

# Deterministic vs probabilistic gamblers

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Laurent Bienvenu (CNRS & Université de Bordeaux + Meiji University)

joint work with

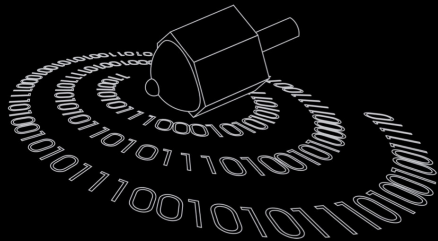
Valentino Delle Rose (Universidad Católica de Chile)

Tomasz Steifer (Universidad Católica de Chile)

*CCC 2023, Kyoto*

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# 1. Algorithmic randomness



# Random infinite sequences

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111000000111000000000111000111000111000111000000111111000
000000111111000000000000111000000111000000111000111111111
1111110001110001110001110000000011100000011100000000111
1110001110000000000000111111111000000111000111111111000....
```

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Not random!

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11101010 10010010 11100010 00010111 11101010....



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1111111011001001000100110101111000111100000111001011001110111010  
11101010 10010010 11100010 00010111 11101010....

Looks random!

# Kolmogorov complexity

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## Definition

Let  $x$  be a **finite** binary string. We call **Kolmogorov complexity of  $x$**  the quantity  $K(x)$  defined by

$K(x)$  = the shortest computer program (in binary) that generates  $x$

Of course formalizing all this needs some care. A sound formalism can be achieved using Turing machines (and programs=inputs of universal Turing machine).

Modulo this formalization, we can now say that a string  $x$  is *random* with randomness deficiency at most  $c$  if  $K(x) \geq |x| - c$ .

# Martin-Löf randomness

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## Definition

An infinite sequence  $X$  is Martin-Löf **random** if and only if for some  $c$  and for all  $n$ ,

$$K(X_0 \dots X_n) > n - c^*$$

\* for this definition we need to consider a variant of Kolmogorov complexity, the so-called prefix-free Kolmogorov complexity

# Unpredictability

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- The bits of the sequence are written on cards, facing down.
- The player tries to predict the values of these cards in order. Starting with a capital of \$1, she bets at each move some amount of her money on the value of the next card.

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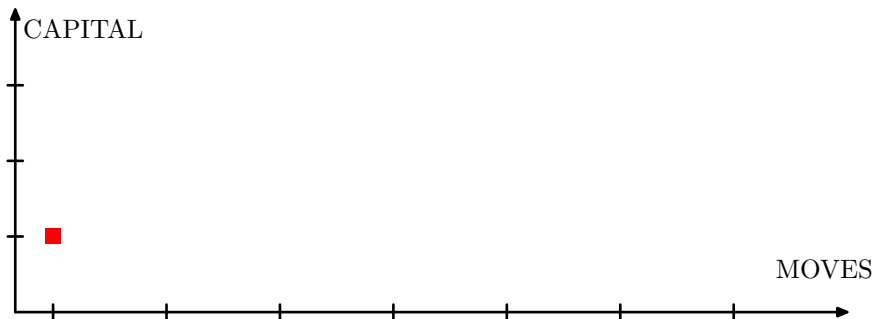
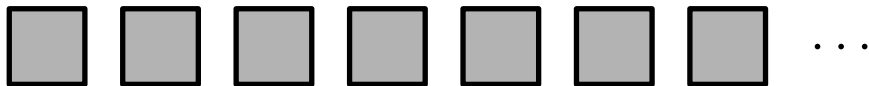
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- The bits of the sequence are written on cards, facing down.
- The player tries to predict the values of these cards in order. Starting with a capital of \$1, she bets at each move some amount of her money on the value of the next card.
- The player wins the infinite game if her capital tends to infinity throughout the game.

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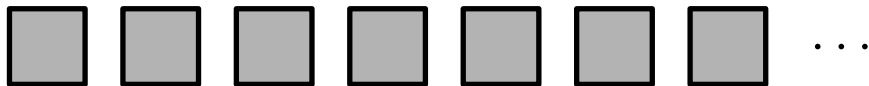
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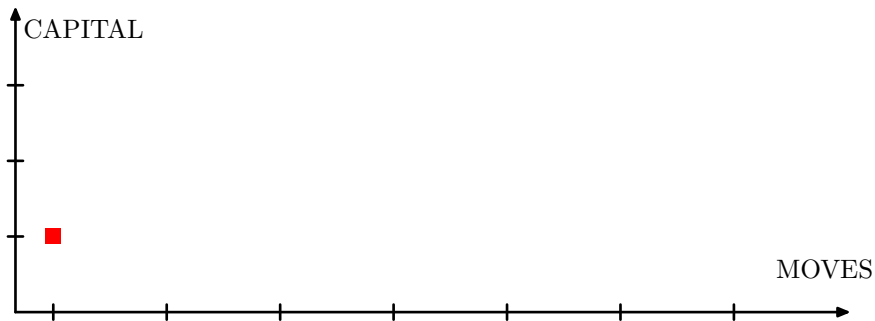


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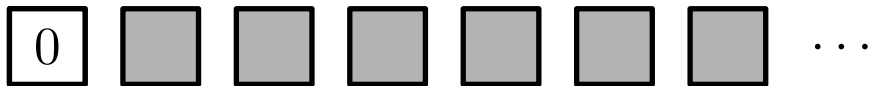


↑  
Bet 0.3 on "0"

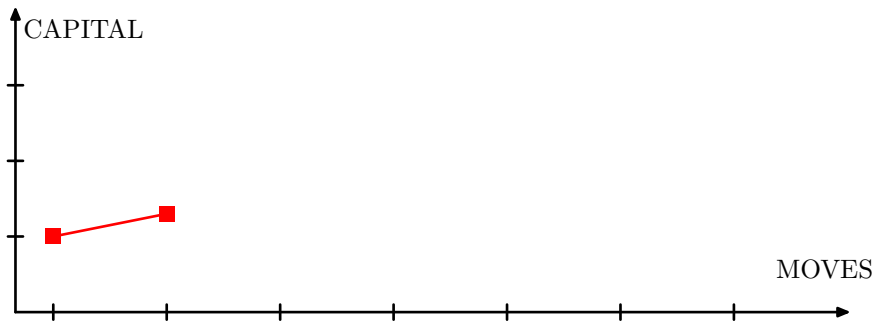


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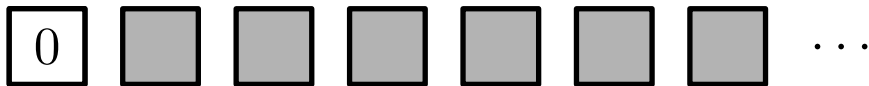
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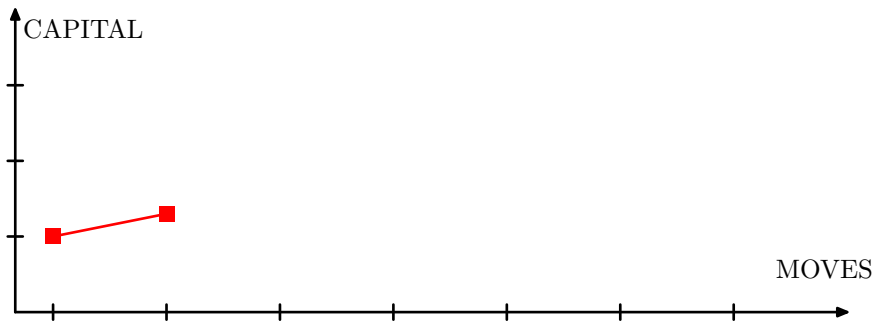
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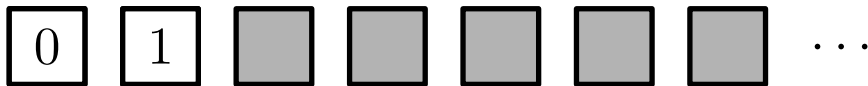
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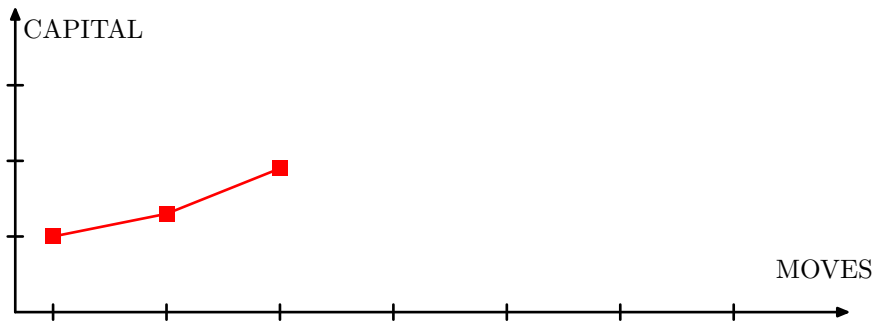
Bet 0.6 on "1"



# Unpredictability

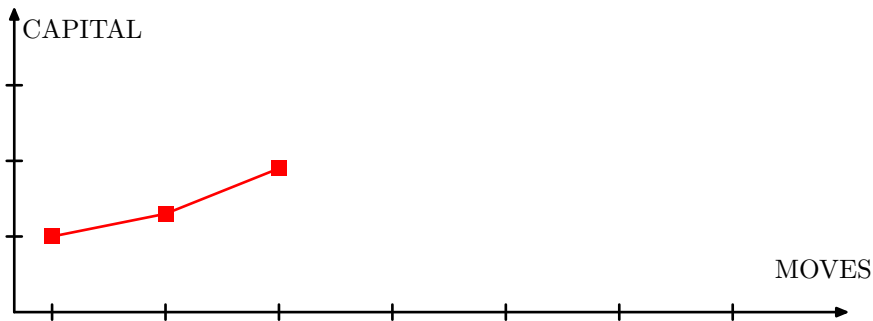
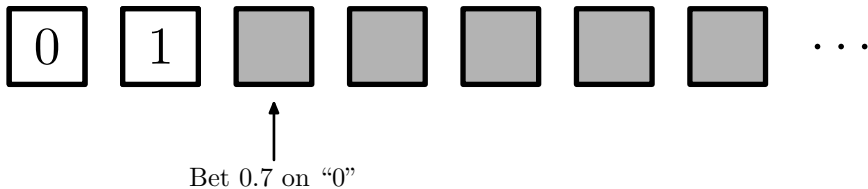


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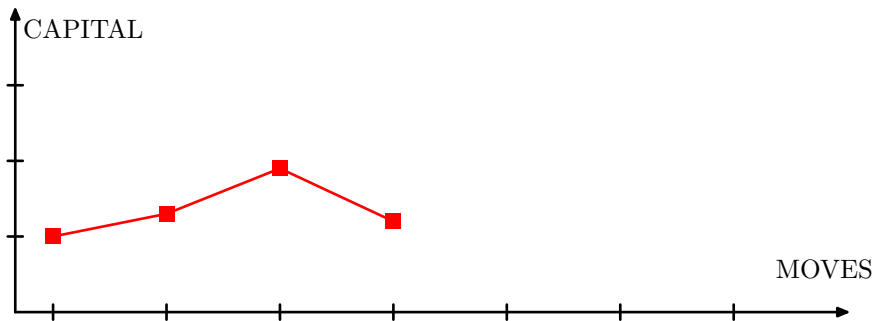
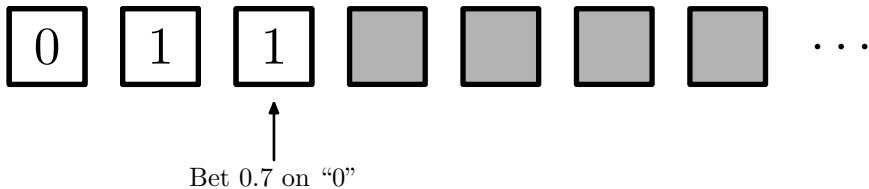


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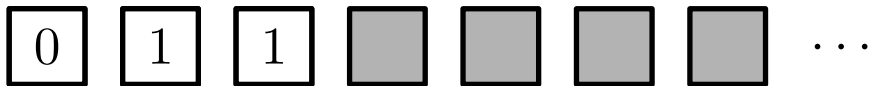
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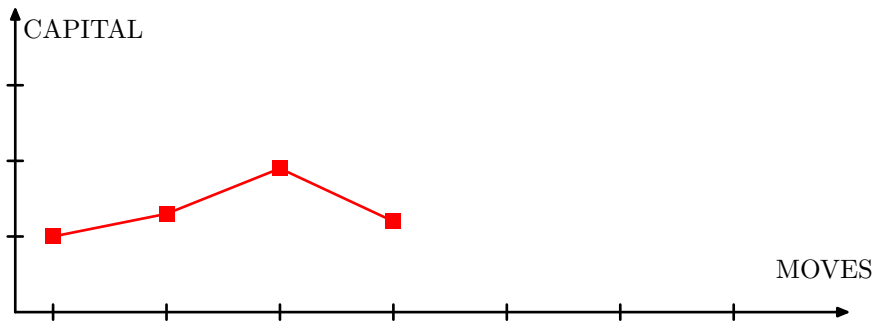
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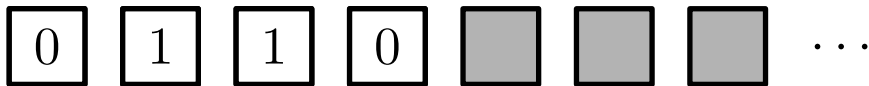
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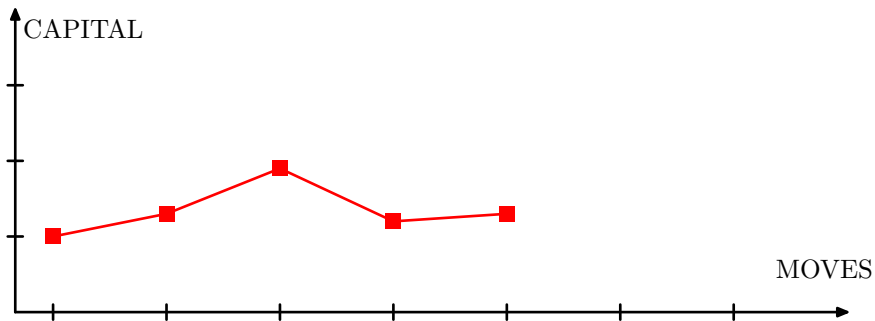
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Bet 0.1 on "0"



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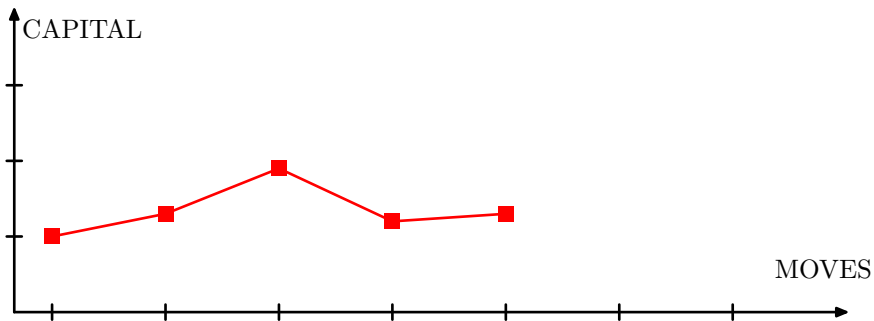
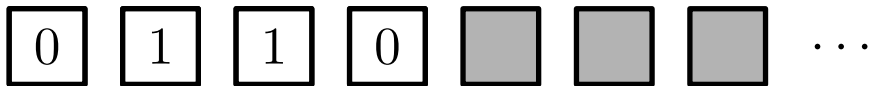


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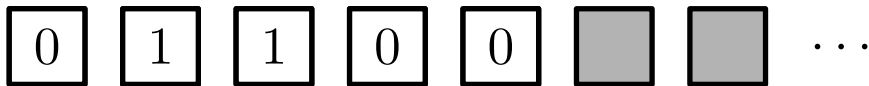




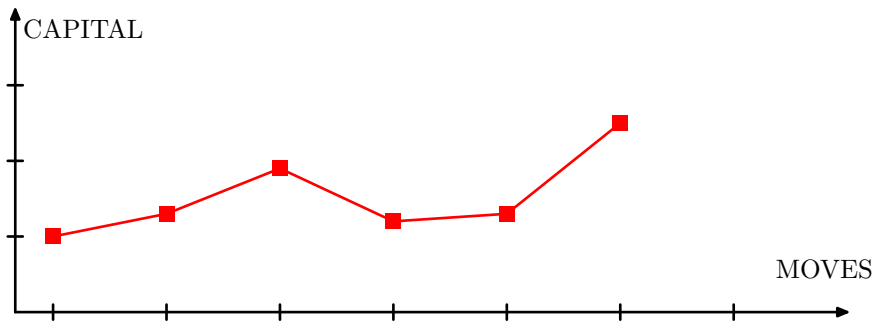
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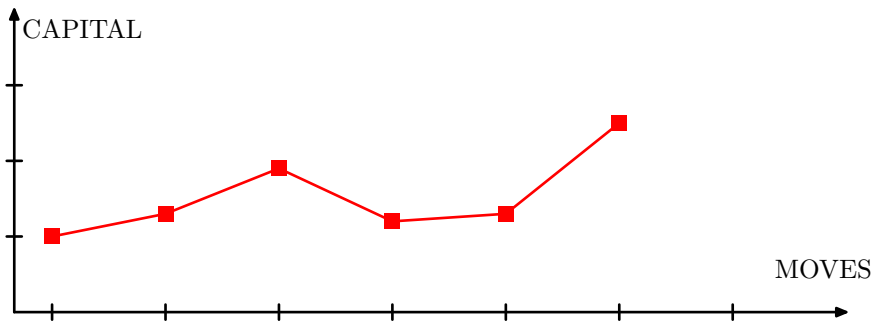
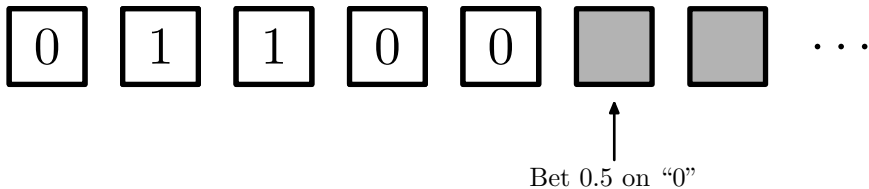
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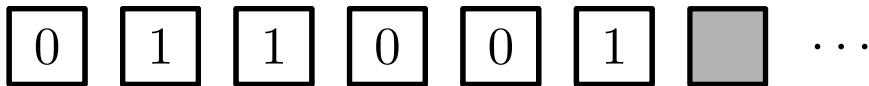
↑  
Bet 1.2 on "0"



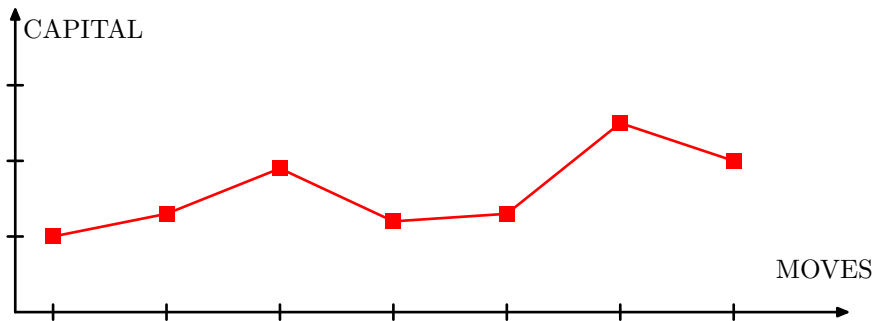
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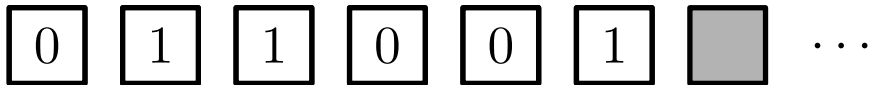
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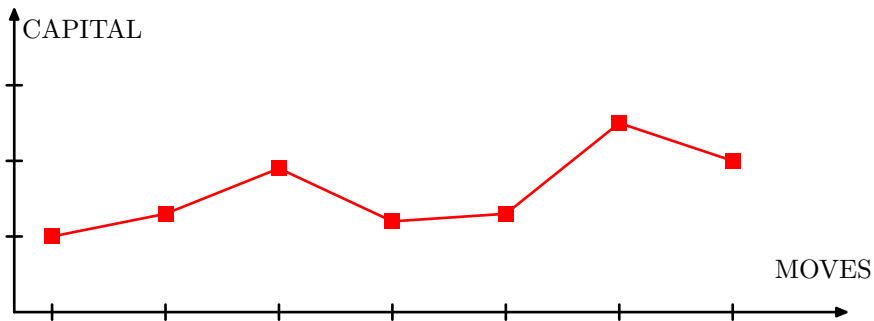
↑  
Bet 0.5 on "0"



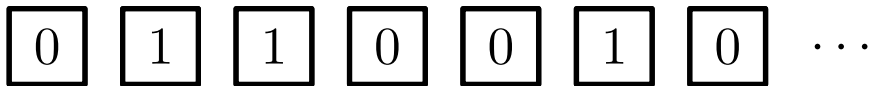
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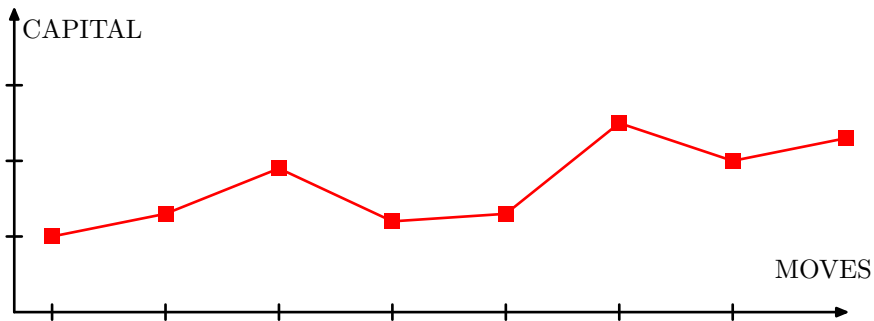
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Nonetheless this is a natural notion worth studying.

## 2. Randomizing things



# Randomized betting strategies

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What happens if we reinforce the betting strategy model, **by allowing the gambler to use a probabilistic algorithm to try to guess  $X$** ?

**Do we get a strictly stronger randomness notion?**

**If so, how does it relate to Martin-Löf randomness?**

# A restricted model

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This model was first studied by Buss and Minnes (2013) who considered a restricted case, namely when the betting strategy must be defined with probability 1. They proved:



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## **Theorem**

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But this leaves open the general question, where gamblers can take even more risk by allowing some random choices to trap them in an infinite loop (more risk, more potential reward!).

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The condition that the strategy must be defined with probability 1 ensures that  $\mu$  is nice, namely, it is a *computable* probability measure.

Thus, the average  $\mathbb{E}_\mu(S)$  is a computable strategy, therefore when ‘playing’ on an unpredictable  $X$ ,  $\mathbb{E}_\mu(S)$  must remain bounded, thus

$$\mu\{S \mid S \text{ remains bounded against } X\} = 1$$

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## **Theorem**

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**Take-home message: probabilistic gamblers are strictly better than deterministic gamblers!**

# A vague idea of the proof

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To prove this result, we use the notion of (computability-theoretic) Cohen genericity, namely the class of 1-generics. We say that an object  $X$  is 1-generic if for every effectively open set  $\mathcal{U}$ ,  $X$  is either in  $\mathcal{U}$  or in  $\text{Int}(\mathcal{U}^c)$ .

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1-genericity is usually defined for infinite binary sequences but is a topological notion, so it can be extended to the topological space of strategies. The topology: we view the space of strategies as a (closed) subspace of the space of functions  $\{f : 2^{<\omega} \rightarrow \mathbb{R}\}$  with the product topology.

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This algorithm induces a (twisted!!) measure  $\xi$  on the space of martingales, with  $\xi(1GEN) > 0.9999$ .

So now we can build an  $X$  so close to computable that

$$\xi\{S \mid S \text{ defeats } X\} > 0.9999$$

... which means that indirectly, we have built a probabilistic martingale which succeeds against  $X$  with high probability!



# Looking forward

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**a.e.-unpredictability.**

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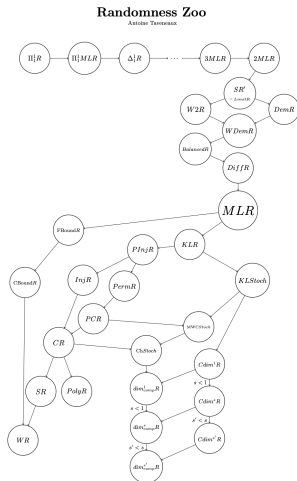
## Theorem

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So we have a truly new notion of randomness, which deserves further study. Also, one now needs to take a new look at the randomness zoo...

# Looking forward

... and see which ones have an non-trivial 'a.e.' counterpart!



# References

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- [1] Sam Buss, Mia Minnes, "Probabilistic Algorithmic Randomness", Journal of Symbolic Logic 78(2), 2013.
- [2] Laurent Bienvenu, Valentino Delle Rose, Tomasz Steifer, "Probabilistic vs deterministic gamblers", STACS 2022 and [arxiv.org/abs/2112.04460](https://arxiv.org/abs/2112.04460)

Thank You!