Title: From observers to physics via algorithmic information theory I

Date: Apr 03, 2018 10:30 AM

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Abstract: Motivated by the conceptual puzzles of quantum theory and related areas of physics, I describe a rigorous and minimal â€œproof of principleâ€• theory in which observers are fundamental and in which the physical world is a (provably) emergent phenomenon. This is a reversal of the standard view, which holds that physical theories ought to describe the objective evolution of a unique external world, with observers or agents as derived concepts that play no fundamental role whatsoever.

Using insights from algorithmic information theory (AIT), I show that this approach admits to address several foundational puzzles that are difficult to address via standard approaches. This includes the measurement and Boltzmann brain problems, and problems related to the computer simulation of observers. Without assuming the existence of an external world from the outset, the resulting theory actually predicts that there is one as a consequence of AIT â€” in particular, a world with simple, computable, probabilistic laws on which different observers typically (but not always) agree. This approach represents a consistent but highly unfamiliar picture of the world, leading to a new perspective from which to approach some questions in the foundations of physics.

From observers to physics
via algorithmic information theory

Markus P. Müller
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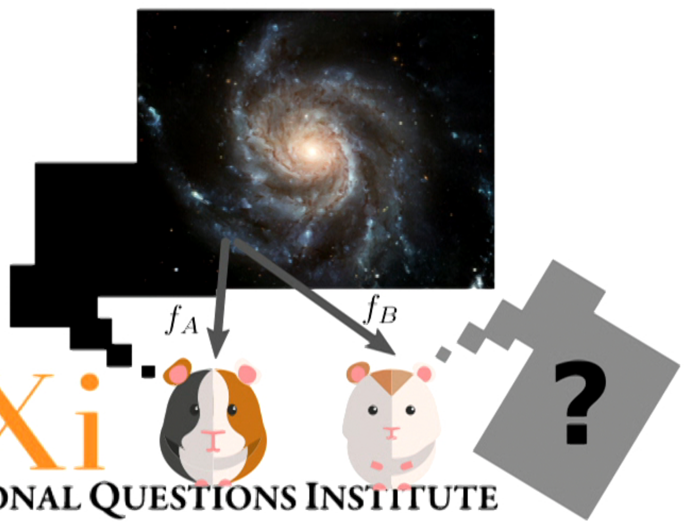
Perimeter Institute for Theoretical Physics, Waterloo



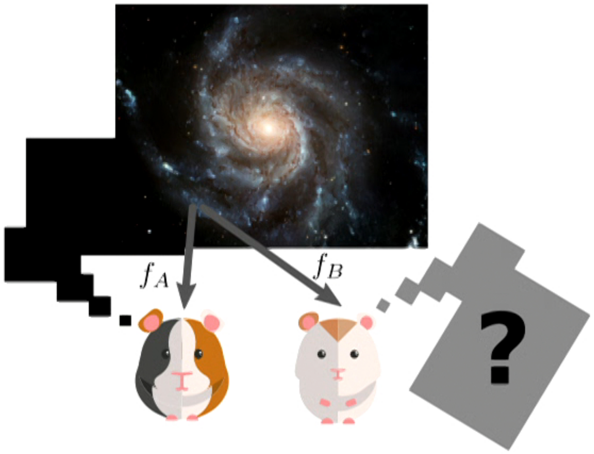
FQXi
FOUNDATIONAL QUESTIONS INSTITUTE

Philosophy aspects
with Mike Cuffaro

Outline for this talk (10:30 — 11:30)

1. Motivation

2. Postulates of the theory

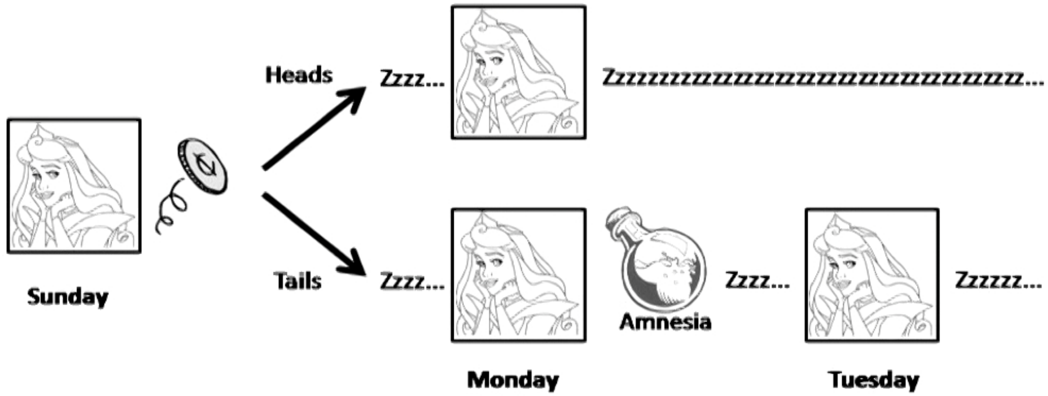


3. How does an external world emerge?

4. What about more than one observer?

The talk later today (14:30 — 15:30)

- 1. Illustration of formalism via the **Sleeping Beauty Problem**



- 2. **Quantum theory**: Bell violation and no-signalling as generic predictions

- 3. **Conceptual comments** and conclusions

In large parts independent from this earlier talk.

Systematic conceptual problems

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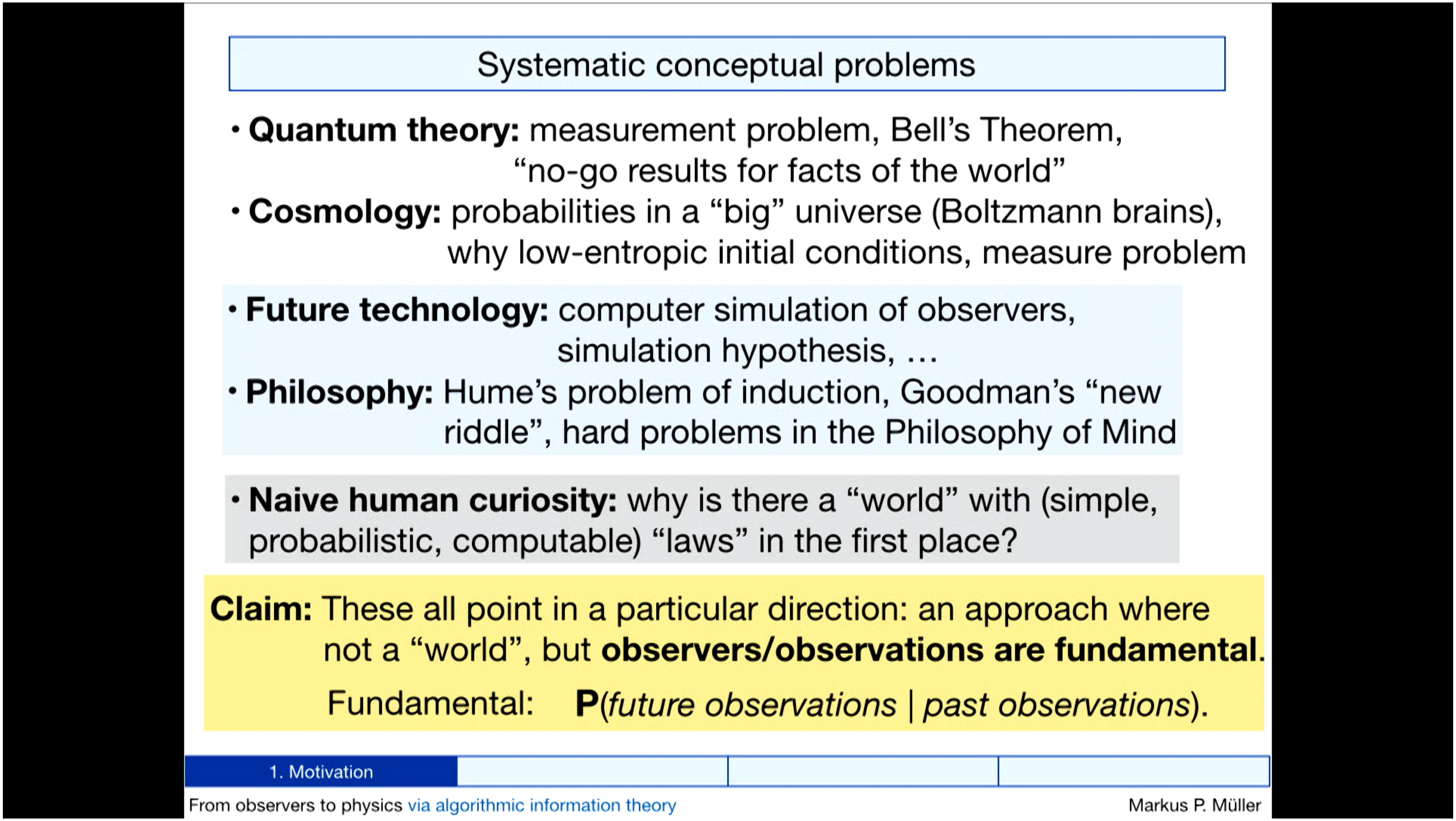

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Claim: These all point in a particular direction: an approach where not a "world", but observers/observations are fundamental.
Fundamental: P(future observations | past observations).
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Boltzmann brain problem

Cosmologists argue about this:

"Wow! I hope I'm not, like, a disembodied brain randomly formed complete with false memories of an existence I never really had, floating in a sea of chaos and disorder. That would really ruin my day...

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Sketch of argumentation:

- Fix a cosmological model **X** that predicts a *very* large universe.
- Count N_{BB} (# of Boltzmann brains) and compare to N_{nat} (# of naturally evolved brains).
- If $N_{BB} \gg N_{nat}$ then a "BB-observation" should be highly probable: *"What the…? I'm in space?! Aargh…"*
- That's not what we see, hence **X** is falsified.

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Is this argumentation valid?
→ seems to rely on *more* than statements about "the world"

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General approach

Approach:

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  privately for every single observer.

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- Drop any assumption of an "external world".
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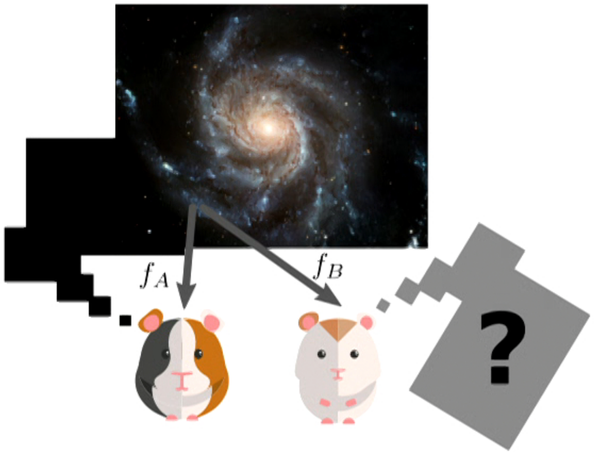
  privately for every single observer.
- Postulate **P=algorithmic probability**, motivated by structural arguments. See what follows, and compare with actual physics.

Disclaimer

- “Observer” is a technical / information-theoretic notion. Not (directly) related to “consciousness” etc.
- Not meant as a “TOE”. Predicts its own limitation. Useless for most things.
- “Reality” of world is not denied, but only its fundamentality. Reproduces standard view to good approximation.

Outline



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2. Postulates of the theory

3. How does an external world emerge?

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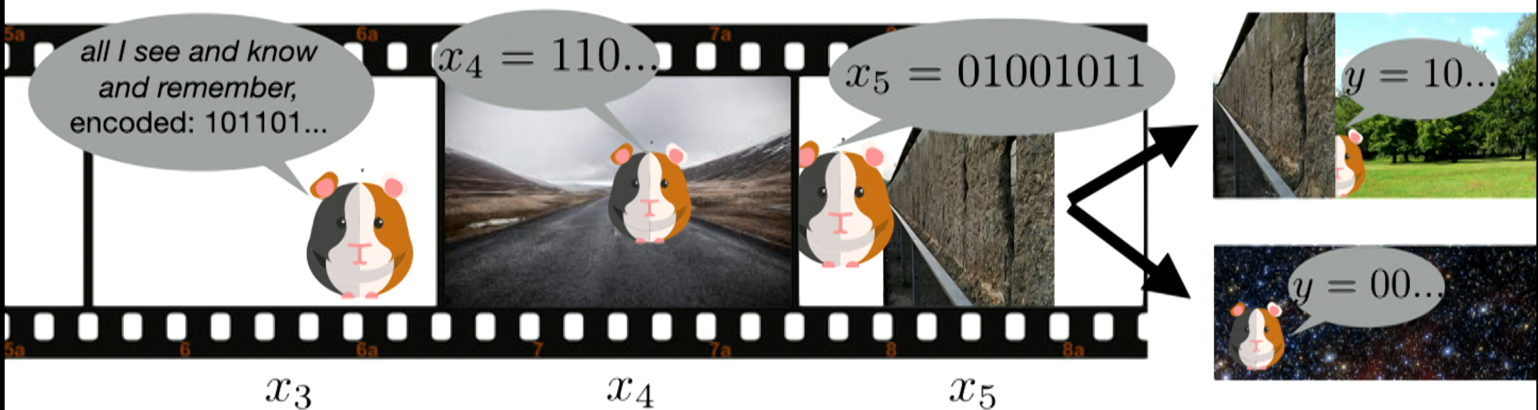
Postulates of the theory

Absolutely minimal ingredients:



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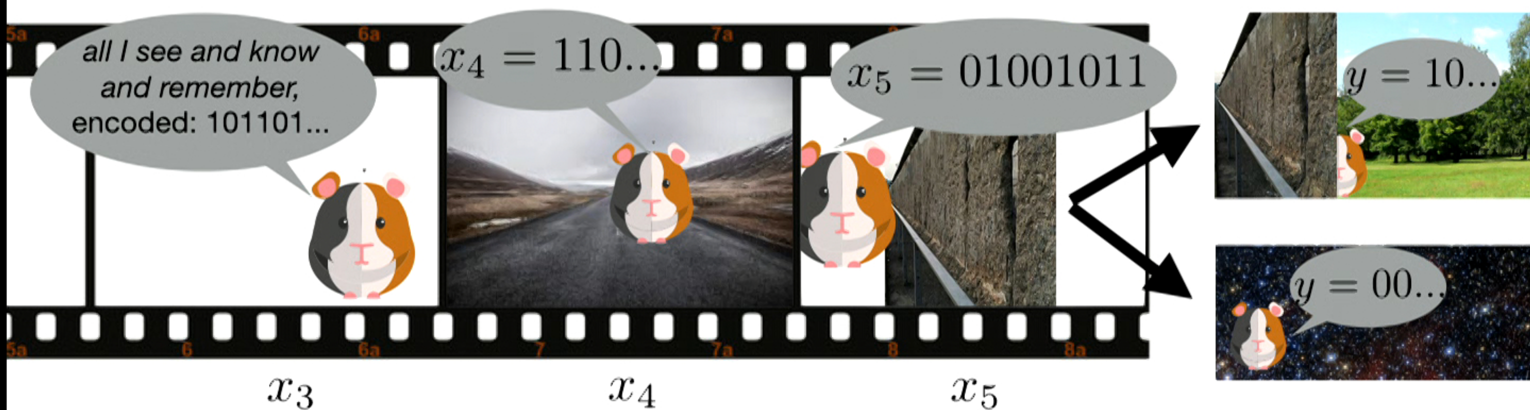
Absolutely minimal ingredients:

- An observer is in some state *x* (at any given moment).
- It will be in some other state *y* next.
- Some future states *y* are more probable than others.



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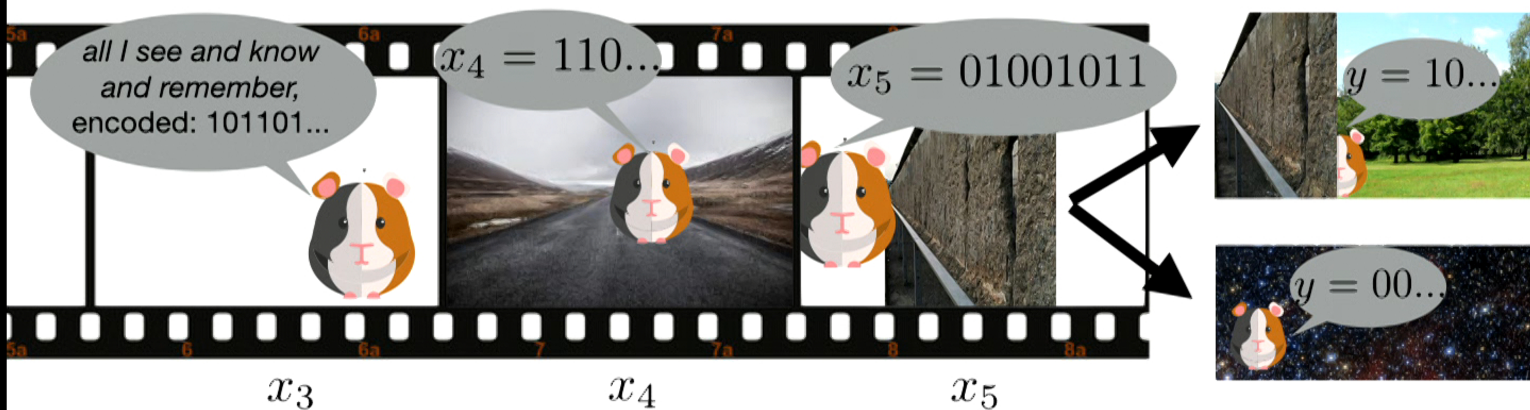

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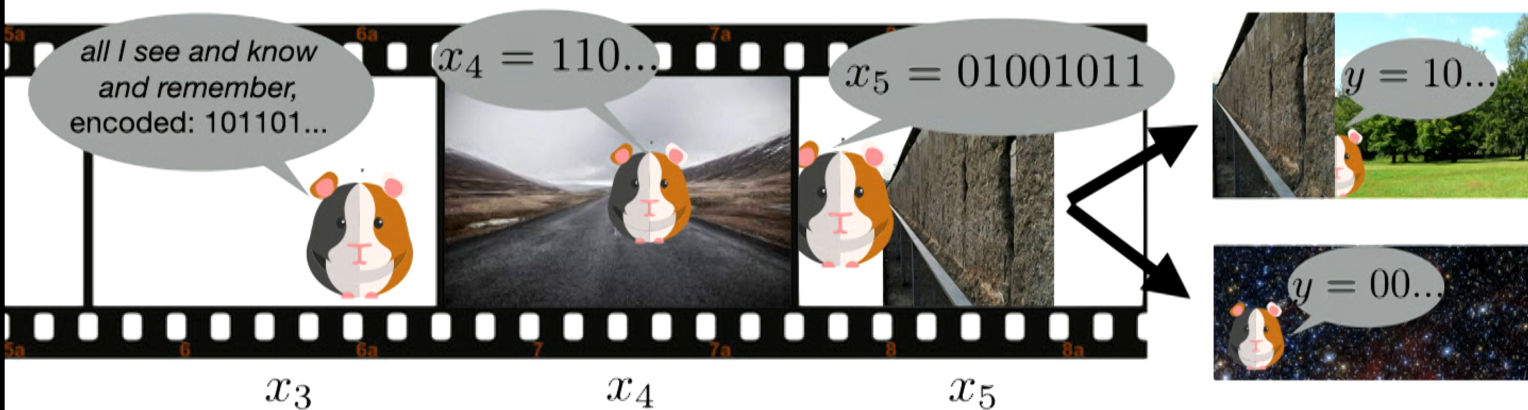
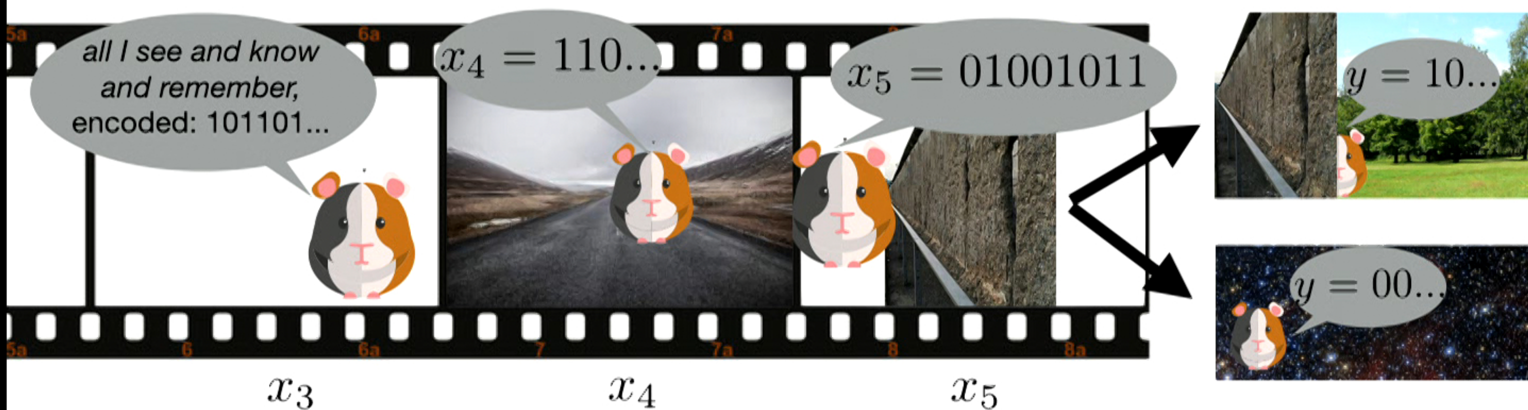
Agency, quantumness, a "world": **not** postulated, but (partially) derived.



An observer's **state** can be represented by a binary string (like $x_1 = 011010$). One (subjective) moment after the other, this yields a sequence $\mathbf{x} = (x_1, x_2, \ldots, x_n)$, and the probability of the next state *y* is

$$\mathbf{P}(y|x_1, x_2, \ldots, x_n),$$

where **P** is conditional **algorithmic probability**.



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- No assumption that this comes from incomplete knowledge / quantum state /… of any "external world".
  The **P** describes fundamental irreducible chances.
- Not the actual 0-1-sequence is relevant, but the **computability structure** that relates the different strings. **Analogy:** in GR, the actual coordinates don't matter, but the differentiable structure.

What is algorithmic probability?

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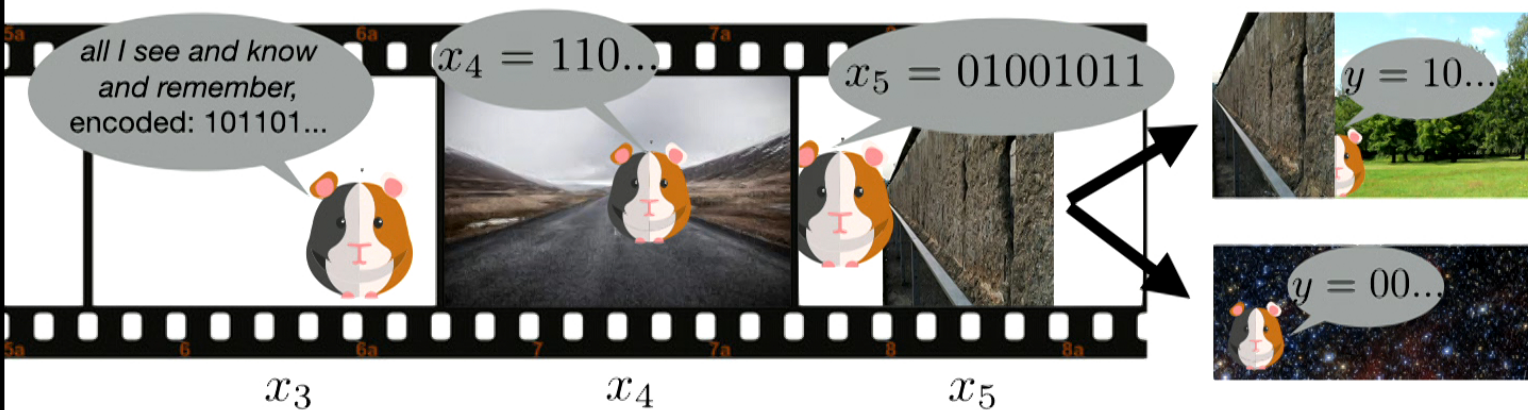
Probability measures on “histories”: $\mathbf{P}(x_1, \ldots, x_n) = ?$



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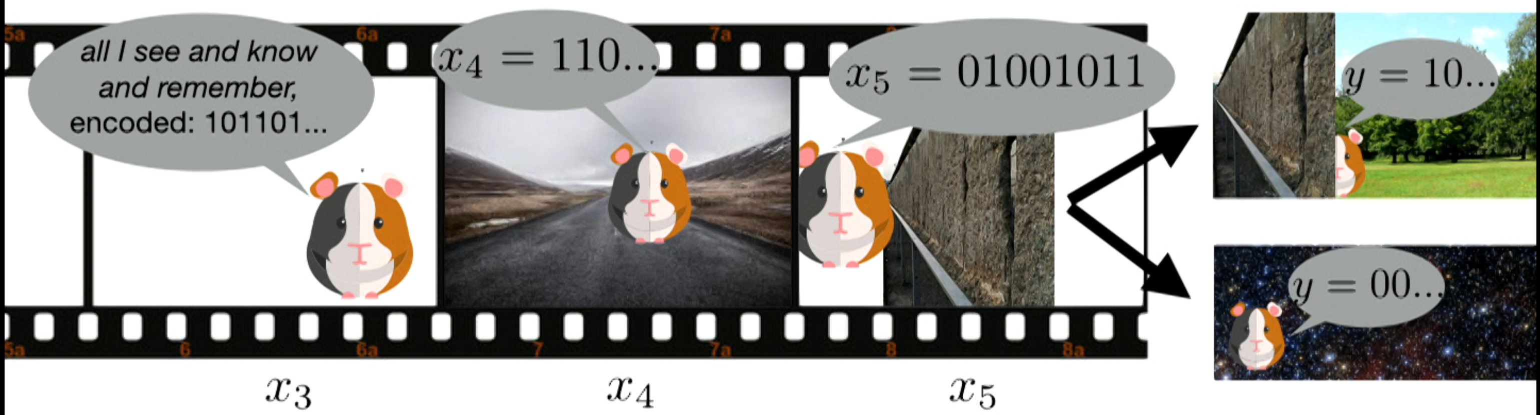
Probability measures on "histories": $\mu(x_1, \ldots, x_n) = ?$

(Boring) example: $\mu(x_1) := 2^{-2\ell(x_1)-1}$, e.g. $\mu(1011) = 2^{-2\cdot 4-1} = 2^{-9}$,



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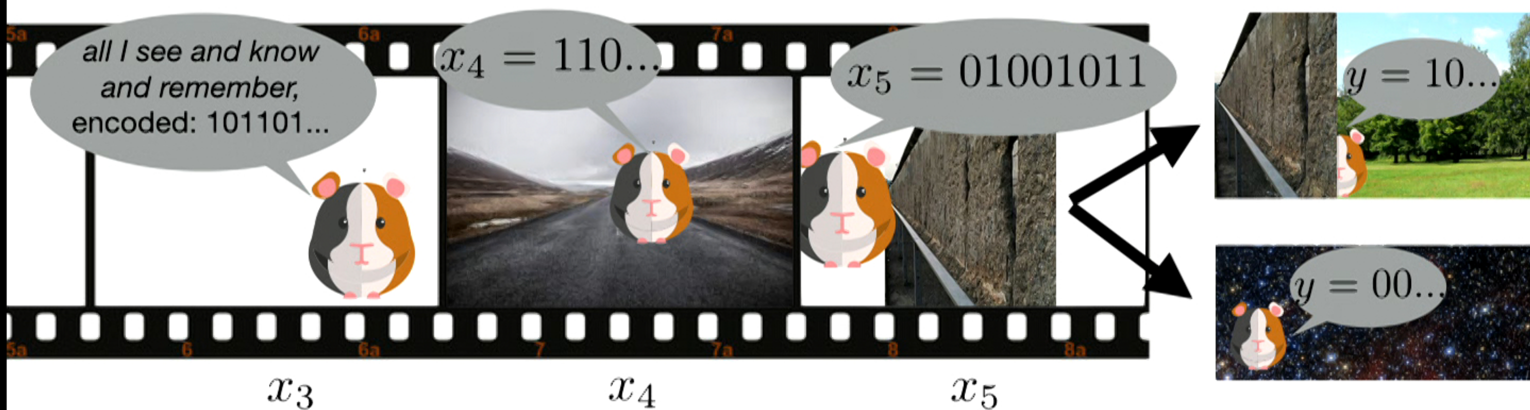

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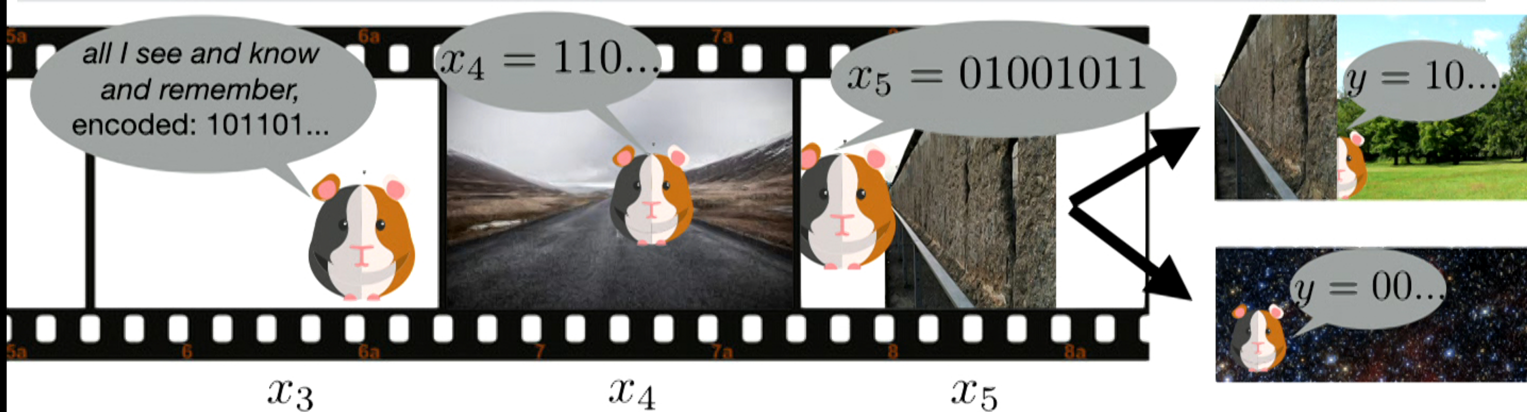
Measure: $\sum_{x_1} \mu(x_1) = 1, \quad \sum_{x_{n+1}} \mu(x_1, \ldots, x_n, x_{n+1}) = \mu(x_1, \ldots, x_n).$

Semimeasure: Same with "$\leq$" instead of "=".



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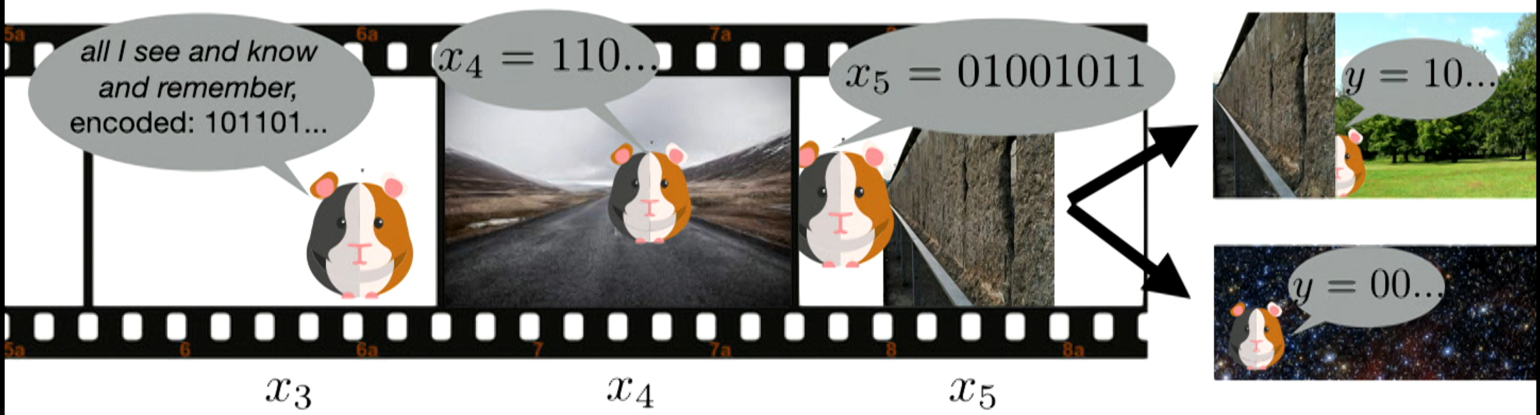
A (semi)measure is **computable** if there is a computer program that, on input $x_1, \ldots, x_n$ and $m \in \mathbb{N}$ outputs an $(1/m)$–approximation to $\mu(x_1, \ldots, x_n)$.



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A (semi)measure is **enumerable** if there is a computer program that, on input $x_1, \ldots, x_n$ and $m \in \mathbb{N}$ outputs some approximation $\mu^{(m)}(x_1, \ldots, x_n)$ such that $\mu^{(m)} \leq \mu$ and $\lim_{m \to \infty} \mu^{(m)} = \mu$.

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A **universal enumerable semimeasure M** is an enumerable semi-measure such that for every enumerable semimeasure μ there exists some constant $c > 0$ such that $\mathbf{M}(x_1, \ldots, x_n) \geq c \cdot \mu(x_1, \ldots, x_n)$.

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on ... to ...

A (... hat, on ... $\mu^{(r}$ ... $(x_1, \ldots, x_n)$ such that ... $\lim_{m\to\infty}$ ...

Pick any universal enumerable semimeasure **M** and normalize it.
This defines **algorithmic probability P**.

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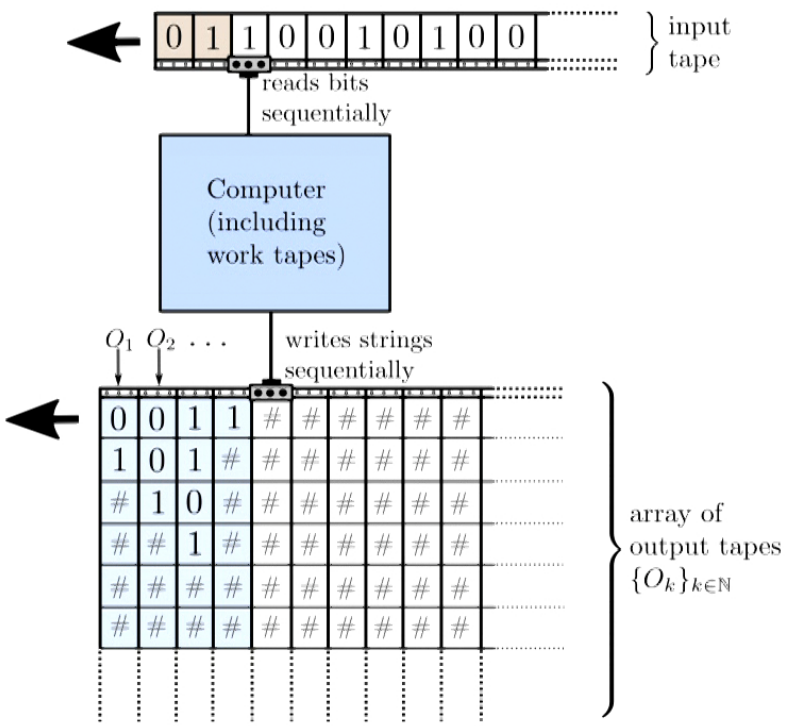
Alternative definition:



Universal monotone Turing machine *U*

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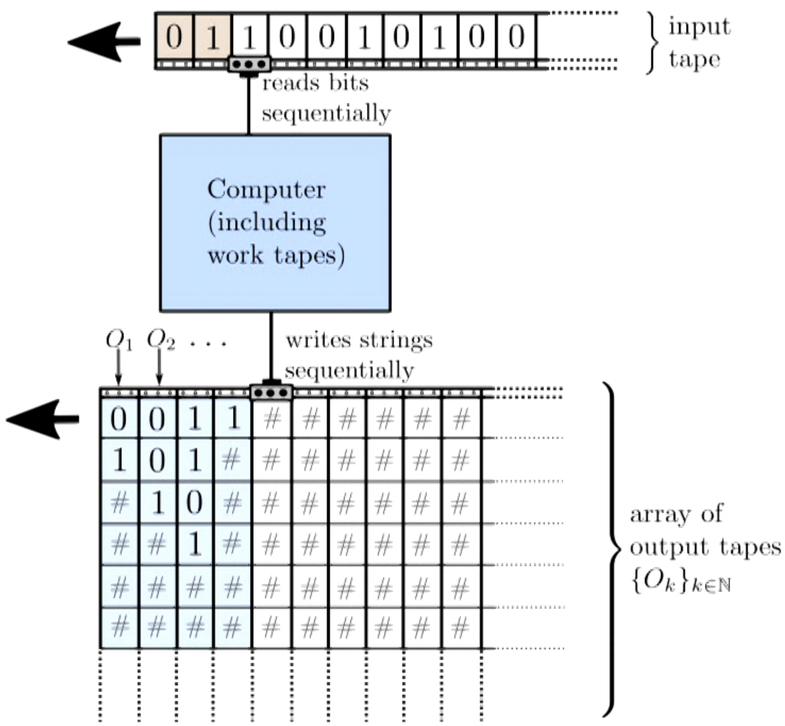

Universal monotone Turing machine *U*

$\mathbf{M}_U$:=distribution of outputs if input is chosen at random. Is universal enumerable.

“Occam’s razor”:

$$\mathbf{M}_U(x_1,\ldots,x_n) \geq 2^{-K(x_1,\ldots,x_n)},$$

where $K(\mathbf{x})$ is the length of the shortest computer program that outputs **x**.

Favors compressibility!

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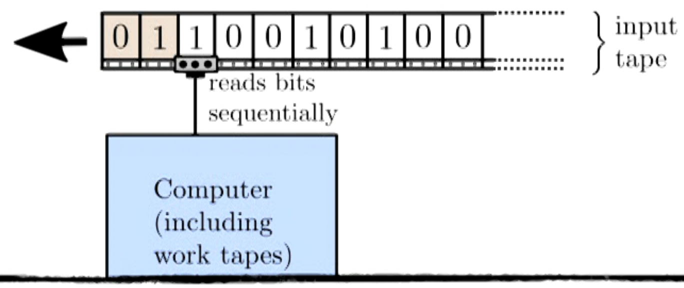

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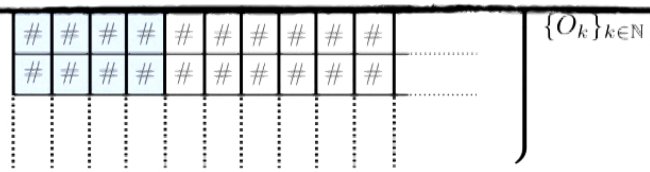
Q: Won't the resulting theory depend on the choice of universal machine *U* / univ. enum. semimeasure **M**?
A: **No,** but non-trivial why not. Maybe ask me later.



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2. Postulates of the theory

An open problem

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Conceptually (much) clearer, but **consequences much harder to work out**. Don't know how to do it (yet).

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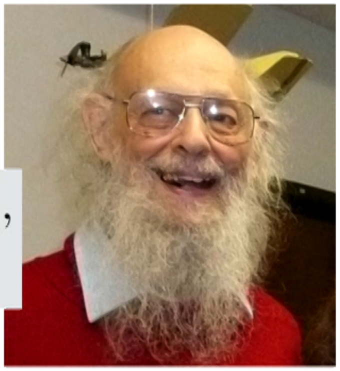

Why algorithmic probability?

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> Gives quickly the correct probabilities in all computable probabilistic environments.

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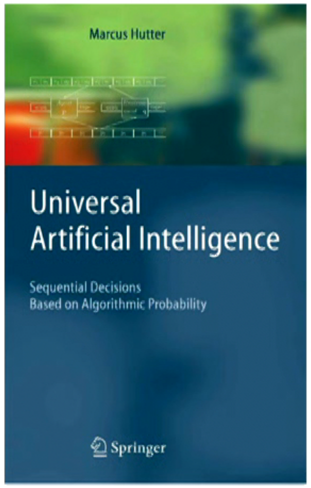

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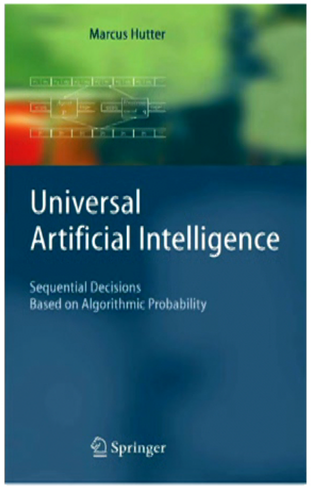

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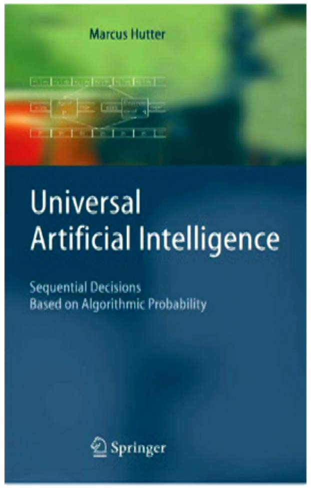

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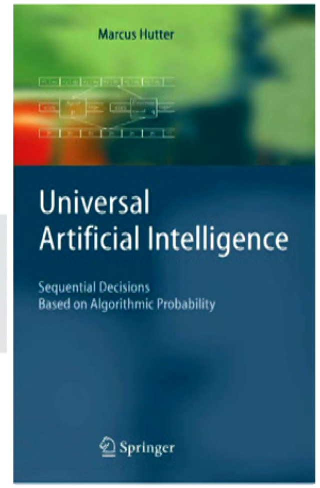

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- Idea: **postulate that Solomonoff induction is "the law"!**
  This will then *have to* be consistent with physics (given our data).

Why algorithmic probability?

2. A structural motivation

Physics is nothing but what makes some future observations more likely than others.
Algorithmic probability is an essentially unique "**canonical propensity structure**".

Outline

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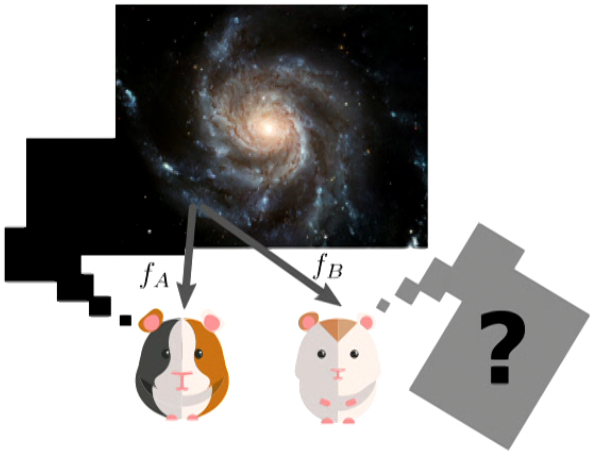
2. Postulates of the theory

3. How does an external world emerge?

4. What about more than one observer?



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Fix any computable test *f*.

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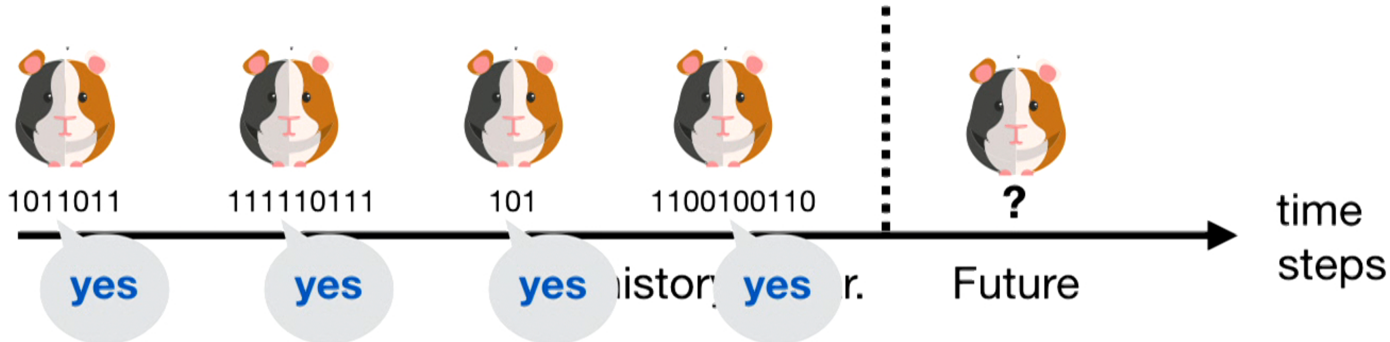

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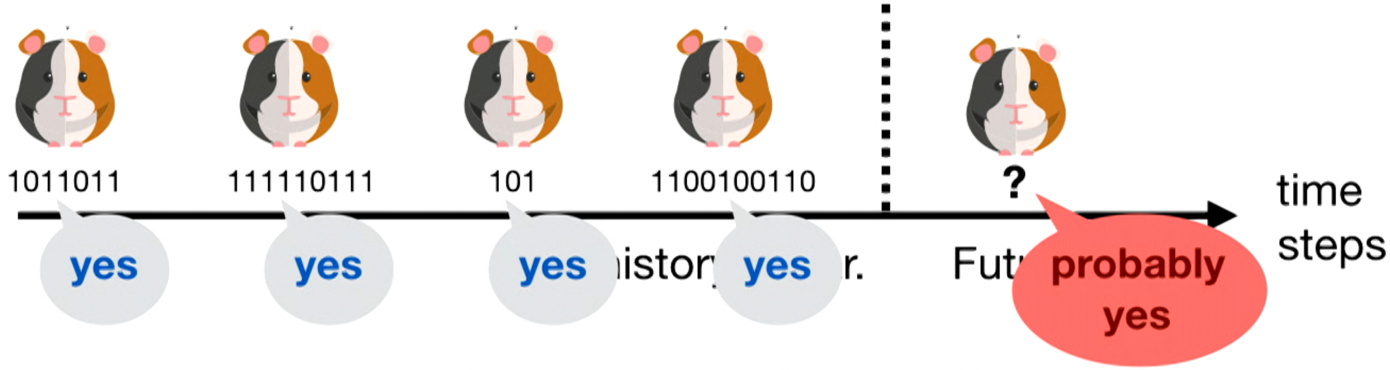

Theorem: Then, with probability close to one, answer will be "**yes**" in the future.

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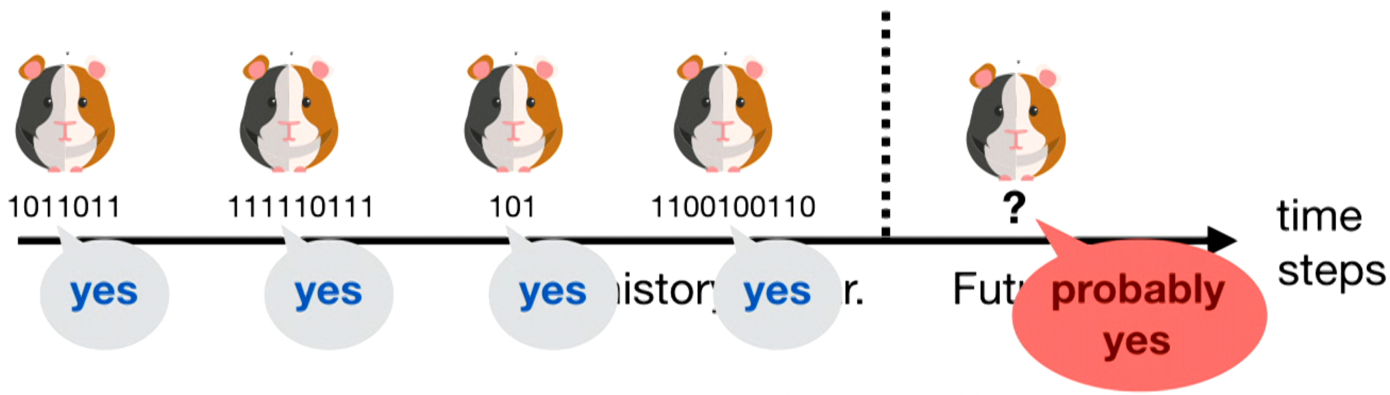

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Intuitive reason: This makes sequence of strings **more compressible**.

Prediction 1: **Principle of persistent regularities**

Rigorous mathematical formulation:

Theorem 8.3 (Persistence of regularities)**.** Let A be a dead-end free observer graph, and f an open computable A-test. For bits $a_1, \ldots, a_n, b \in \{0,1\}$, define the measure p as

$$p(b|a_1 a_2 \ldots a_n) := \mathbf{P}\{f(\mathbf{x}_1^{n+2}) = b \mid f(\mathbf{x}_1^2) = a_1, \ldots, f(\mathbf{x}_1^{n+1}) = a_n\},$$

and similarly define the semimeasure m with $\mathbf{P}$ replaced by $\mathbf{M}$. Then we have[38] $m(0|1^n) \leq 2^{-K(n)+\mathcal{O}(1)}$, and for the measure p we have the slightly less explicit statement

$$p(1|1^n) \stackrel{n\to\infty}{\longrightarrow} 1, \qquad (10)$$

but the convergence is rapid since $\sum_{n=0}^{\infty} p(0|1^n) < \infty$. Thus, e.g., $p(1|1^n) > 1 - \frac{1}{n}$ for all but finitely many n. Moreover, the probability that $f(\mathbf{x}_1^{n+1}) = 1$ for all $n \in \mathbb{N}$ is non-zero.

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Theorem applies to both f and $\tilde{f}$. Contradiction?! **No.**

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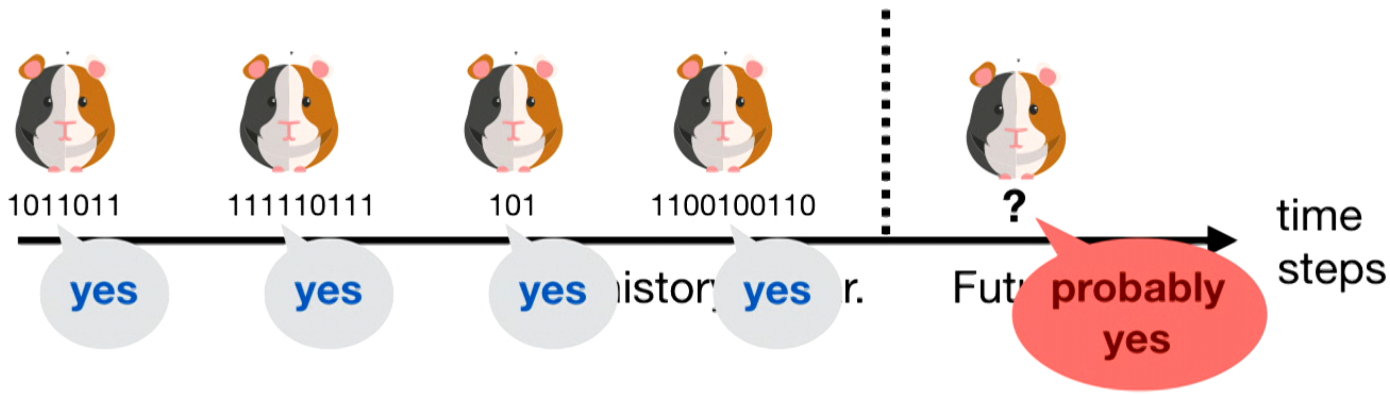

Boltzmann brain experience ("*what the... I'm suddenly in space... argh!!*") is highly unlikely.

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Will the different regularities "fit together" coherently? **Yes!** →

Prediction 2: **Simple, computable, probabilistic "world"**

Theorem. Consider any **computable probabilistic process** that has description length *L* on a universal computer. Suppose it generates outputs $x_1, x_2, x_3, \ldots$ according to the (computable) distribution $\mu(x_1, \ldots, x_n)$.

Then, with **P**-probability at least 2^{-L} we have

$$\mathbf{P}(y|x_1, \ldots, x_n) \stackrel{n\to\infty}{\longrightarrow} \mu(y|x_1, \ldots, x_n),$$

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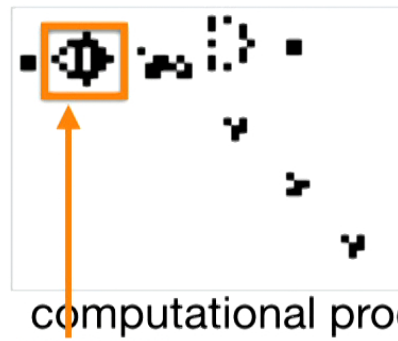

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- It is **contingent** which process (and thus μ) will emerge, but **simpler** ones are highly preferred (simpler = smaller L = higher probability)
- Thus, observer's probabilities will equal the marginal distribution of some random variable that's part of a **probabilistic process** with **computable laws of short description** (a simple algorithm).

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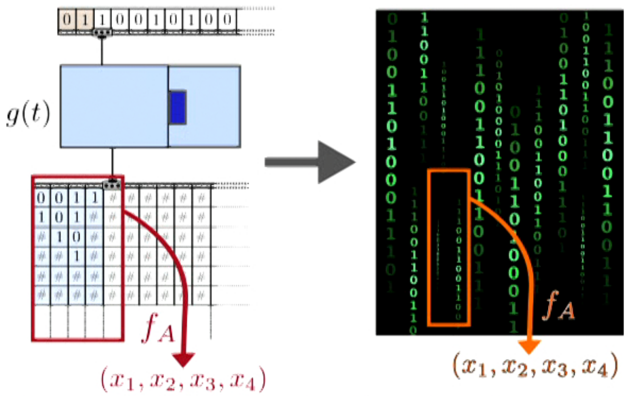

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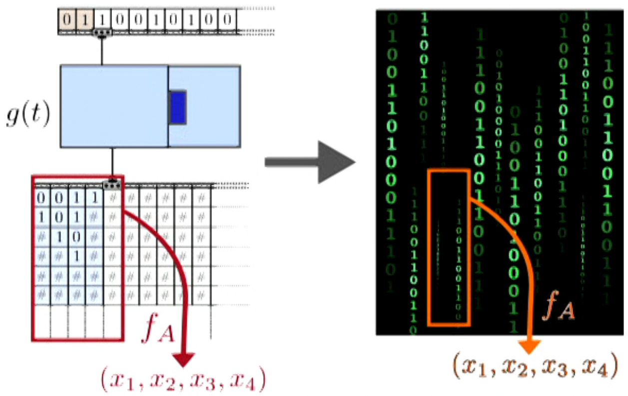

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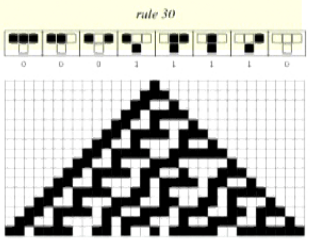

- There are generic features of (simple) computational processes, e.g. that they **start in some simple initial state**. This seems to be consistent with what we see in physics ("low-entropic initial conditions").

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2. Postulates of the theory

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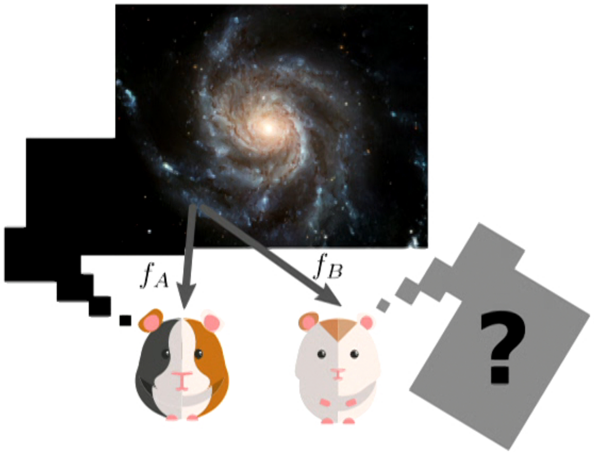

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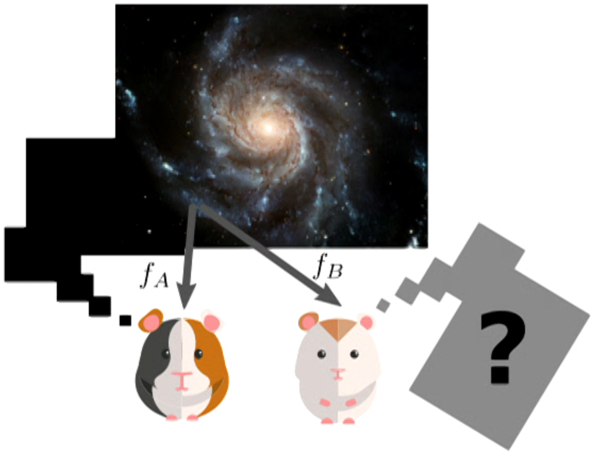

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Prediction 3: **An emergent notion of objectivity**

Apriori, different observers make their *own* "private" observations.

Abby

$$\mathbf{P}(y^A | x_1^A, \ldots, x_n^A)$$

Bambi

$$\mathbf{P}(y^B | x_1^B, \ldots, x_m^B)$$

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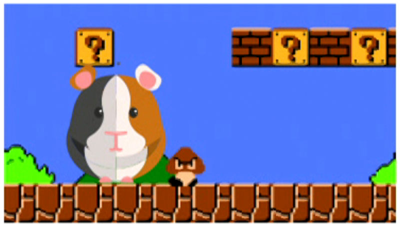
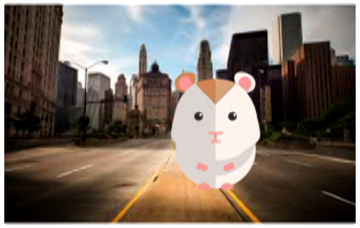
A-world   **B**-world

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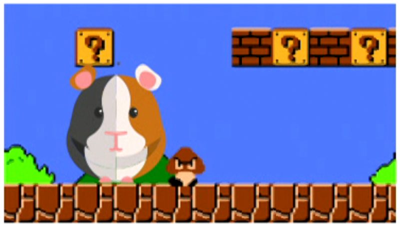
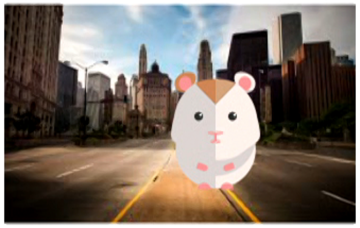
A-world   **B**-world

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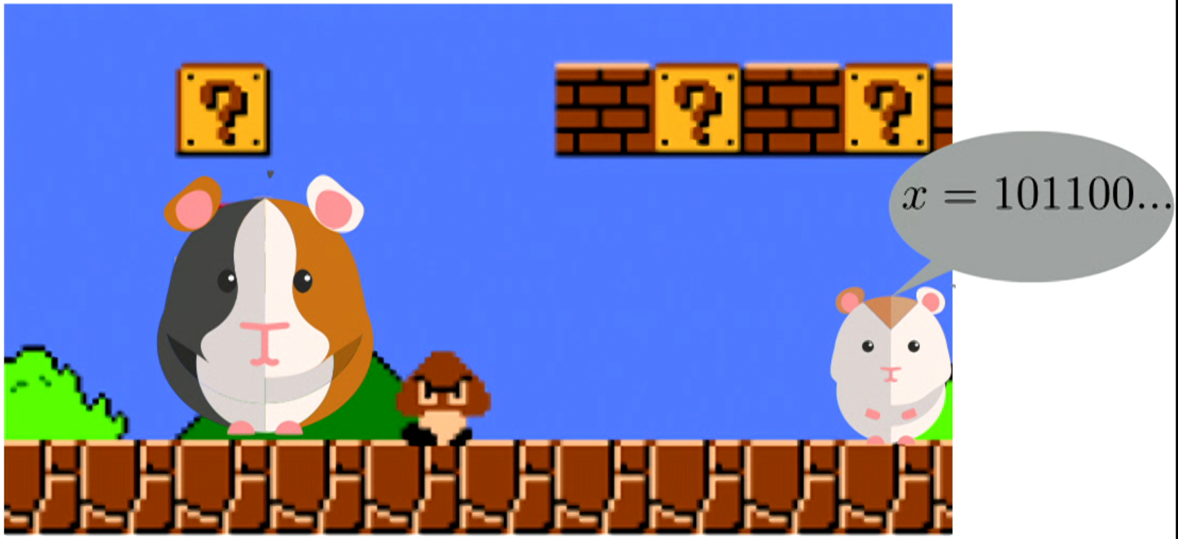

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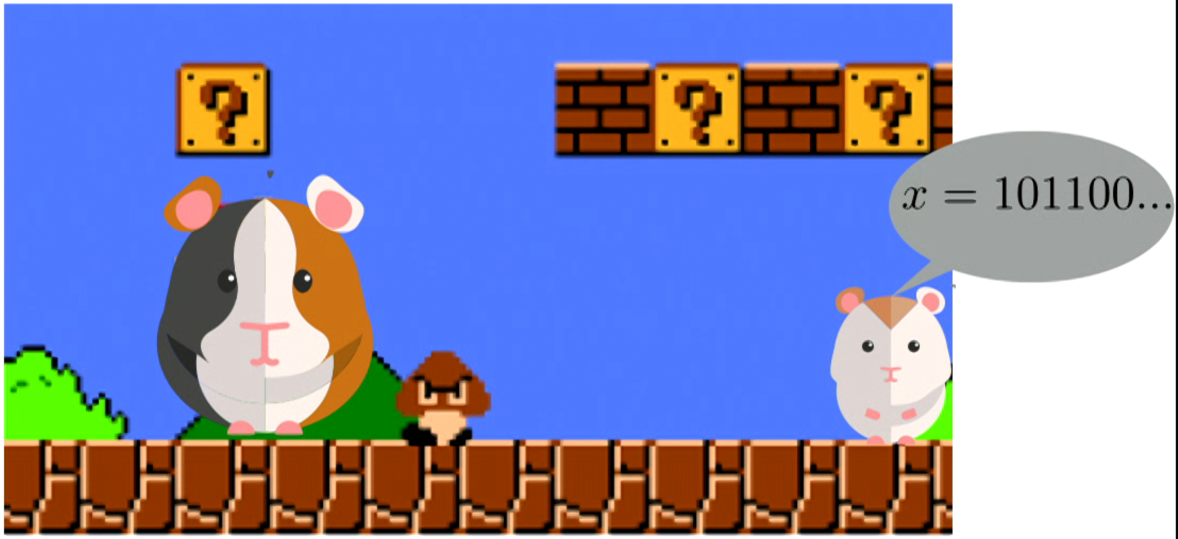

But suppose that **A** sees something in her external world that seems like another observer **B** to her...

Does what **A** sees really correspond to the first-person perspective of another observer?

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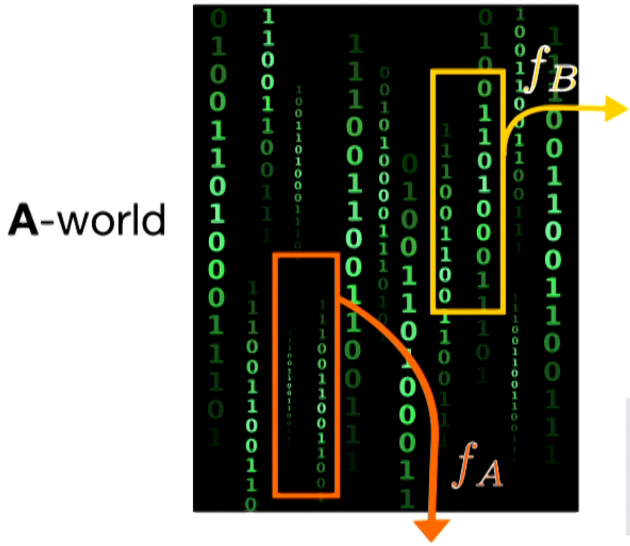
How to formalize this:



$x = 101100\ldots$

Choose some (simple) computable function f_B that, at any time step, "reads out" some binary string (interpreted as **B**'s current state)

f_B encodes "what other thing in her world **A** is looking at".

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Two probability distributions:

$\nu(x_1, x_2, \ldots, x_n) :=$ prob. that **B** is in states $x_1, \ldots, x_n$ acc. to **A**-world

$\mathbf{P}(x_1, \ldots, x_n) =$ algorithmic probability that **B** is in states $x_1, \ldots, x_n$ (the real private chances for **B**!)

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Let's consider a colourful example:

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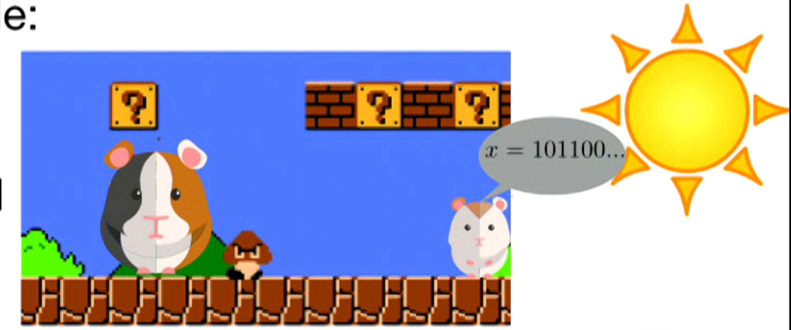

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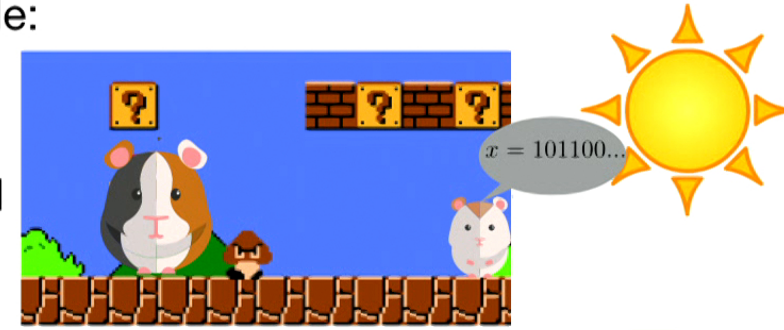

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Theorem: With ν-probability one,

$$\mathbf{P}(y|x_1,\ldots,x_k) \stackrel{k\to\infty}{\longrightarrow} \nu(y|x_1,\ldots,x_k).$$

So the answer is "**yes**", asymptotically.

(In other words: $\mathbf{P} \approx \nu$ if **B** is "old enough" in **A**-world.)

Surprise 1: Probabilistic zombies

- "Objective reality" is a theorem, not an assumption:
  $$\mathbf{P}(y|x_1,\ldots,x_k) \stackrel{k\to\infty}{\longrightarrow} \nu(y|x_1,\ldots,x_k).$$
  Sometimes premises of theorem not satisfied ⟶ **"zombies"!**

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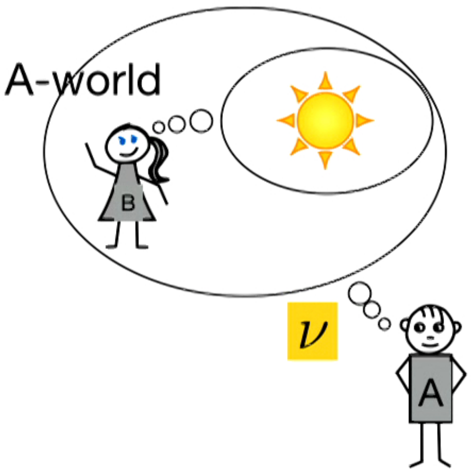

but

B is a probabilistic zombie for *A*.

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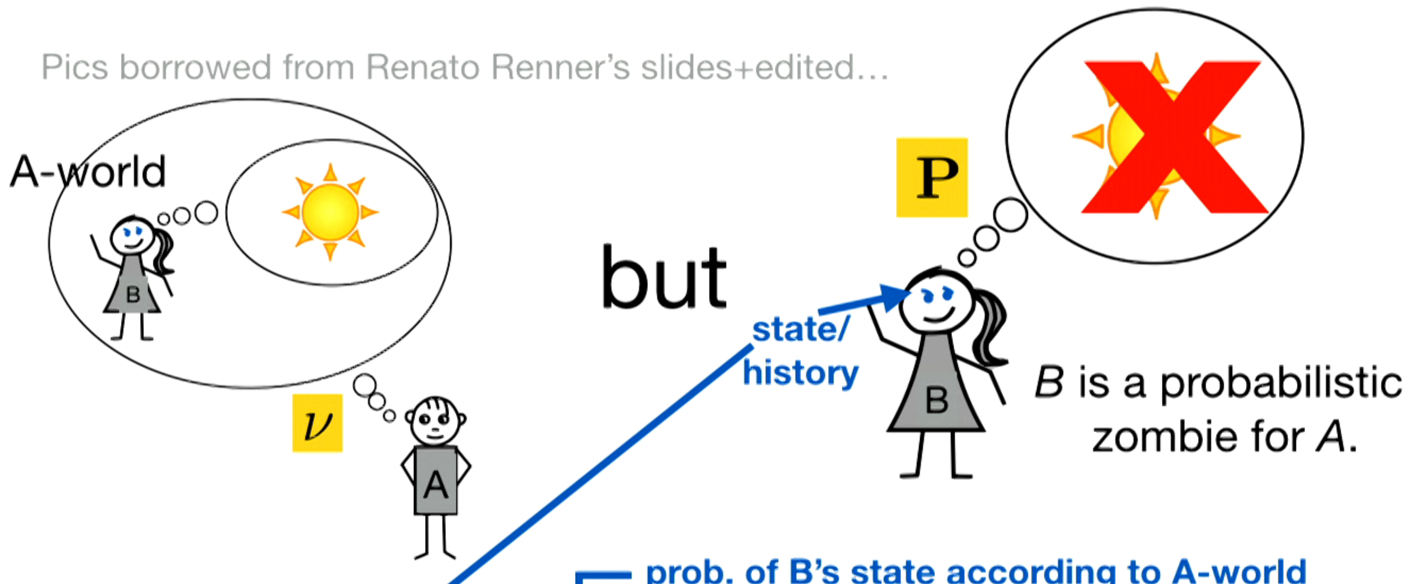
  Sometimes premises of theorem not satisfied ⟶ **"zombies"!**

Pics borrowed from Renato Renner's slides+edited…



Theorem: if $K(\mathbf{x}) \ll K(\nu)$ then zombie, i.e. $\mathbf{P} \neq \nu$.

Surprise 1: Probabilistic zombies

- $K(\mathbf{x})$ too small: **A** “points to” something in his world that is too simple (e.g. a single bit, written on a blackboard)
- $K(\nu)$ too large: **A** “points to” something in a too complicated way (example: **Boltzmann brains**, because very hard to localize.)

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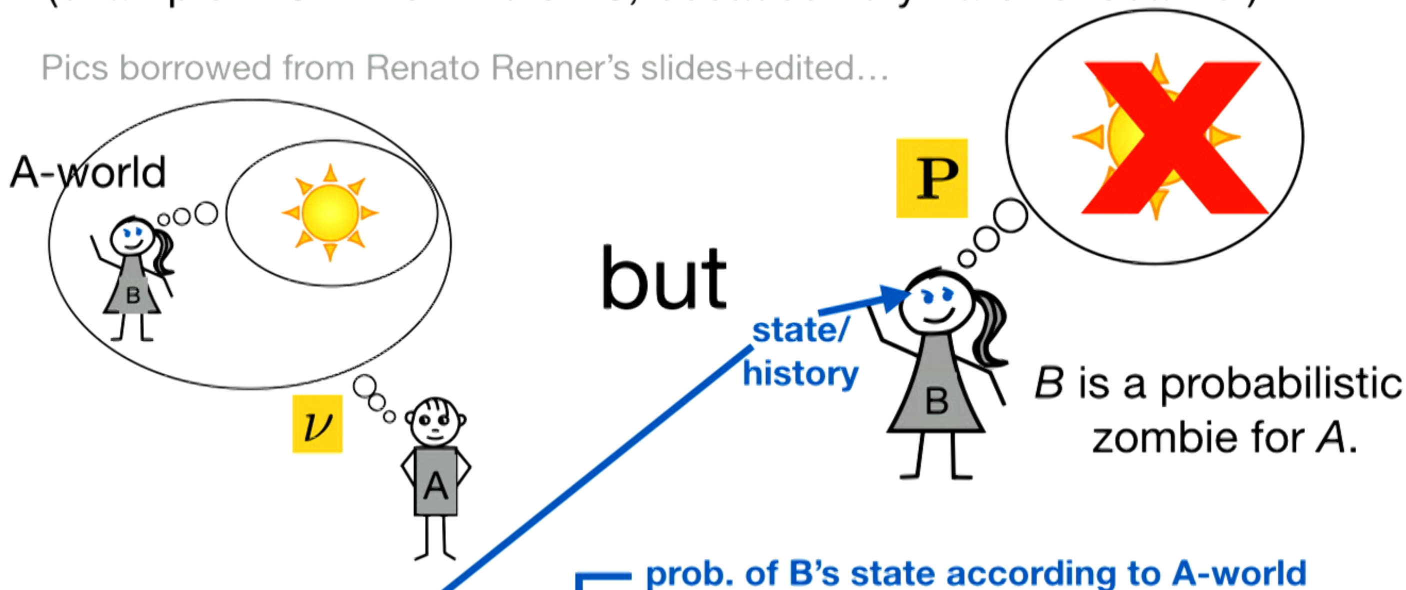

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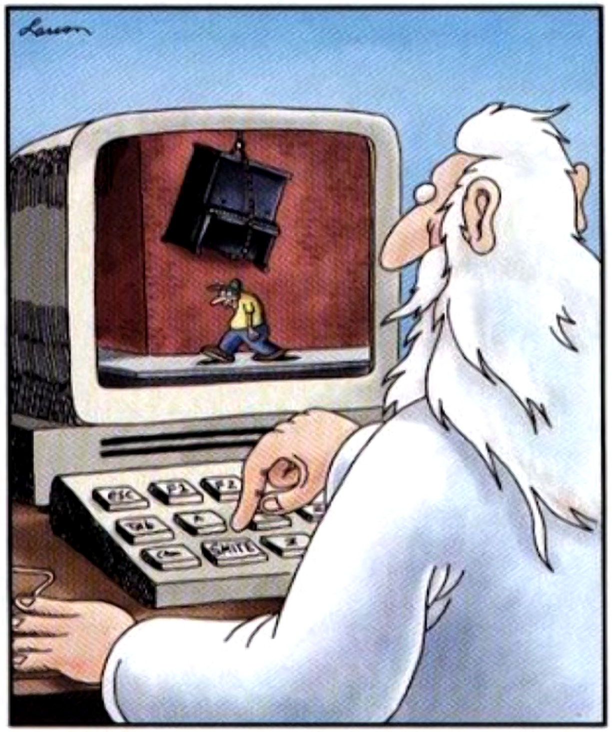
Surprise 2: Brain emulation



God at His computer

Get also concrete criteria for when **simulation** of an agent corresponds to an “actual first-person perspective” (similarly as in the zombie case).

Turns out: makes big difference if simulation is **“open” or “closed”** (feed in outside data or not). More details in paper.

Conclusions

- **Yes, we can** start with the first-person perspective, and obtain a notion of "emergent external world", consistent with known physics.

− Far from the usual regime of physics; useless for most things.

+ Allows to address **fundamental problems rigorously** that we tend to address with much less rigor: "*why a world with simple laws at all*", *Boltzmann brain problem, etc.*

− Not the final word (see open problem etc.), but fun.

+ **Proof of principle:** can have physical theory of completely new kind (first person first) that is consistent, rigorous, and has explanatory and predictive power (for some questions, but not for others).

Full version: **arXiv:1712.01826**
Short version (not as good, v2 soon): **arXiv:1712.01816**

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Thank you!