

Online probability, complexity and randomness

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but not all

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→ observed behavior

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Probability distribution P

sequence α

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Martin-Löf: sequence α may be *random* or
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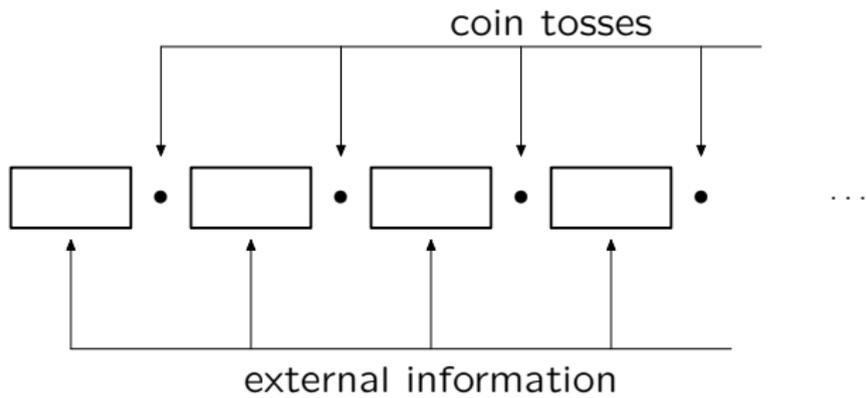
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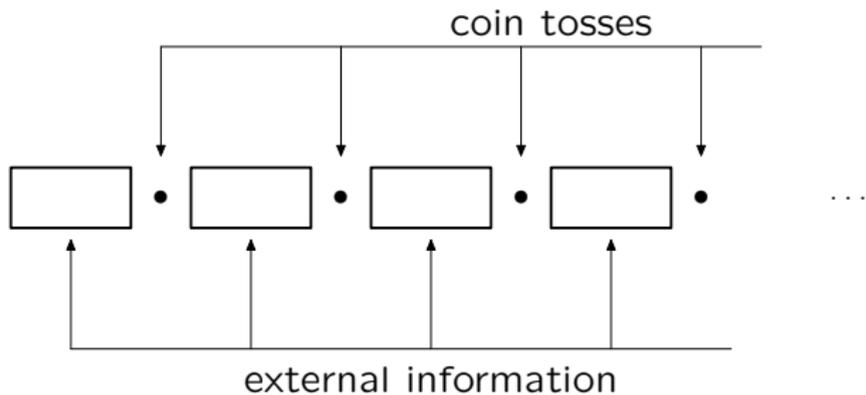
Martin-Löf: sequence α may be *random* or *non-random* with respect to P

(P is a computable distribution on the Cantor space $\{0, 1\}^\infty$ of binary sequences)

“Real” life:

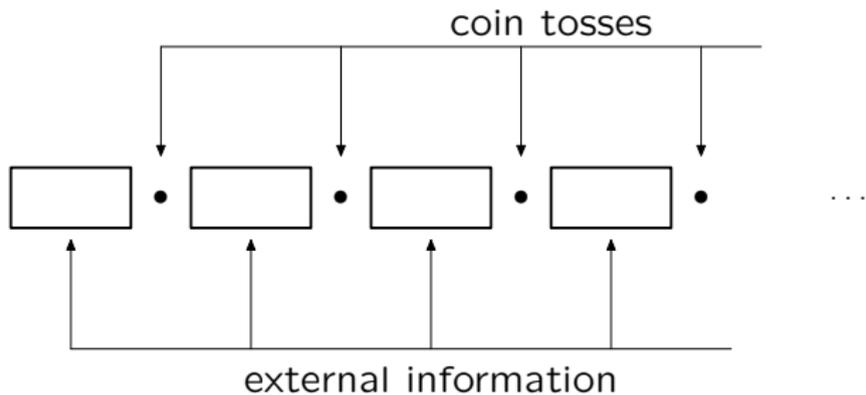


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Asking whether bits look random, we should take context into account

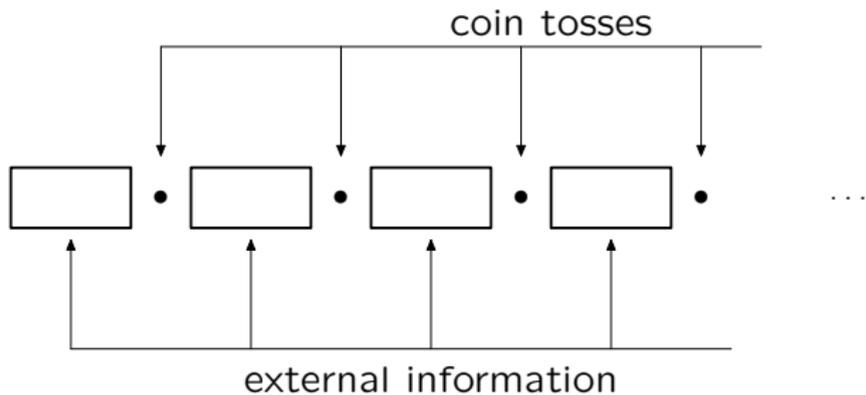
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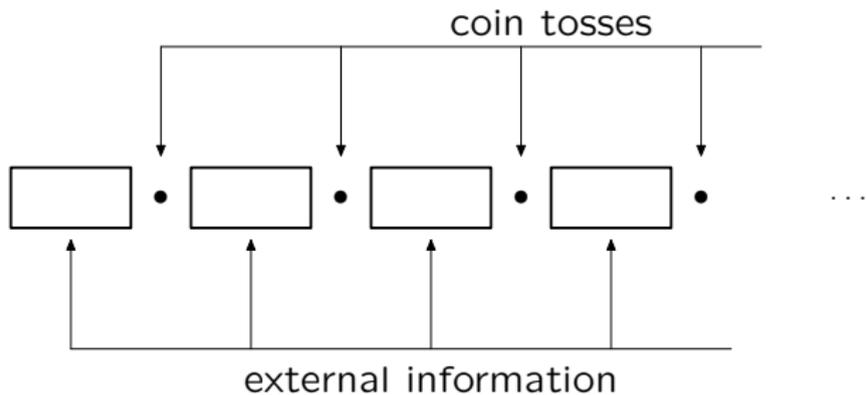
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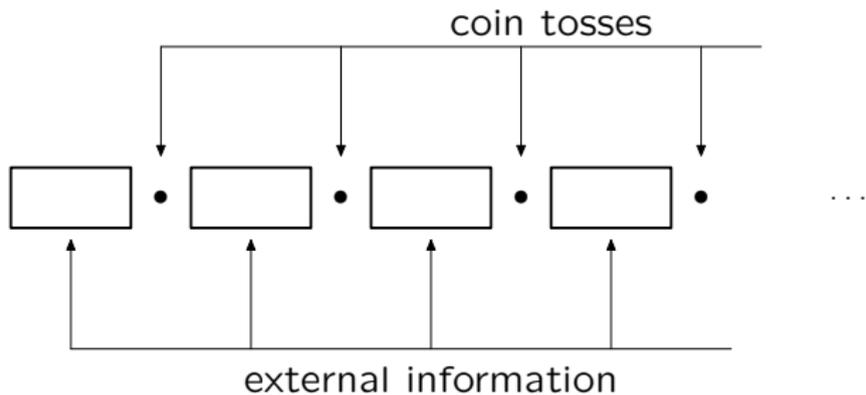


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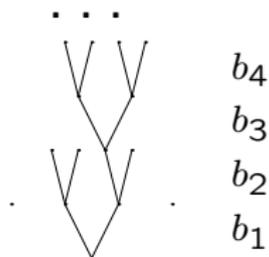
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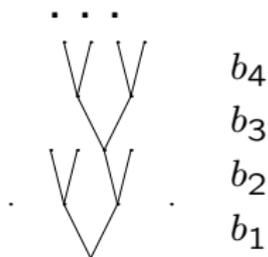
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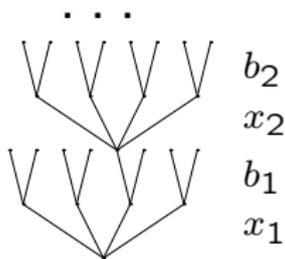


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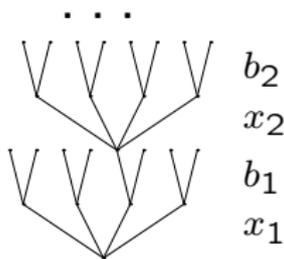
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rather special class of distributions: other notions of algorithmic information theory can be generalized for the on-line framework

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On-line *a priori* probability of $x_1, b_1, x_2, b_2, \dots, x_n, b_n$ is a probability that a universal probabilistic machine, getting x_1 as input, produces b_1 , then getting x_2 as input, produces b_2 , etc.

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- ▶ This function is a **martingale**, i.e.,

$$m(b_1 \dots b_n) = \Pr[b_{n+1} = 0 | b_1 \dots b_n] m(b_1 \dots b_n 0) + \Pr[b_{n+1} = 1 | b_1 \dots b_n] m(b_1 \dots b_n 1).$$

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- ▶ Betting is fair:

$$\begin{aligned} m(\dots x_n, b_n, x_{n+1}) = & \\ & \Pr[b_{n+1} = 0 \mid \dots x_n, b_n, x_{n+1}] m(\dots, x_n, b_n, x_{n+1}, 0) + \\ & + \Pr[b_{n+1} = 1 \mid \dots x_n, b_n, x_{n+1}] m(\dots, x_n, b_n, x_{n+1}, 1) \end{aligned}$$

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In other terms, $1/\Pr[E]$ is the "market value" for the right to start playing with initial capital 1 and the insider information "outcome will be in E "

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Game: you choose x_i while b_i are generated with given (conditional) probabilities; you win if the outcome belongs to E . The winning probability is upper probability of E .

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“On-line Cournot principle”: events with negligible upper probabilities never happen.

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If P is computable, the notion of **effectively on-line null** sets is defined; there exists maximal one; its complement is the set of **on-line random sequences**.

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A formal definition: we require that $p_1, b_1, p_2, b_2, \dots$ is on-line random wrt on-line distribution where

$$\Pr[b_i = 1 | p_1, b_1, \dots, p_i] = p_i$$

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Andrei A. Muchnik [1958–2007]: negative answer