \in \omega$.

Then for every $\sigma\in 2^{<\omega}$ of length n, $\mu_{ec{p}}(\sigma^\frown 0\mid\sigma)=p_n$.

More changes (1)

What if we generalize even further, so that the sequence of coins we toss depends not only on the trial but also on the previous outcomes?

In this most general case, we're dealing with arbitrary probability measure on 2^{ω} .

More changes (2)

In these more general settings, von Neumann's trick won't work.

Is there a more general effective procedure for converting such biased random sequences into unbiased random sequences?

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Is there a more general effective procedure for converting such biased random sequences into unbiased random sequences?

Yes, if we recast the question in terms of algorithmic randomness.

Computable measures In what follows, we will restrict our attention to computable probability measures on 2^{ω} .

A measure μ on 2^{ω} is computable if there is a computable function $\widehat{\mu}: 2^{<\omega} \times \omega \to \mathbb{Q}$ such that for every $\sigma \in 2^{<\omega}$ and every $i \in \omega$, $|\mu(\llbracket \sigma \rrbracket) - \widehat{\mu}(\sigma, i)| \leq 2^{-i}$.

Random Sequences

We will also restrict our attention to sufficiently random sequences.

How do we guarantee that a sequence is sufficiently random?

There are a number of ways to make the notion of random sequence precise.

The Law of Large Numbers

$X \in 2^{\omega}$ satisfies the law of large numbers if

 $\lim_{n \to \infty} \frac{\#_0(X \restriction n)}{n} = \frac{1}{2}$

where $\#_0(\sigma)$ is the number of 0's in $\sigma \in 2^{<\omega}$.

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After n steps, if $\psi(X | n) = 1$, we include the (n+1)st bit of X in our subsequence; otherwise, we exclude the (n+1)st bit.

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stochastic Sequences (2) Let $X\!\!\upharpoonright_{\psi(X)}$ denote the subsequence extracted from X using ψ . $X \in 2^{\omega}$ is stochastic if (1) X satisfies the law of large numbers, and (2) for every computable selection rule $\psi: 2^{\ll \omega} \to \{0, 1\}, X \upharpoonright_{\psi(X)}$ satisfies the law of large numbers.

stochastic Sequences (3)

Not sufficient for randomness:

There is a stochastic sequence $X \in 2^{\omega}$ such that for all n,

 $\frac{\#_0(X \restriction n)}{n} > \frac{1}{2} \quad .$

Martin-Löf Tests

A Martin-Löf test is a sequence $(U_i)_{i\in\omega}$ of open subsets of 2^{ω} that are uniformly enumerated by some effective procedure and satisfy

 $\lambda(U_i) \le 2^{-i}$

for every $i \in \omega$.

















































Marlin-Löf Randomness

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 $X \notin \bigcap_{i \in \omega} U_i$. MLR denotes the collection of Martin-Löf random sequences.

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 $i \in \omega$ MLR denotes the collection of Martin-Löf random sequences. Sufficient for randomness?








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 $MLR_{\mu} = \mu - ML$ -random sequences

Extraction (1)

Monotonic functions $\phi: 2^{<\omega} \to 2^{<\omega}$ can be extended to maps $\Phi: 2^{\omega} \to 2^{\omega}$:

$$\Phi(X) = \bigcup_{n \in \omega} \phi(X \restriction n)$$

 Φ is a Turing functional if it is induced by a computable, monotonic ϕ .

Extraction (2)

Given $X, Y \in 2^{\omega}$, X is Turing reducible to Y if there is a Turing functional Φ such that $\Phi(Y) = X$.

X and Y are Turing equivalent if there are Turing functionals Φ and Ψ such that $\Phi(Y) = X$ and $\Psi(X) = Y$.

The main result

Levin and Kautz independently proved:

Theorem: Let μ be a computable measure on 2^{ω} . For every $X \in MLR_{\mu}$ such that X is not computable, there is some $Y \in MLR$ such that X and Y are Turing equivalent.

Some comments (1)

Unlike von Neumann's Erick, the Levin/Kautz conversion procedure works for any computable measure (in fact, it works for any noncomputable measure as well).

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Unlike von Neumann's trick, the Levin/Kautz conversion procedure works for any computable measure (in fact, it works for any noncomputable measure as well).

However, the conversion requires that we also have access to the underlying biased measure.

Some comments (2)

Joint work with Laurent Bienvenu:

There are biased random sequences such that there is no computable bound on the number of biased input bits needed to guarantee the output of n unbiased bits for any effective conversion procedure.

