From observers to physics
via algorithmic information theory

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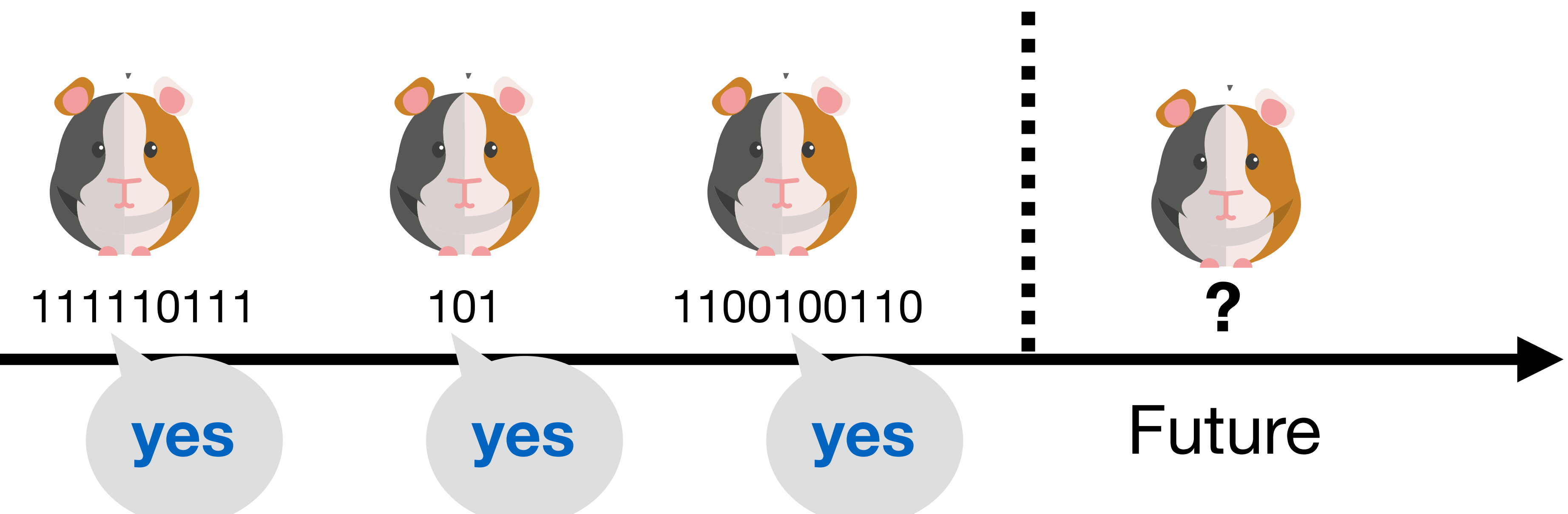

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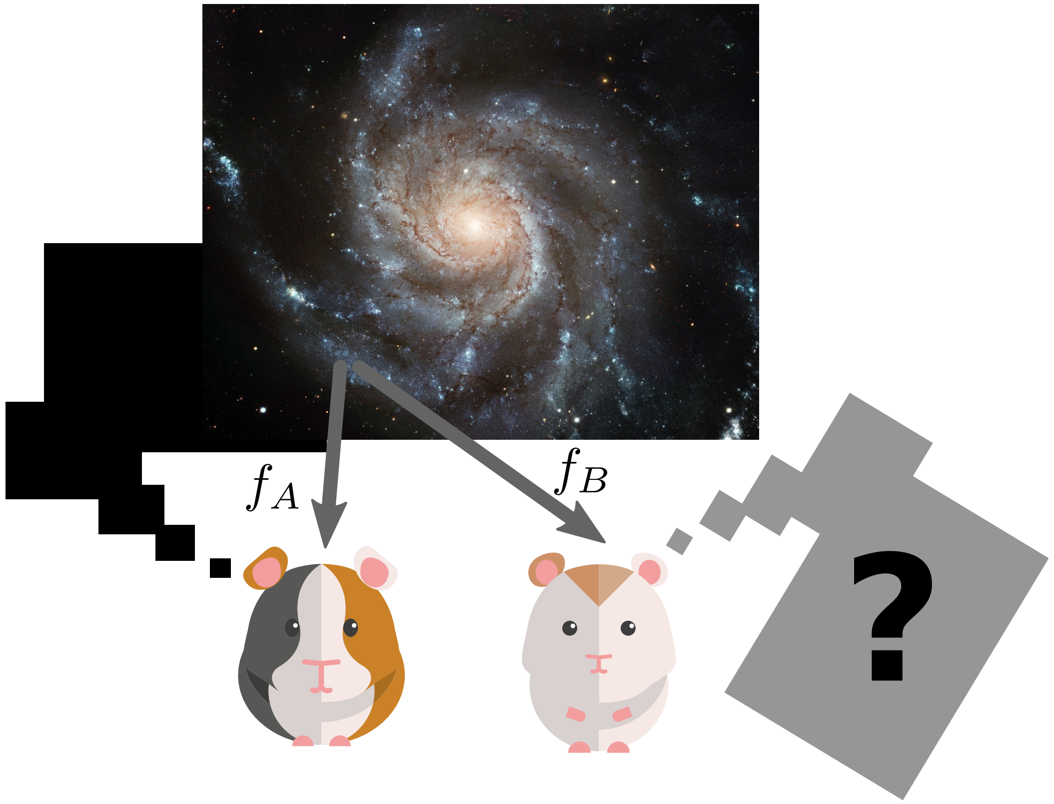
philosophy: w/ **Mike Cuffaro**

Outline



1. Motivation

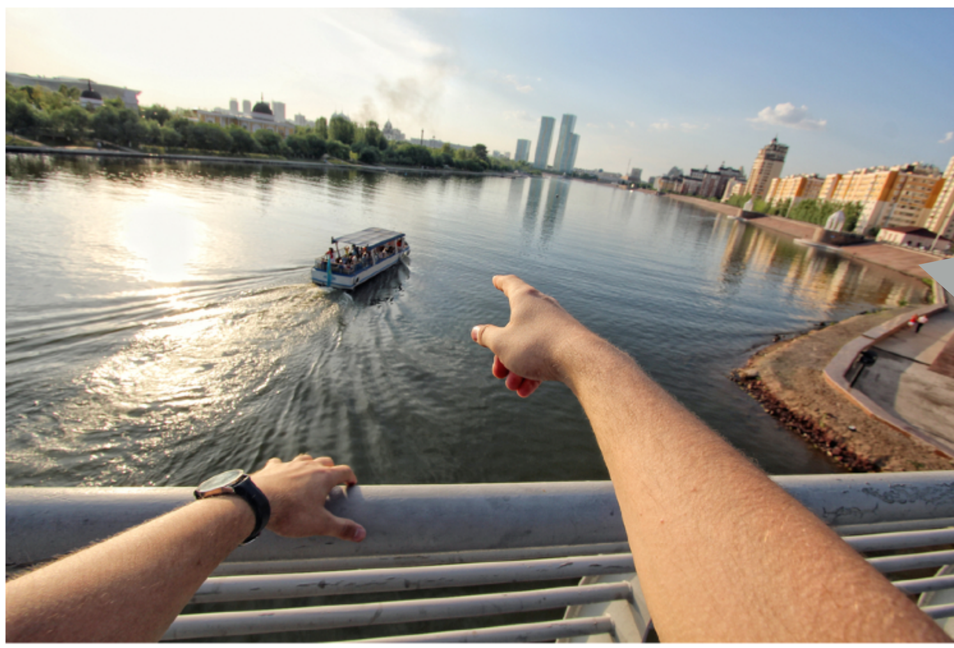
2. Postulates of the theory

3. How does an external world emerge?

4. What about more than one observer?

Standard view of “us” and the world

“observations” (what an observer sees, remembers etc., the full first-person state at some time)



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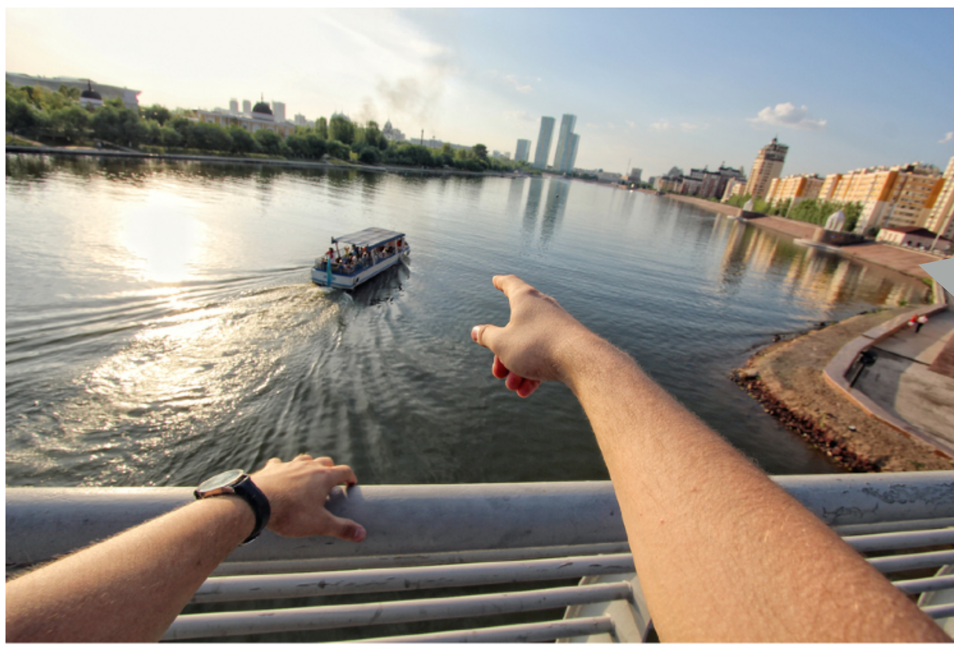

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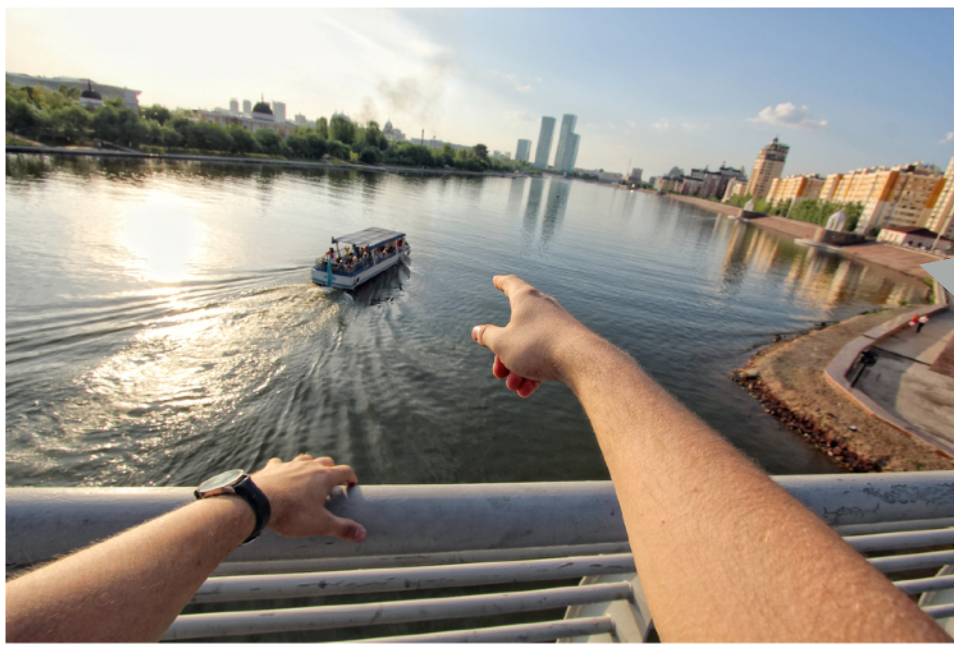

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Boltzmann brain problem

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?
→ **what probability** should you assign to a "BB-observation"?

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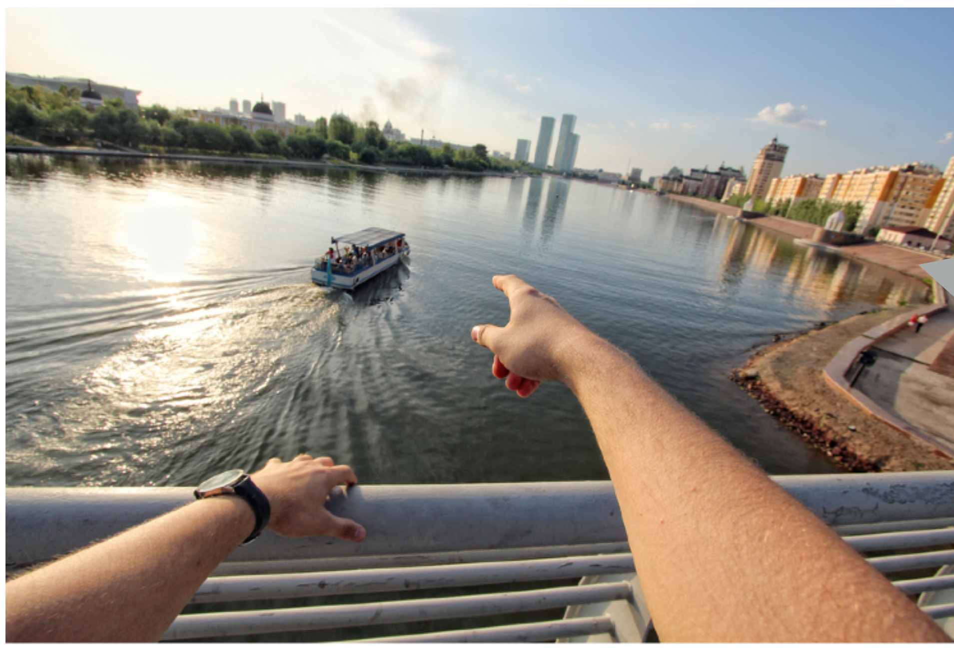

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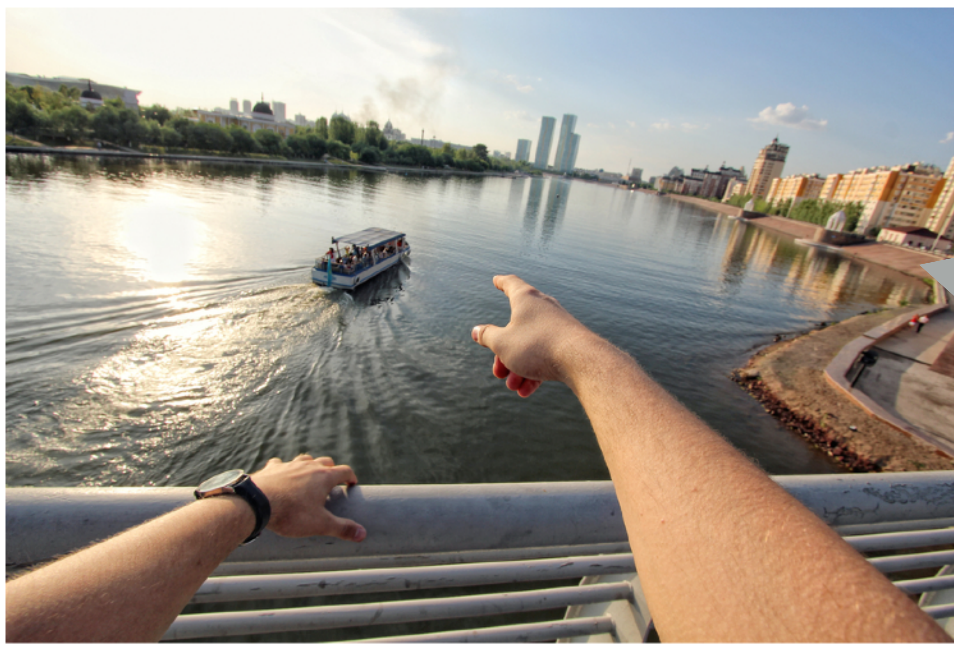

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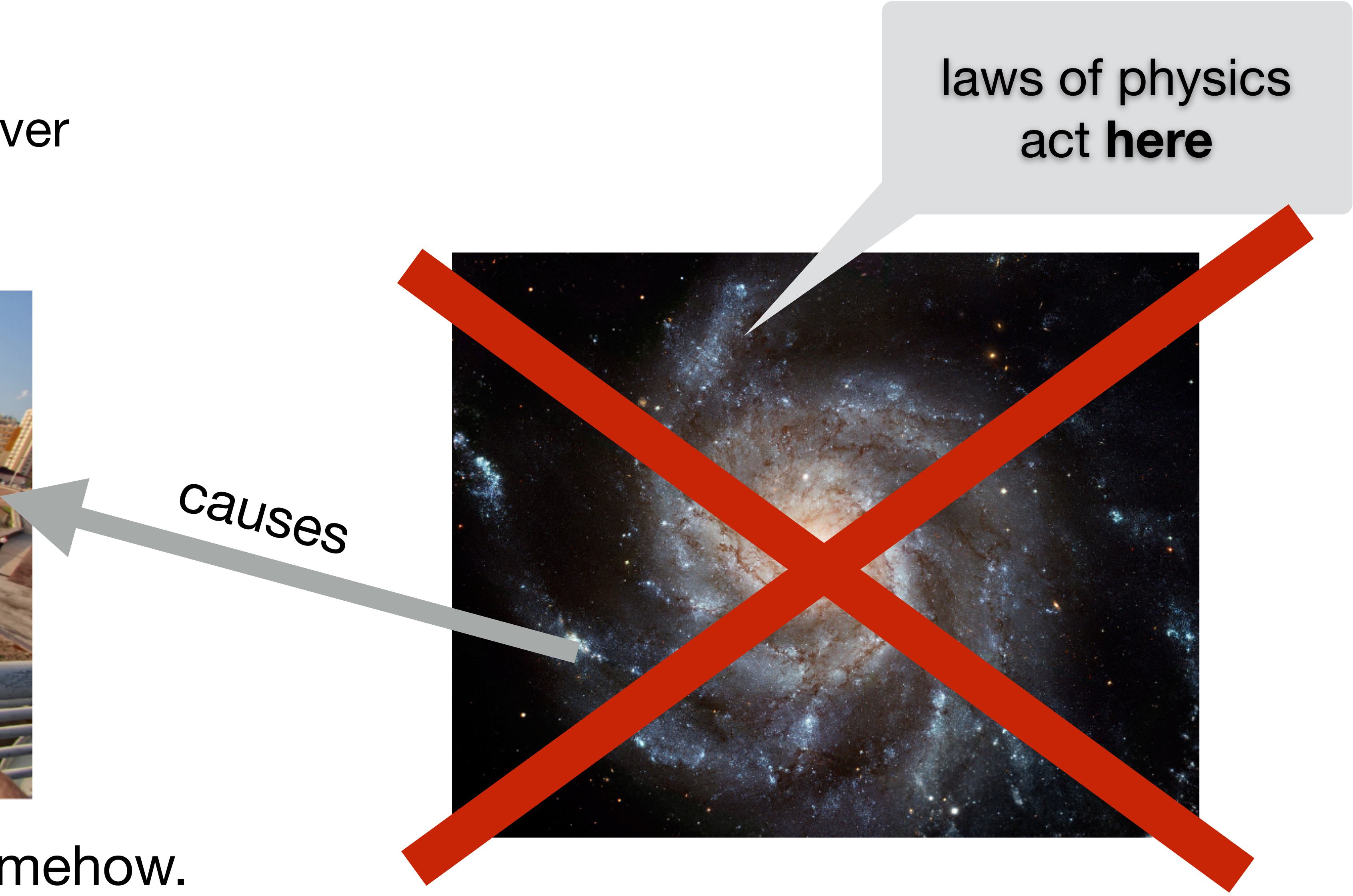

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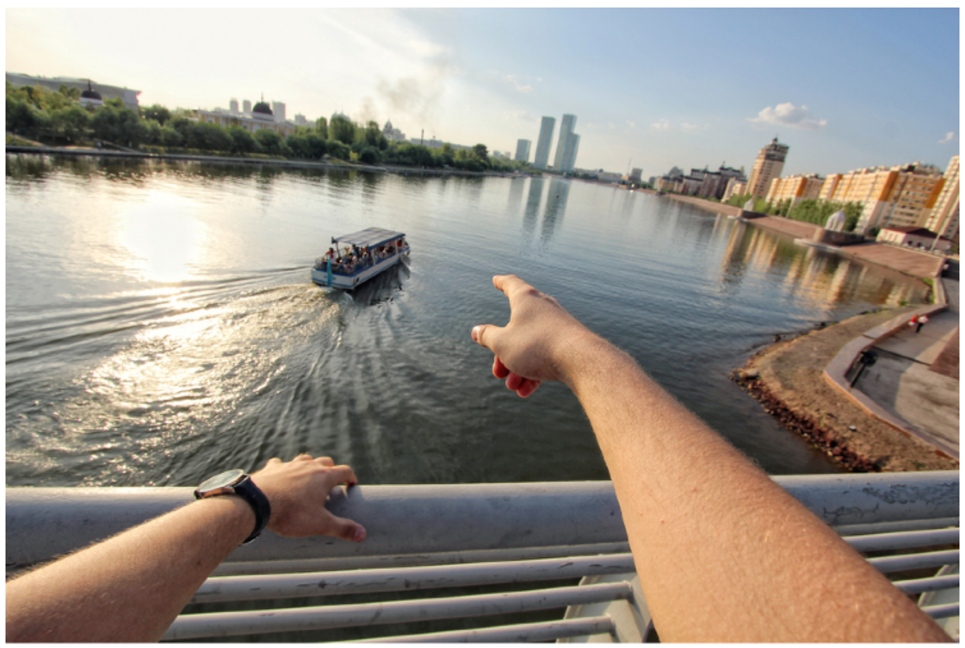

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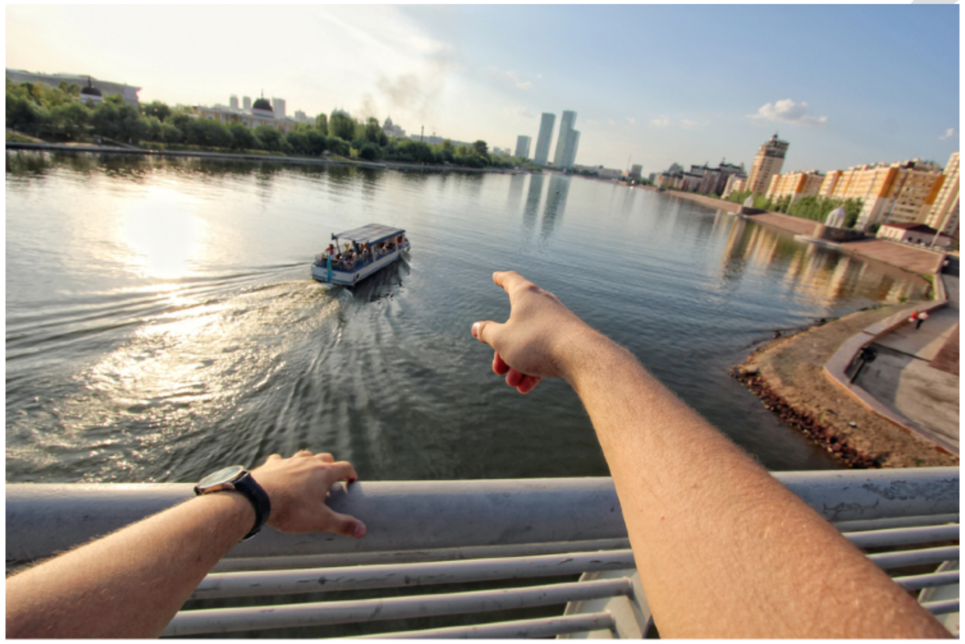

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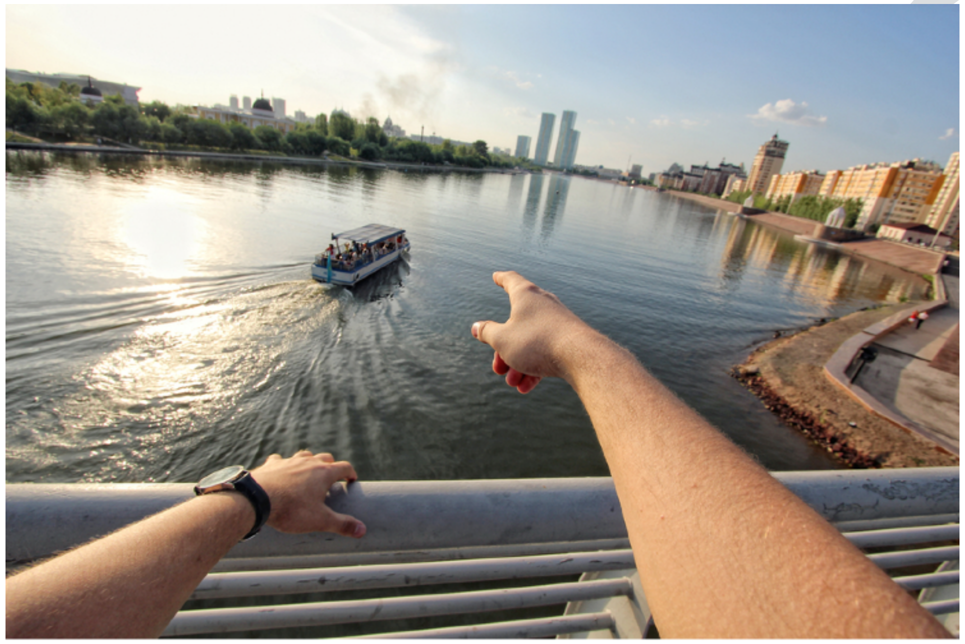

(Probabilistic) **law**: What will be observed next is **what is most compressible**, given the previous observations.

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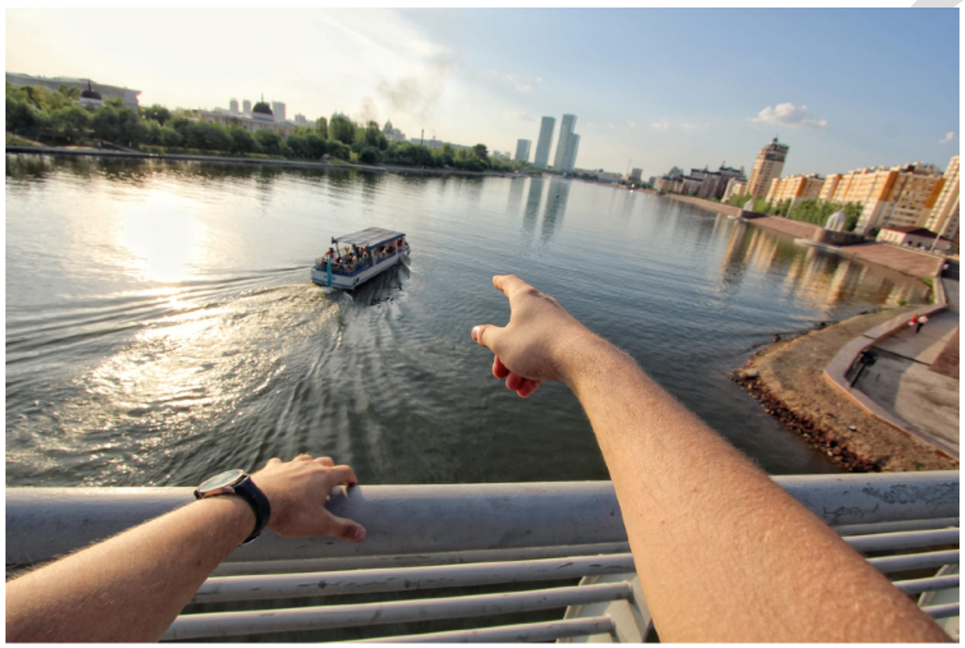

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Provable **consequence**: what's observed looks in most cases **as if** it came from an algorithmically simply computable probabilistic **world**.

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Advertisement: consequences

Consequences:

- Dissolves each and every of the afore-mentioned problems, up to calculation.
- Tells us “why” there is a world with simple, probabilistic, computable laws.
- New predictions: probabilistic zombies, subjective immortality, “open” versus “closed” simulation of agents, we might all be the *same* observer meeting different instances of ourselves…
- Math. rigorous and **fun**. :-)

Disclaimer

- “Observer” is a technical / information-theoretic notion. Not (directly) related to “consciousness” etc.
- Not meant as a “TOE”. Predicts its own limitations. Useless for most questions that physicists care about.
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Blueprint / **proof of principle** of a certain *kind* of theory

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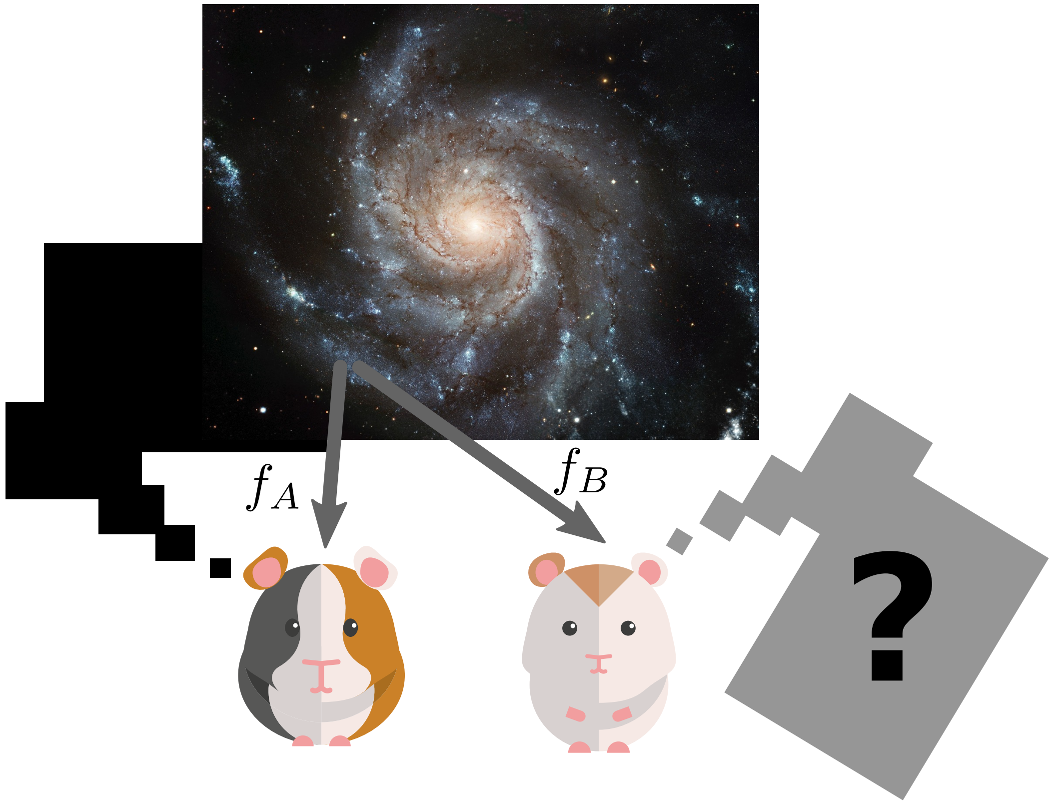

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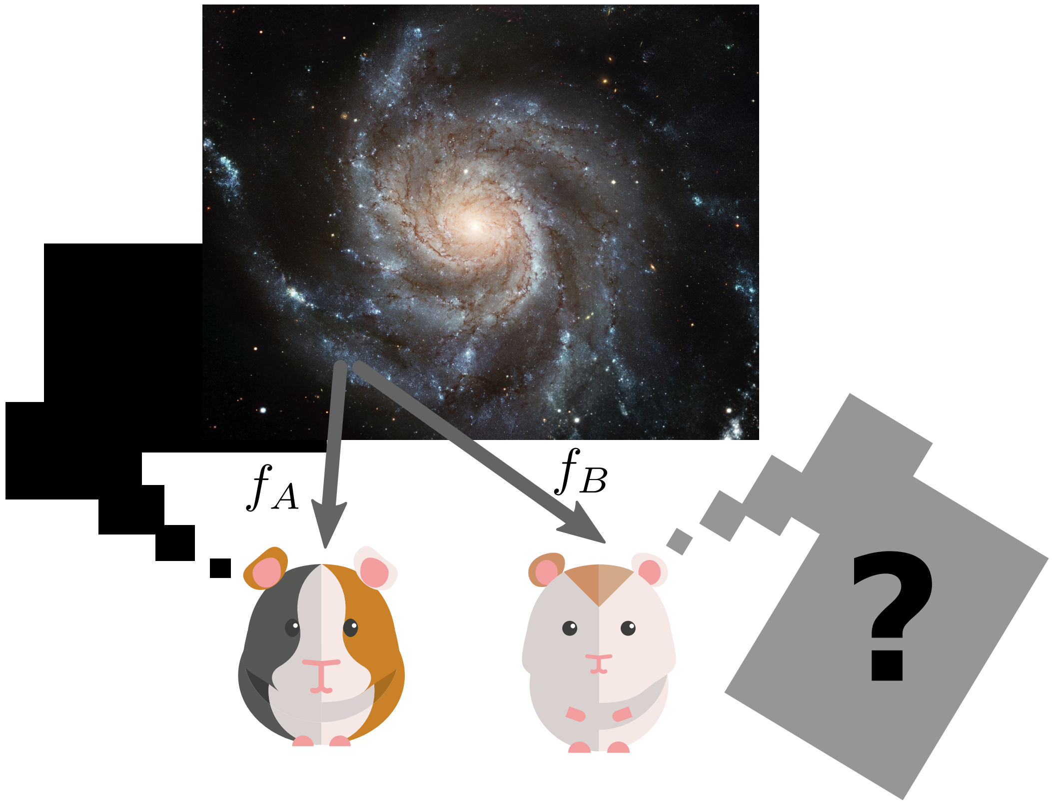

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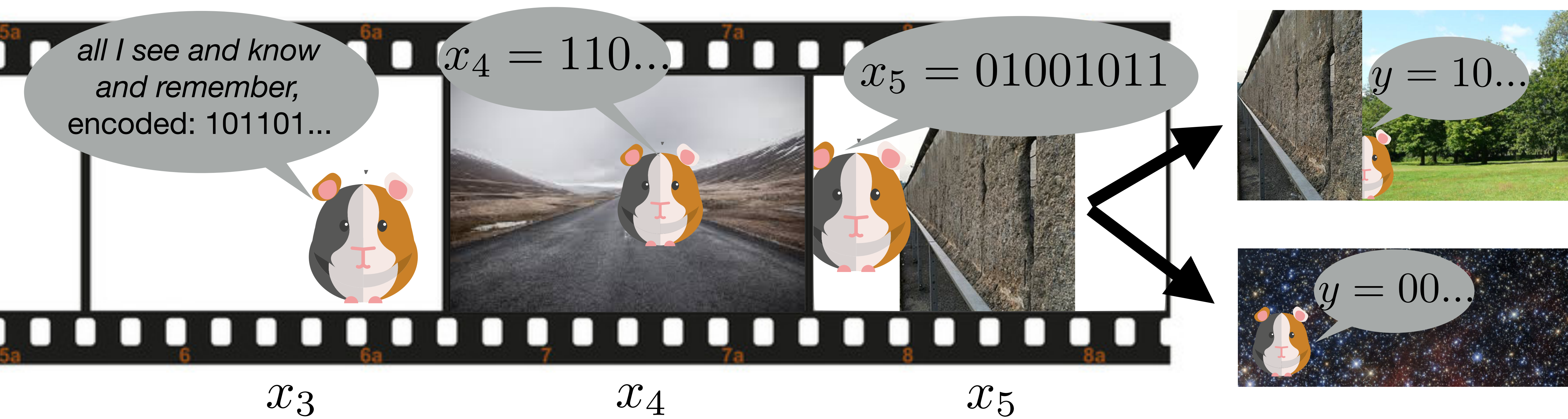
Absolutely minimal ingredients:



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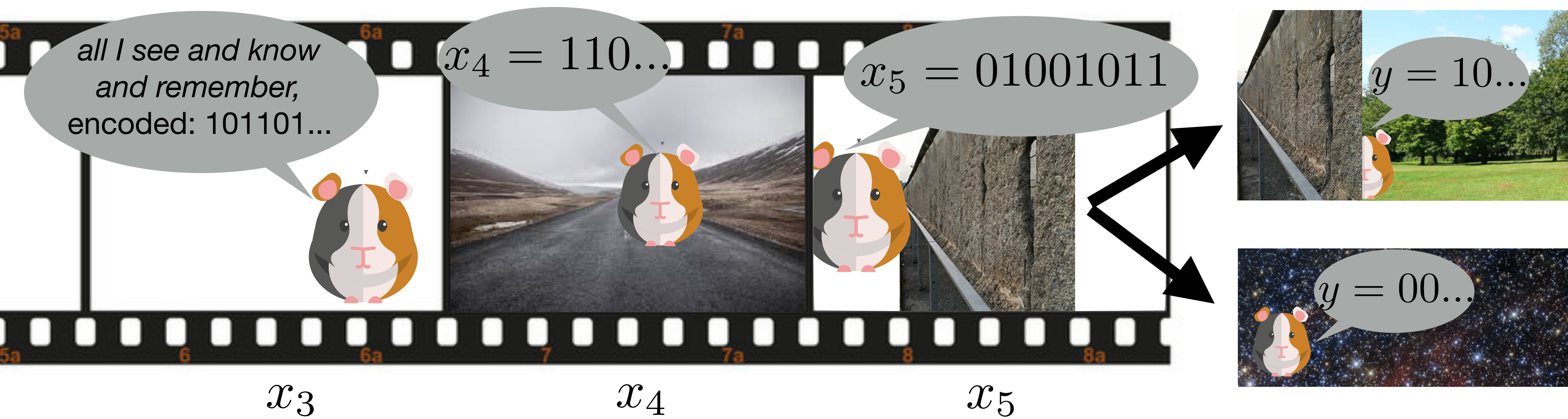
Absolutely minimal ingredients:

- 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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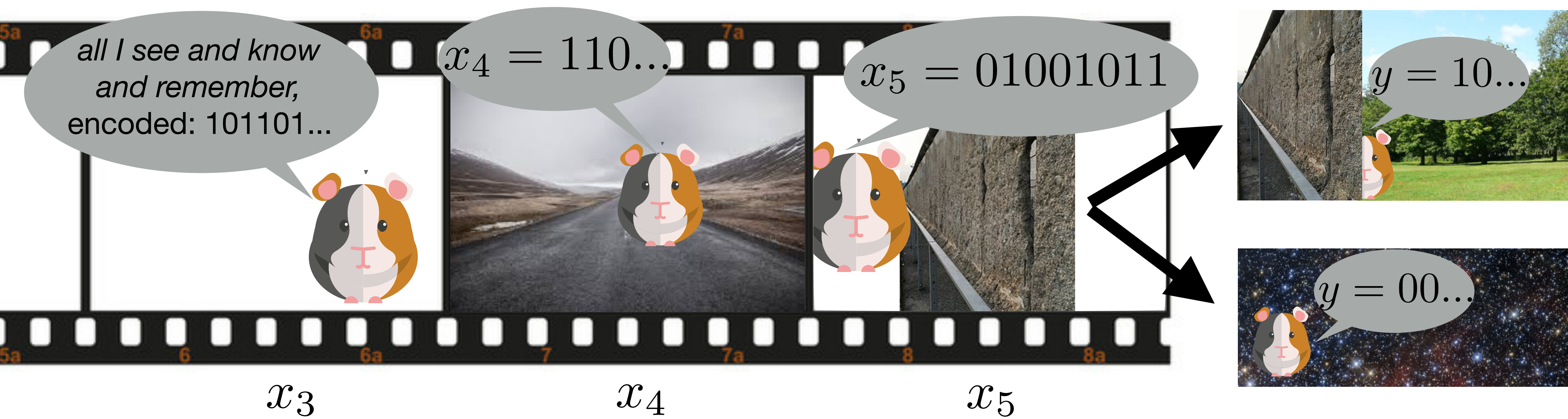

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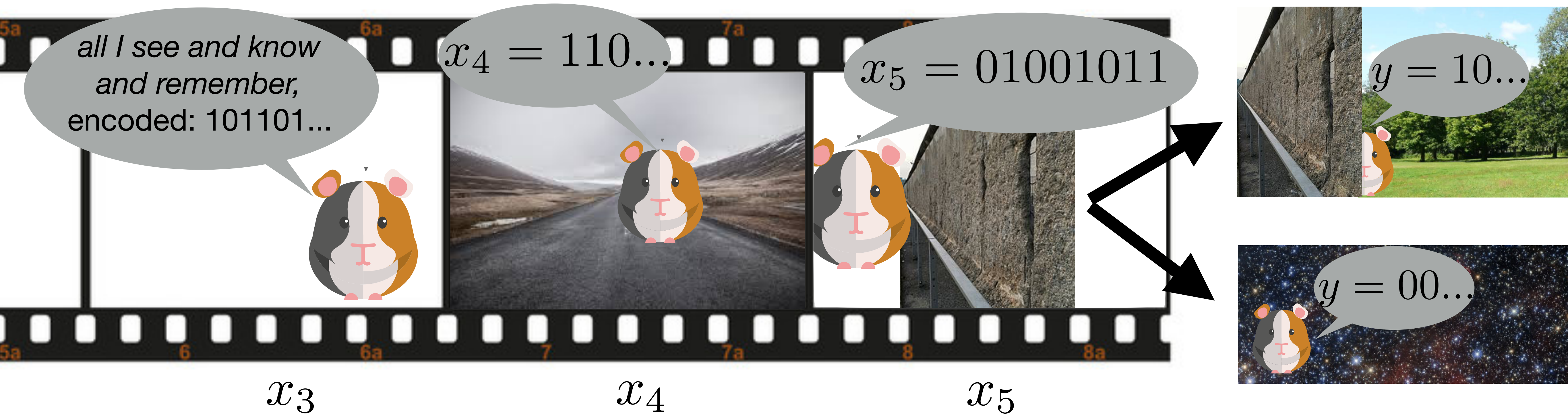
"Universe" and all else: **not** postulated, but hoped to be derived.

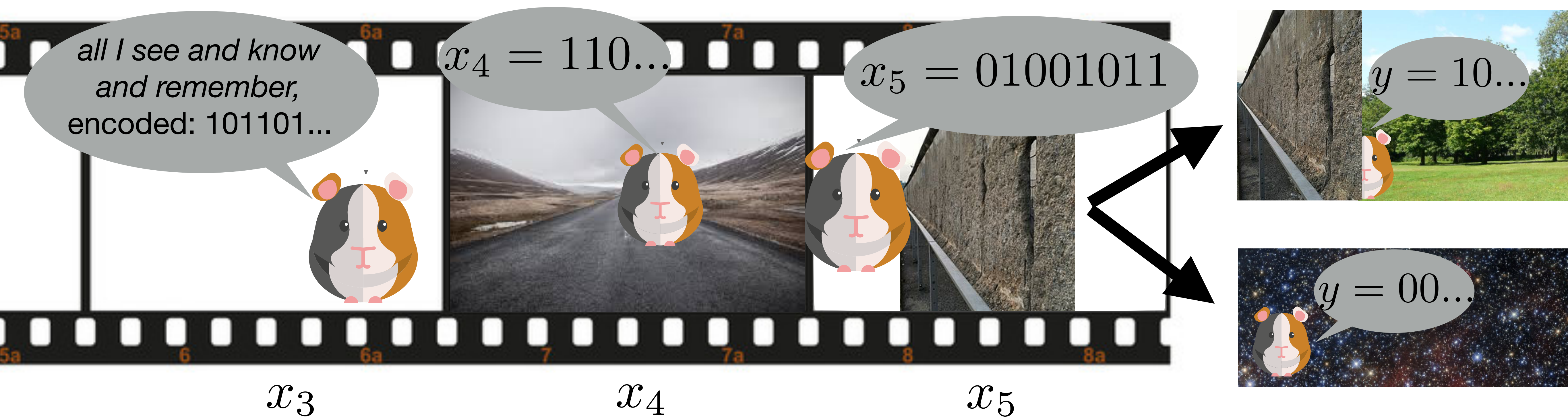


Postulates of the theory

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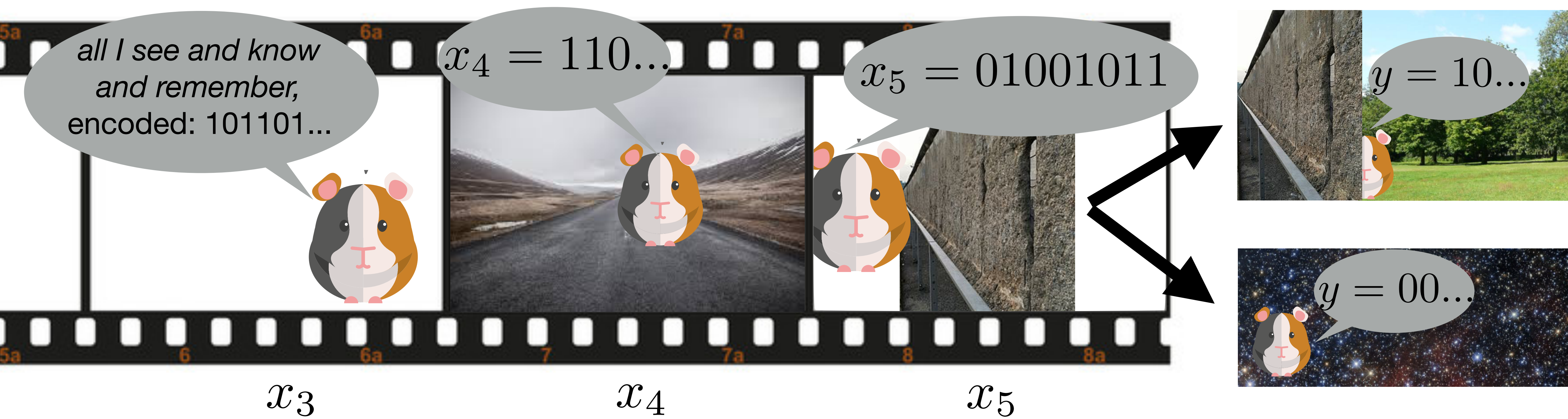
Probability measures on "histories": $\mathbf{P}(x_1, \ldots, x_n) = ?$



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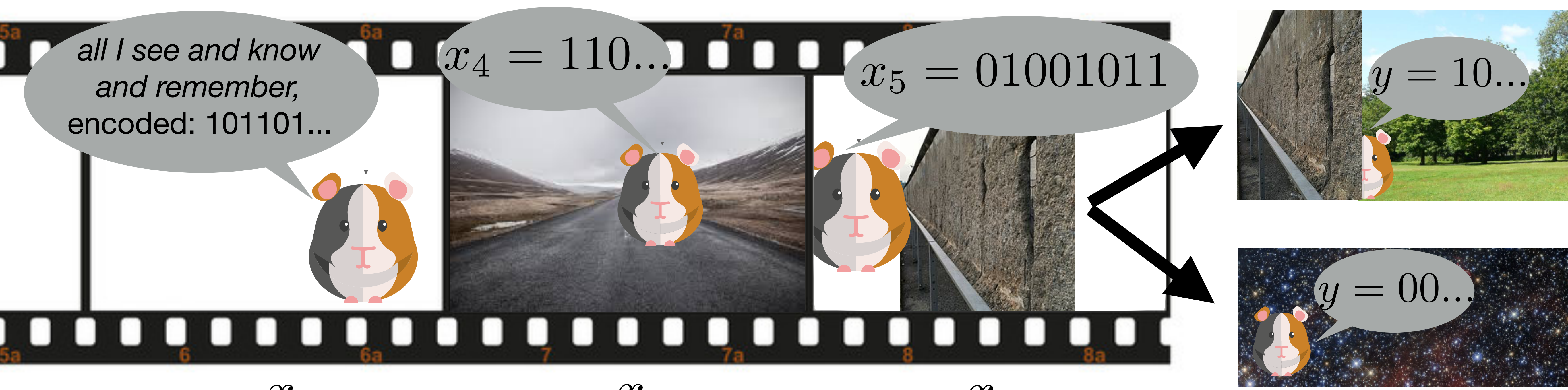

x_3 x_4 x_5

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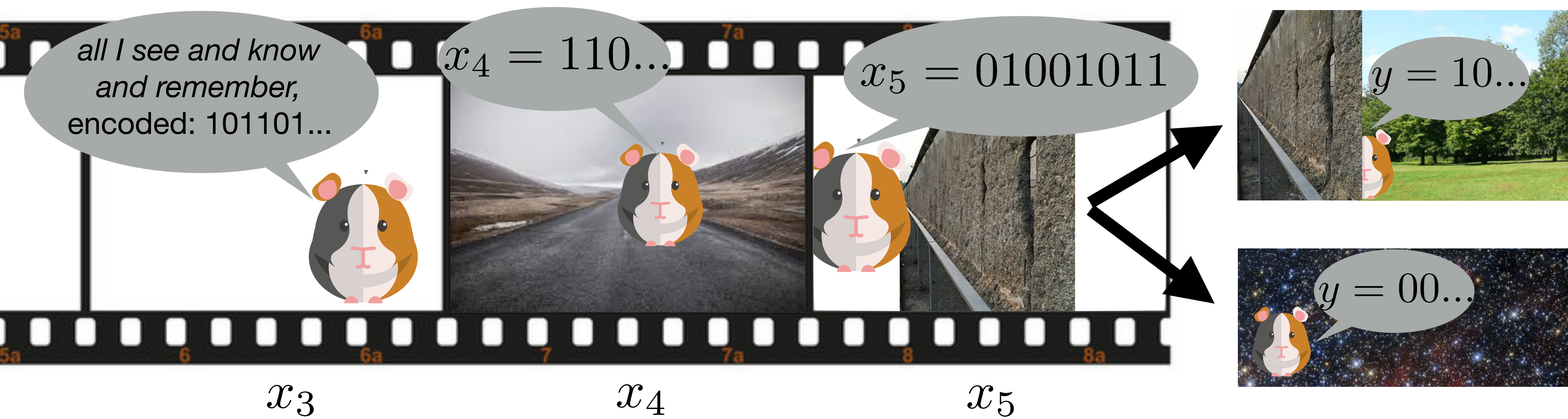
(Boring) example: $\mu(x_1):=2^{-2\ell(x_1)-1}$, e.g. $\mu(1011)=2^{-2\cdot 4-1}=2^{-9}$,



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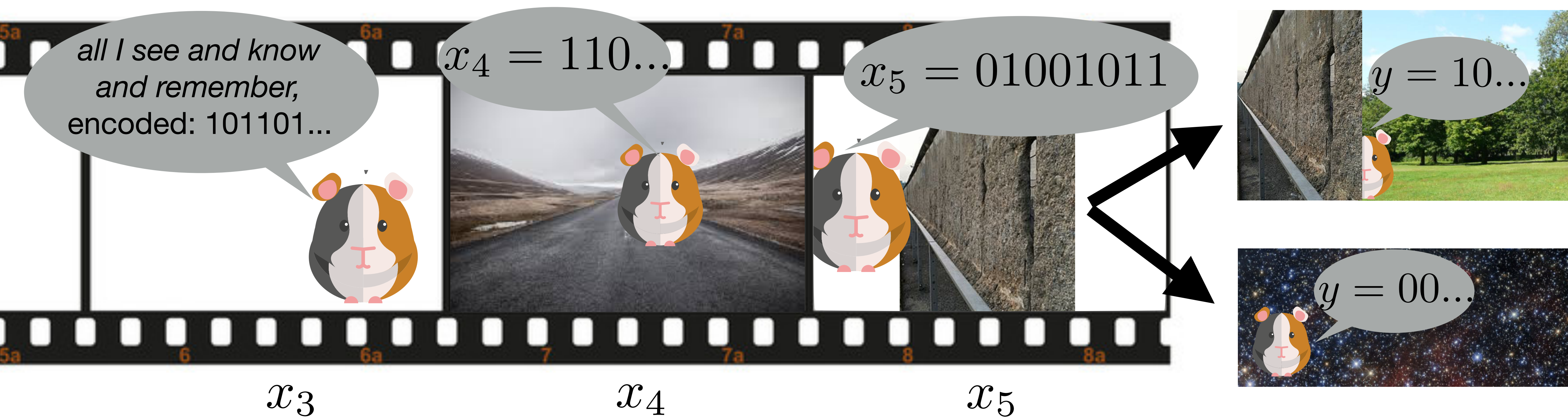

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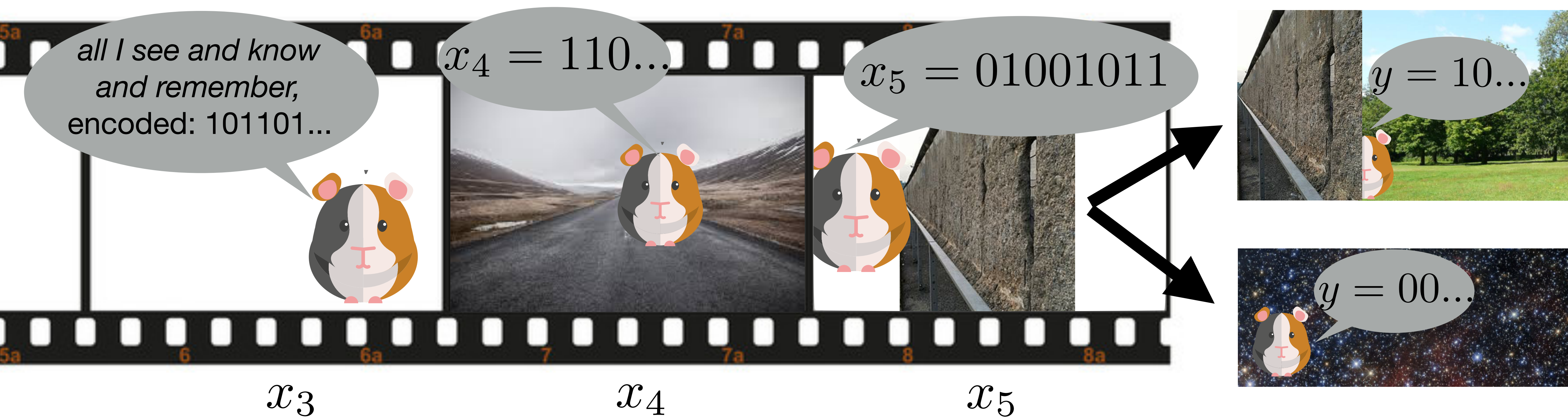
Semimeasure: Same with "$\leq$" instead of "=".



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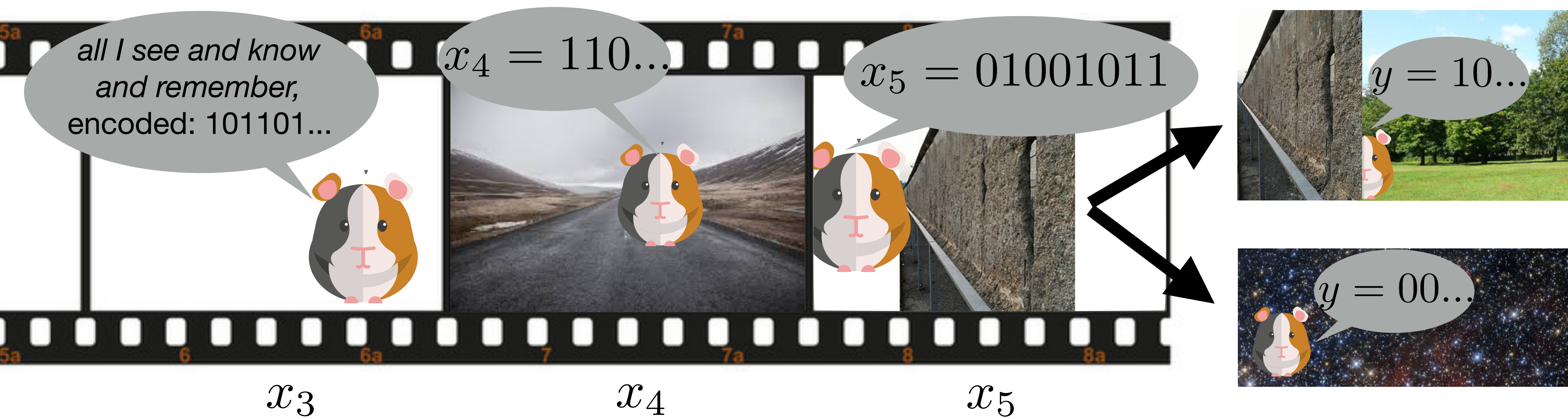

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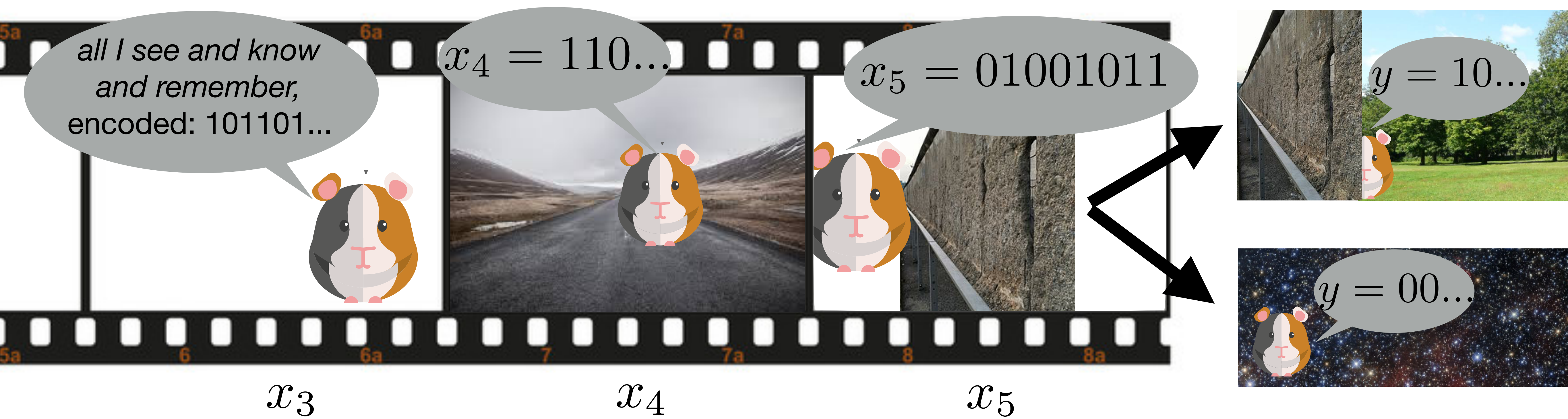

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A **universal enumerable semimeasure M** is an enumerable semi-measure such that for every enumerable semimeasure μ there exists some constant $c > 0$ such that $\mathbf{M}(x_1, \ldots, x_n) \geq c \cdot \mu(x_1, \ldots, x_n)$.

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

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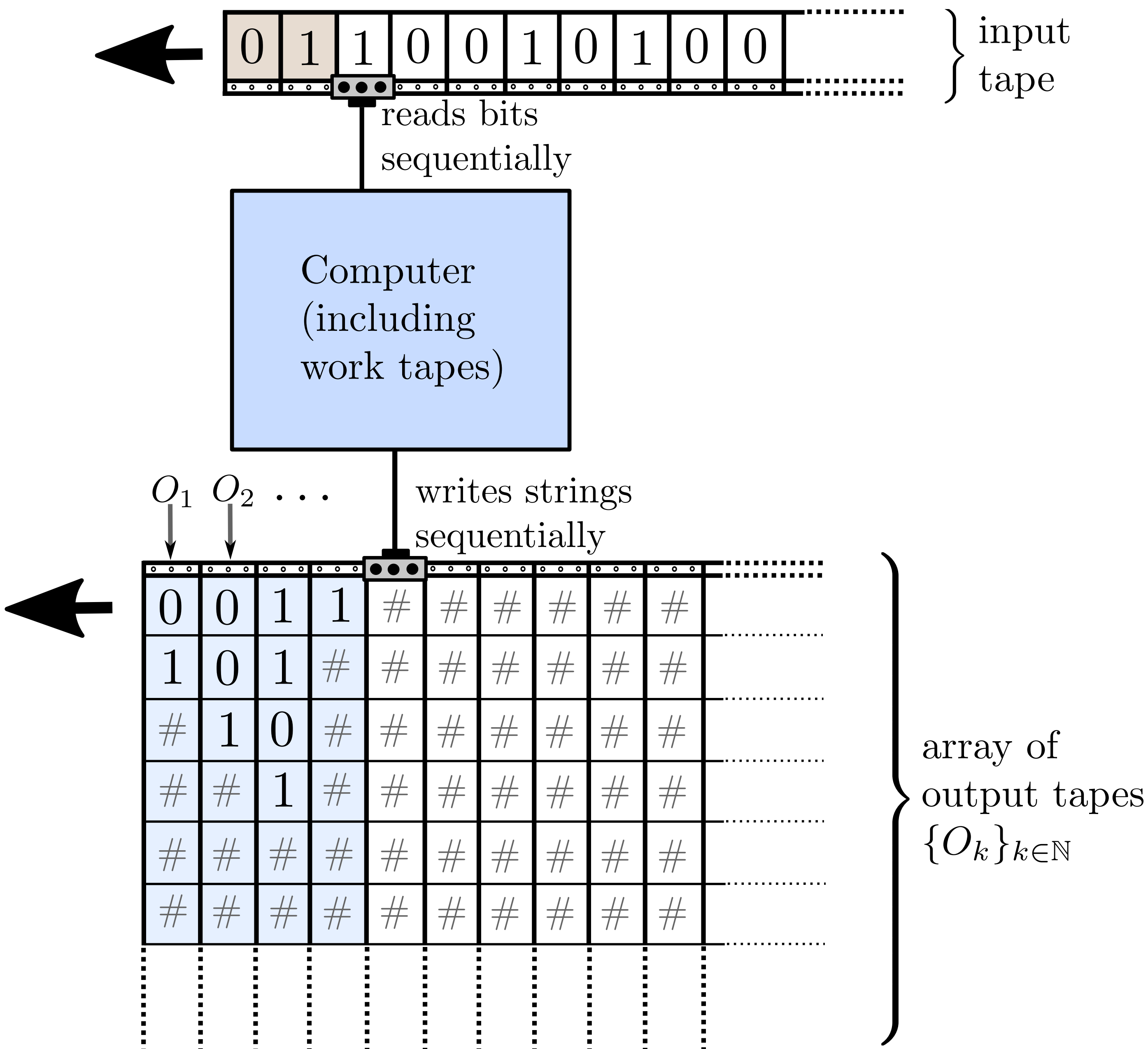

Universal monotone Turing machine U

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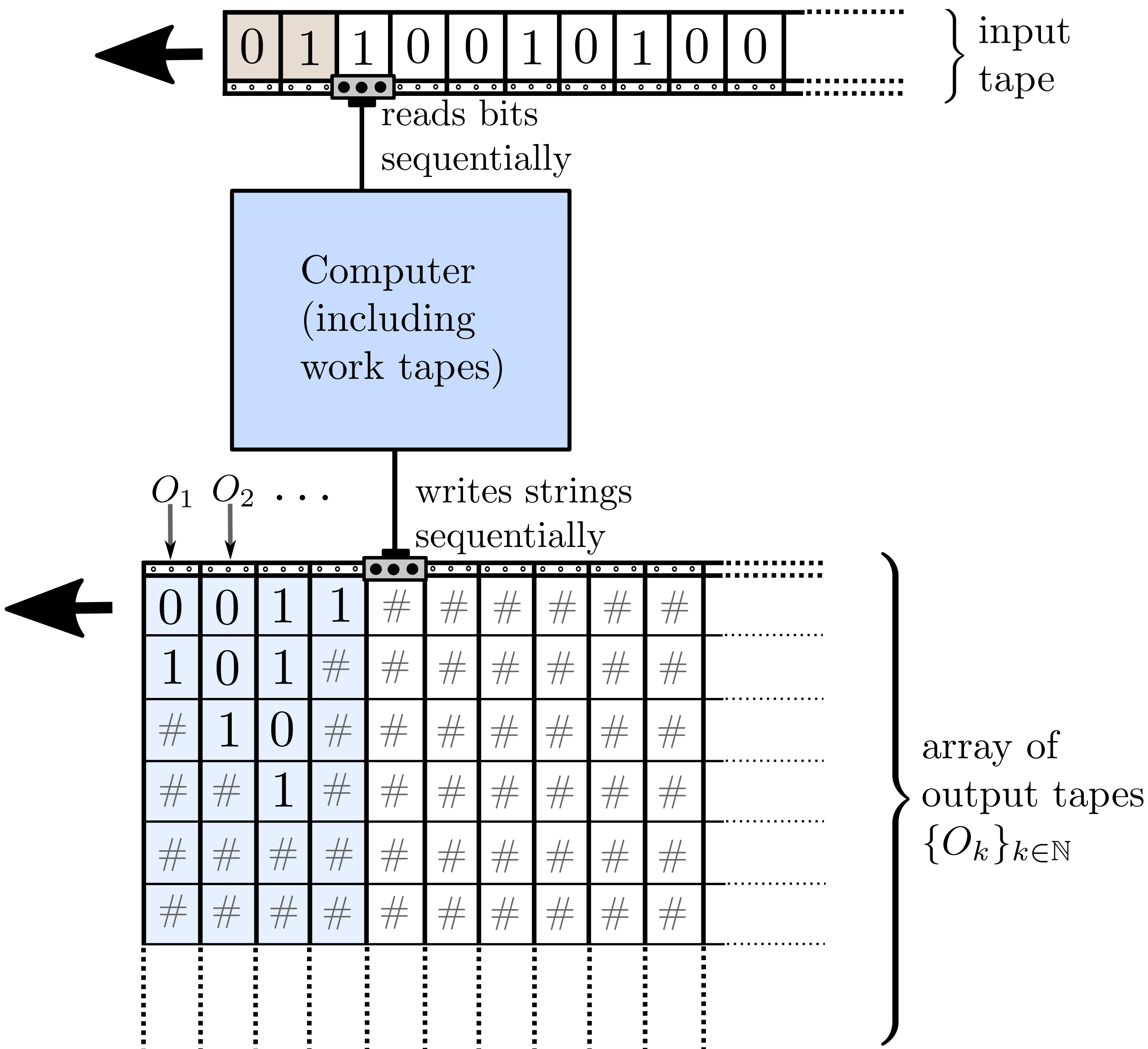

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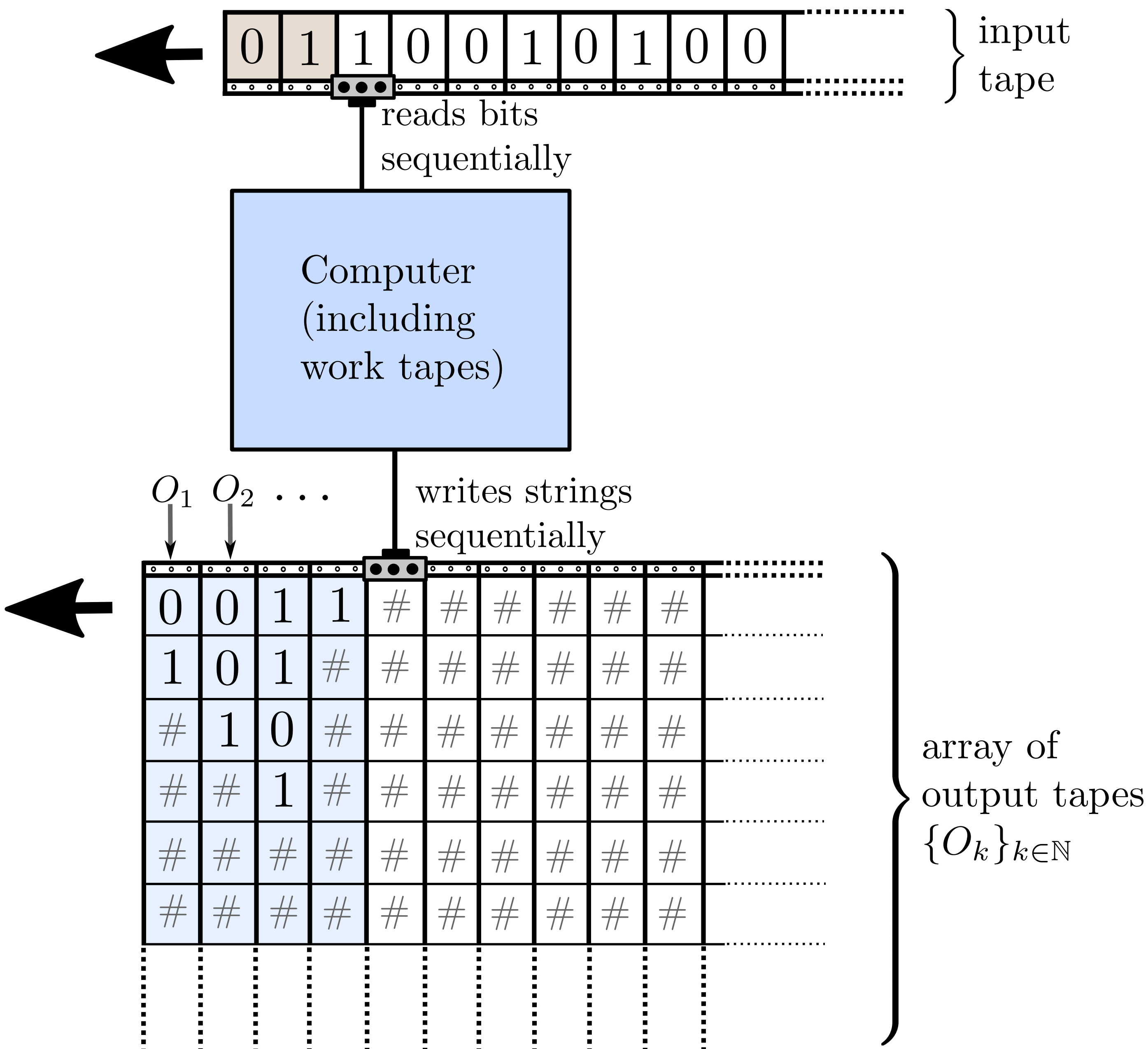

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"Occam's razor":

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

where *K*(**x**) is the length of the shortest computer program that outputs **x**.

Favors compressibility!

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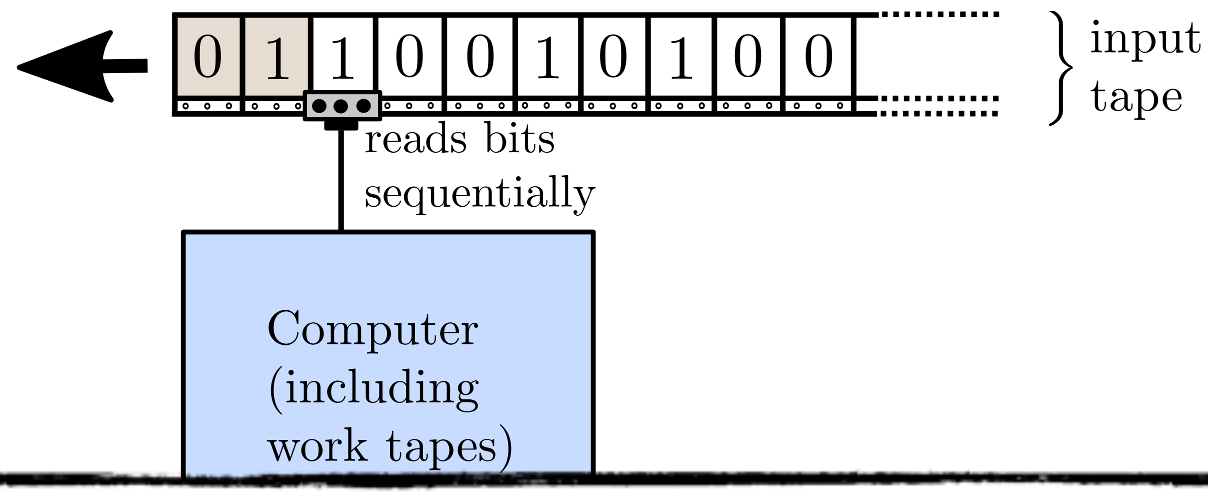


$\mathbf{M}_U$:=distribution of outputs if input is chosen at random. Is universal enumerable.

Q: Won’t the resulting theory depend on the choice of universal machine *U* / univ. enum. semimeasure **M**?

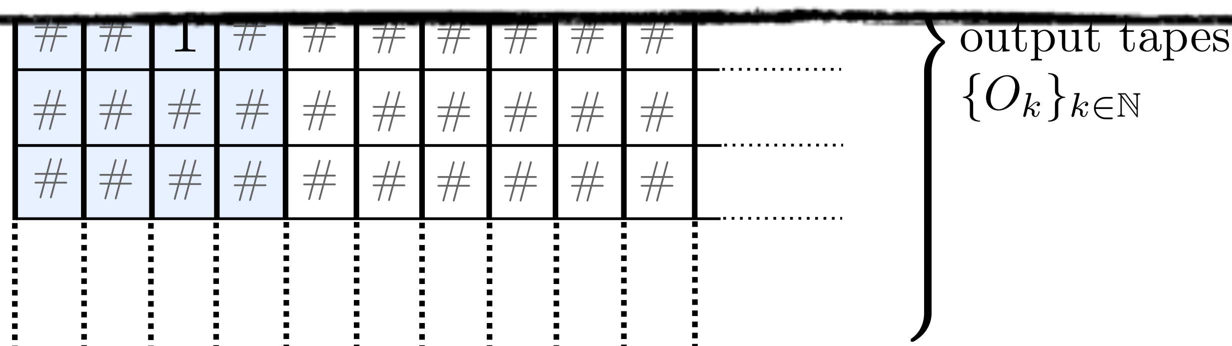
A: **No,** but non-trivial why not. Maybe ask me later.

$x_n)$,

he

that outputs **x**.

Favors compressibility!



Universal monotone Turing machine *U*

An open problem

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

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$$\mathbf{P}(y|x_n).$$

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

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Several possible arguments:

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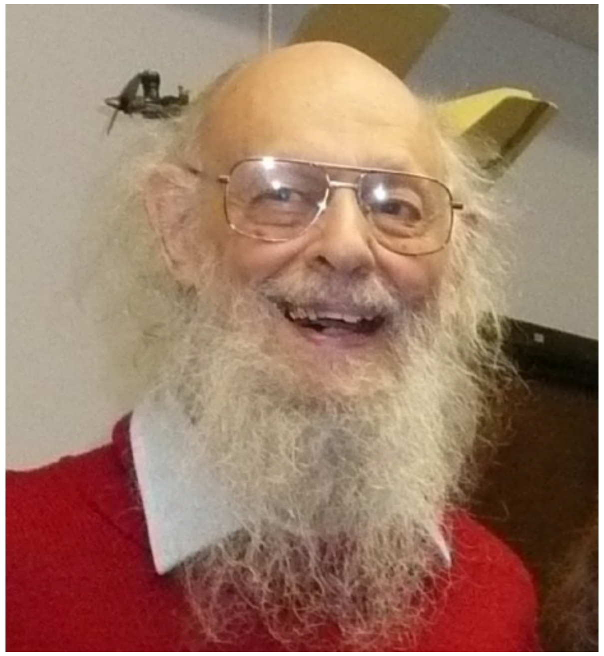

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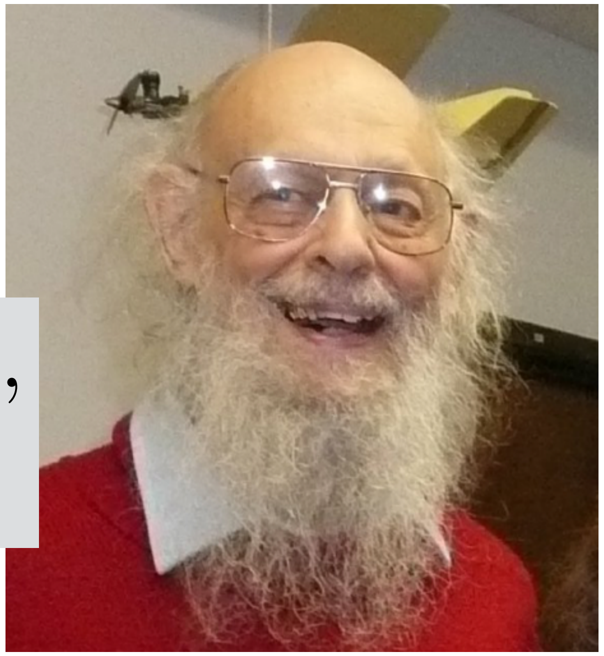

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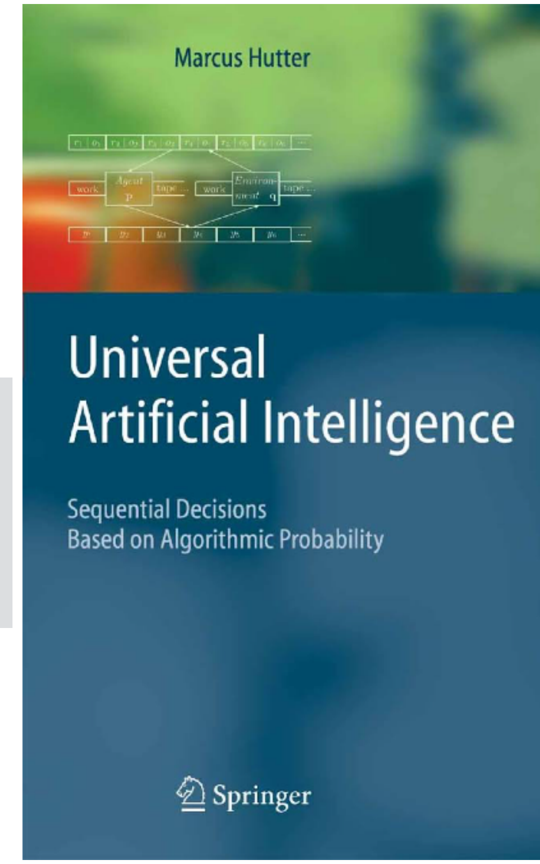

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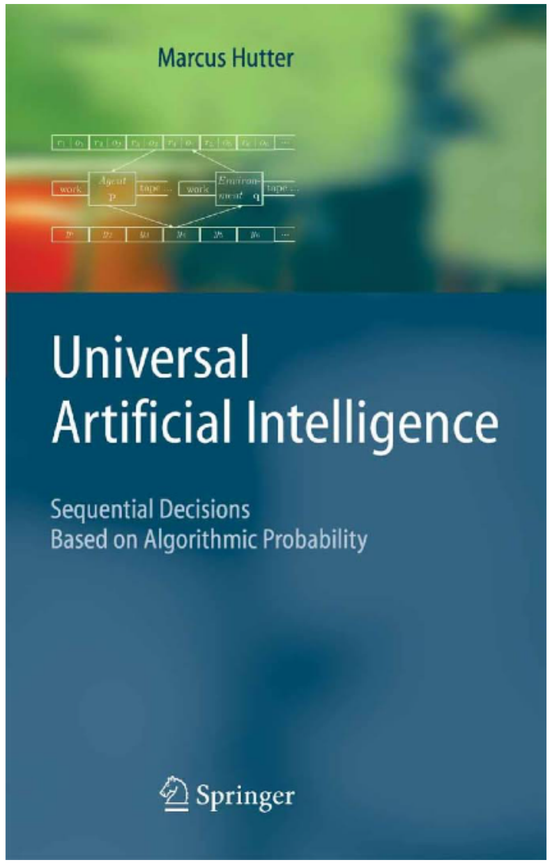

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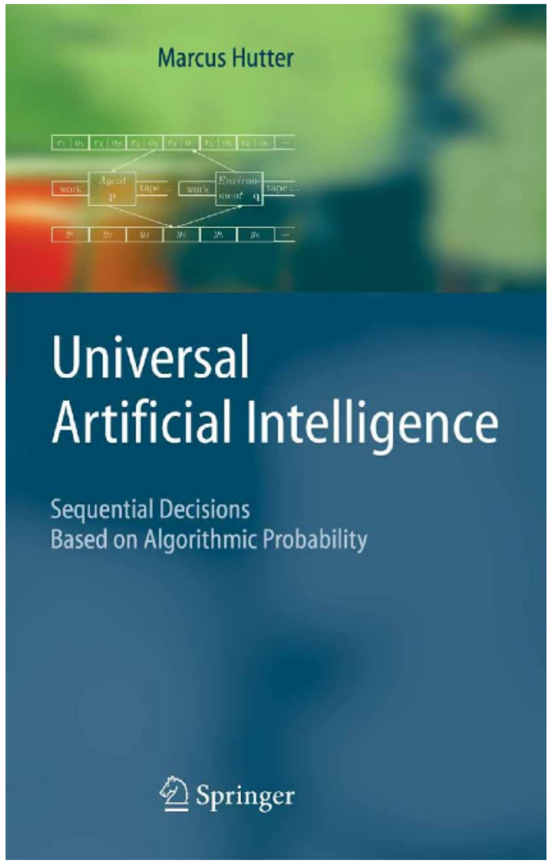

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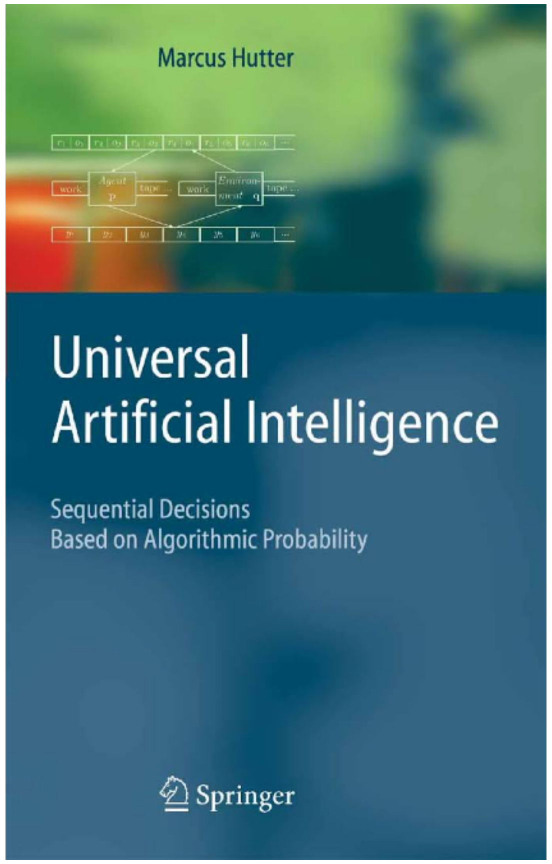

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- Idea: **postulate that Solomonoff induction is "the law"!**
  This will then *have to* be consistent with physics (given our data).

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Physics is nothing but what makes some future observations more likely than others.
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3. A "many worlds"-like motivation

P can be interpreted as describing what an observer sees who doesn't know in which (computable) world she is located (or who is "objectively delocalized").

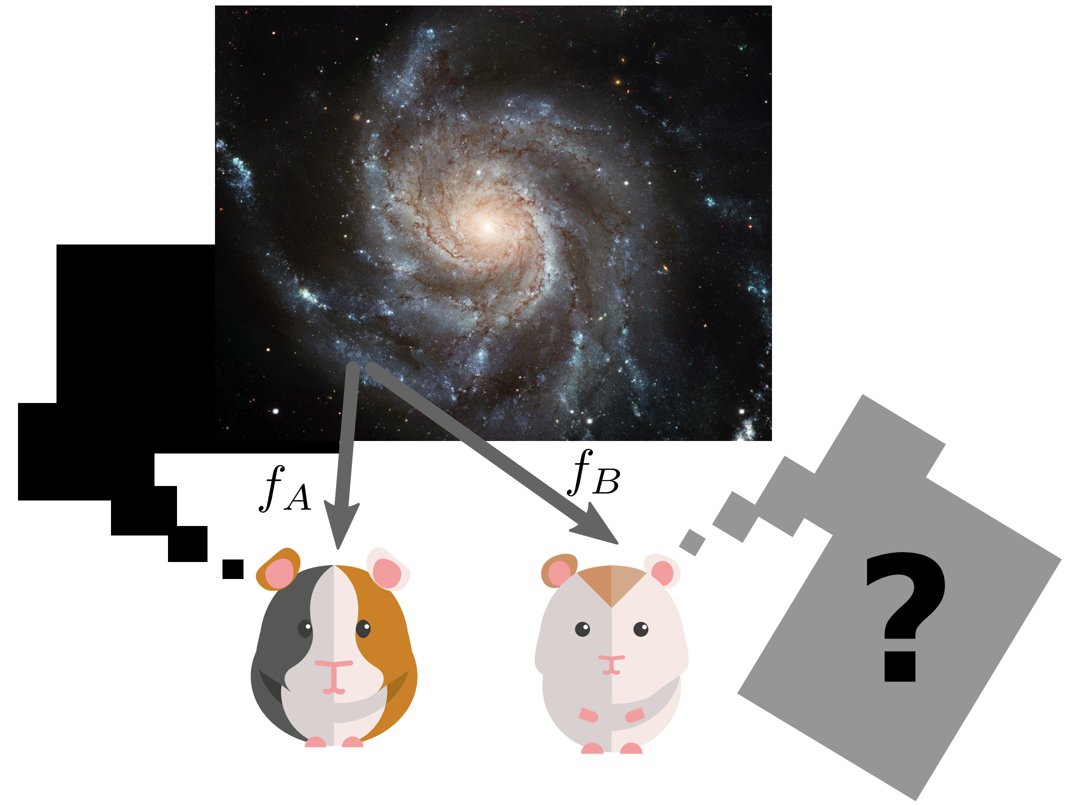
Outline

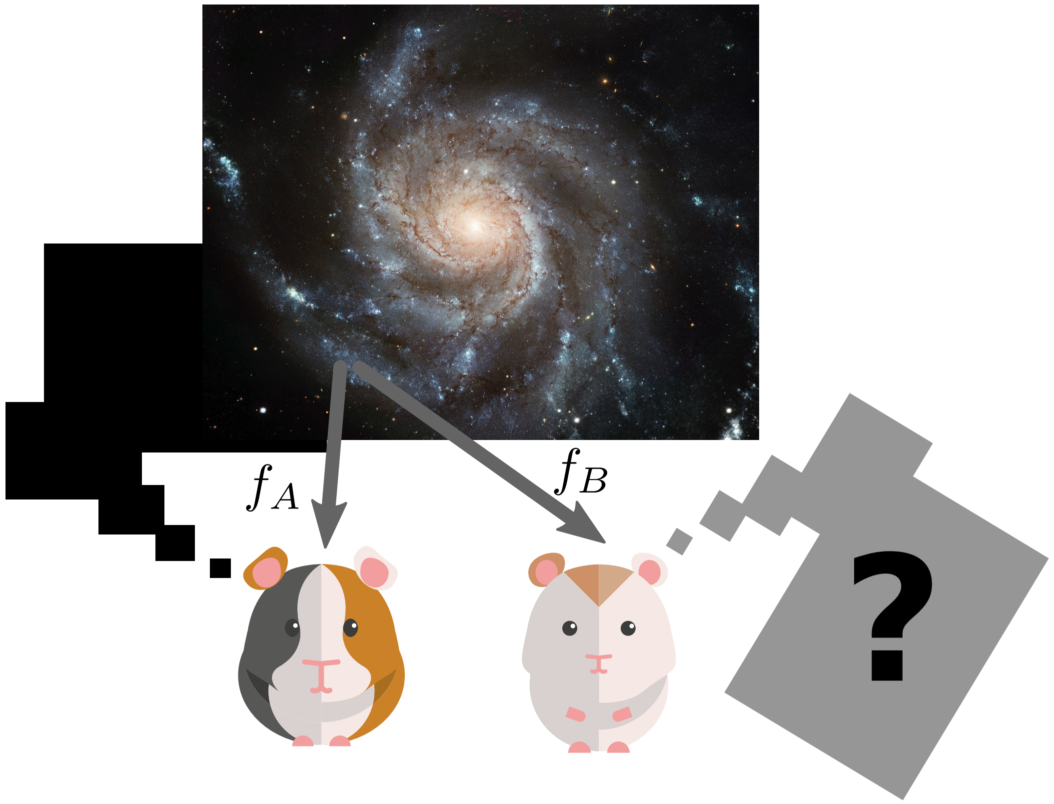
1. Motivation

2. Postulates of the theory

3. How does an external world emerge?

4. What about more than one observer?





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How does physics emerge?

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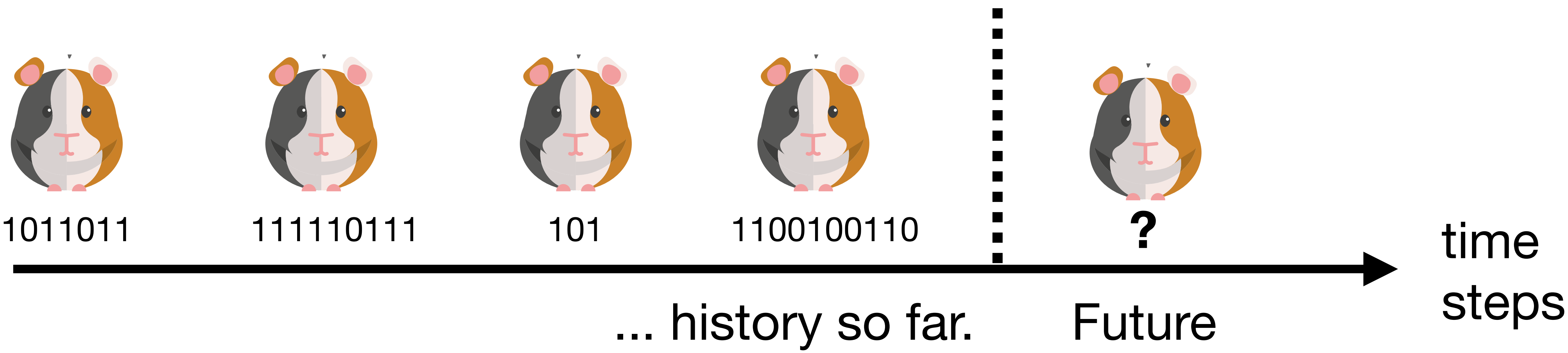

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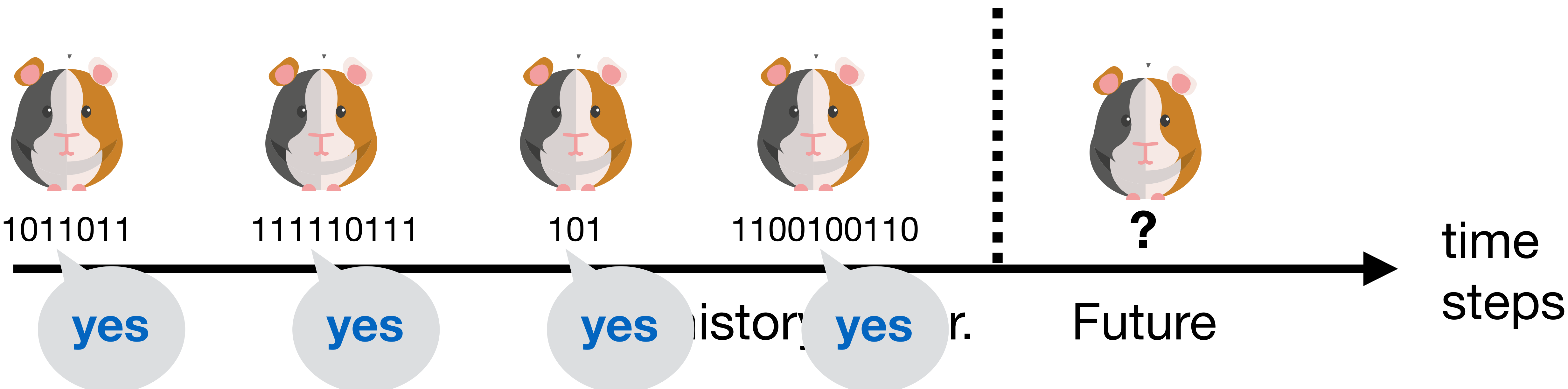

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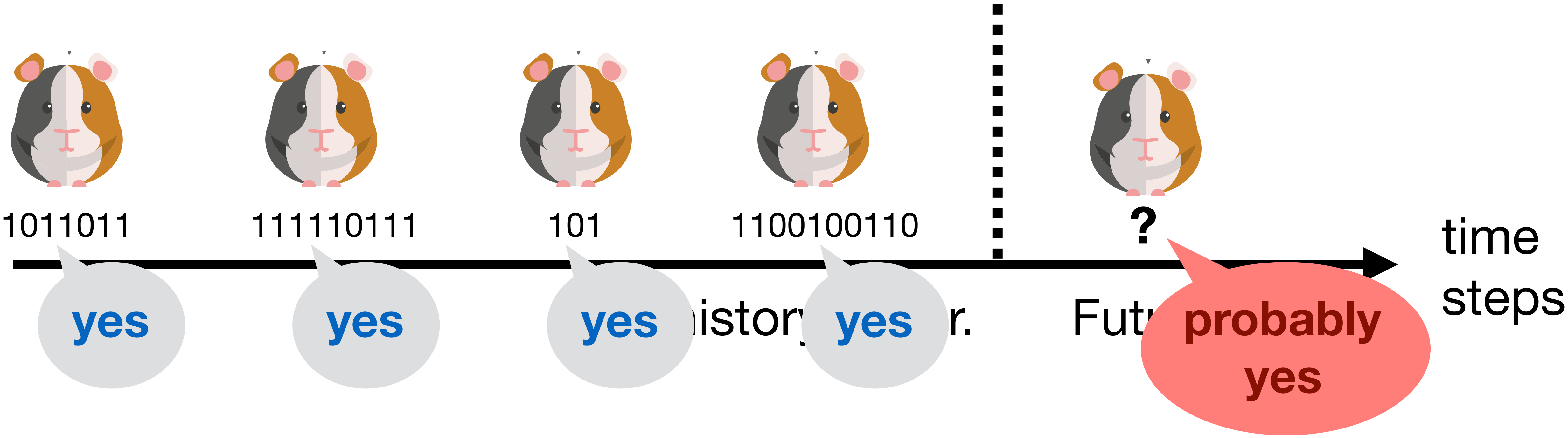

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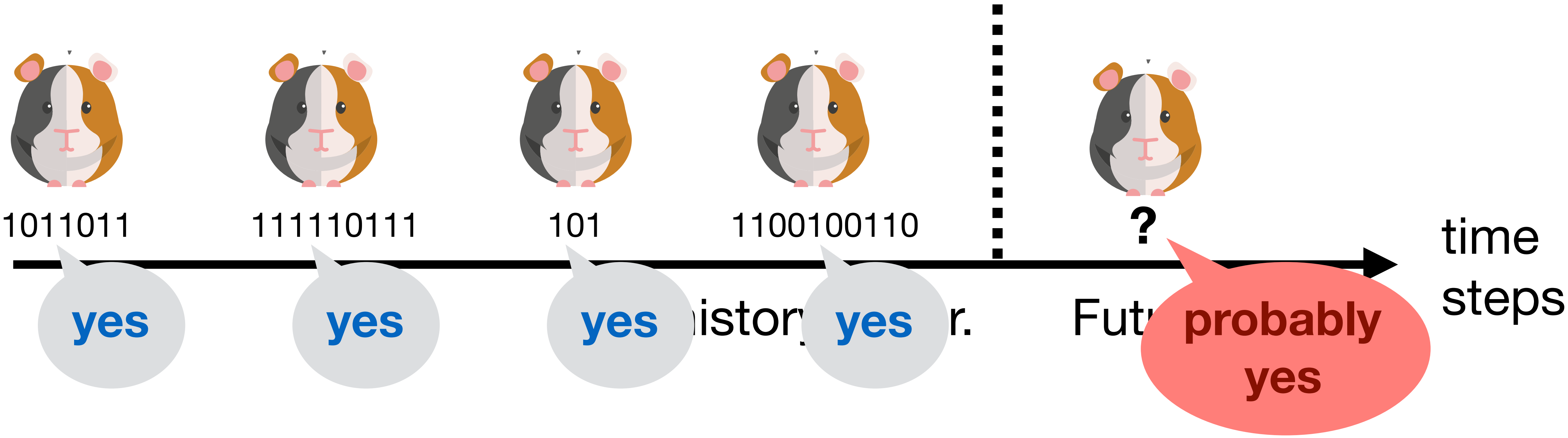

Theorem: Then, with probability close to one, answer will be "**yes**" in the future.

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

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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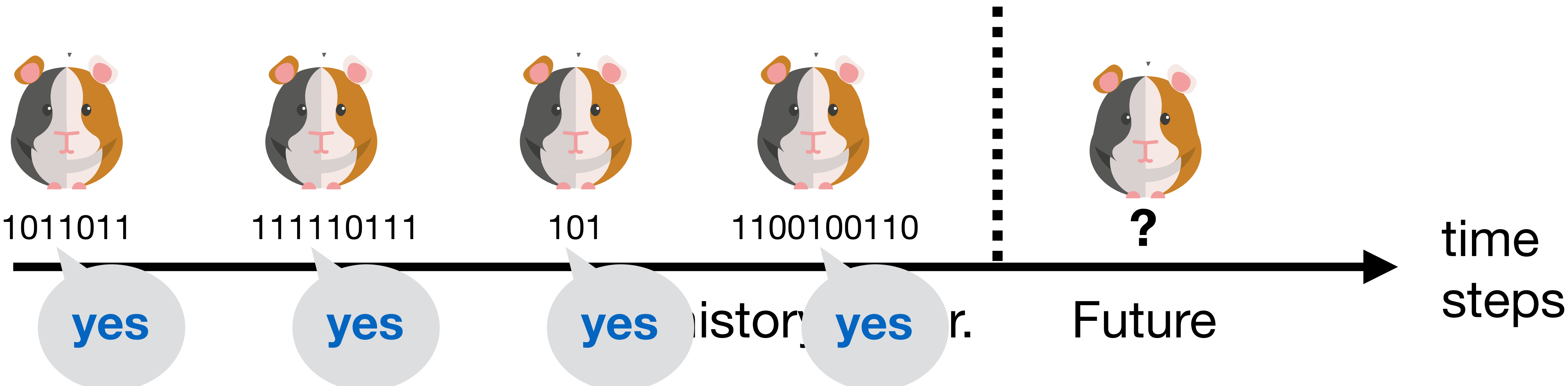

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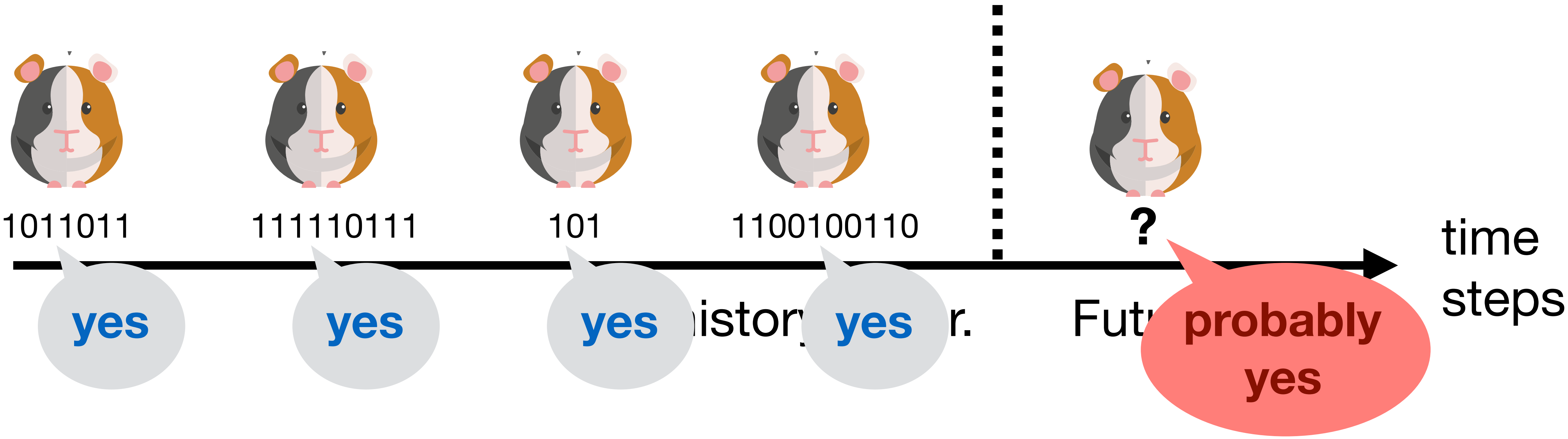

Boltzmann brain experience ("*what the... I'm suddenly in space... argh!!*") is highly unlikely.

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

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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 $\mu(x'_1, \ldots, x'_n)$.

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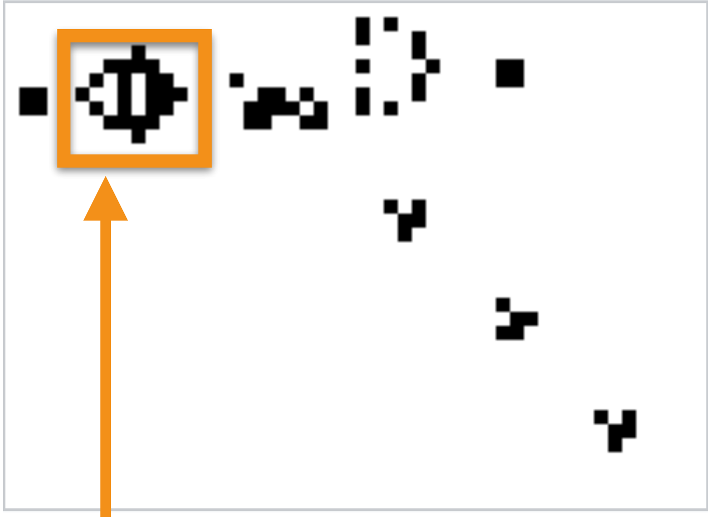

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- Thus, observer's probabilities will equal the marginal distribution of some random variable that's part of a **probabilistic process** with **computable laws of short description** (a simple algorithm).

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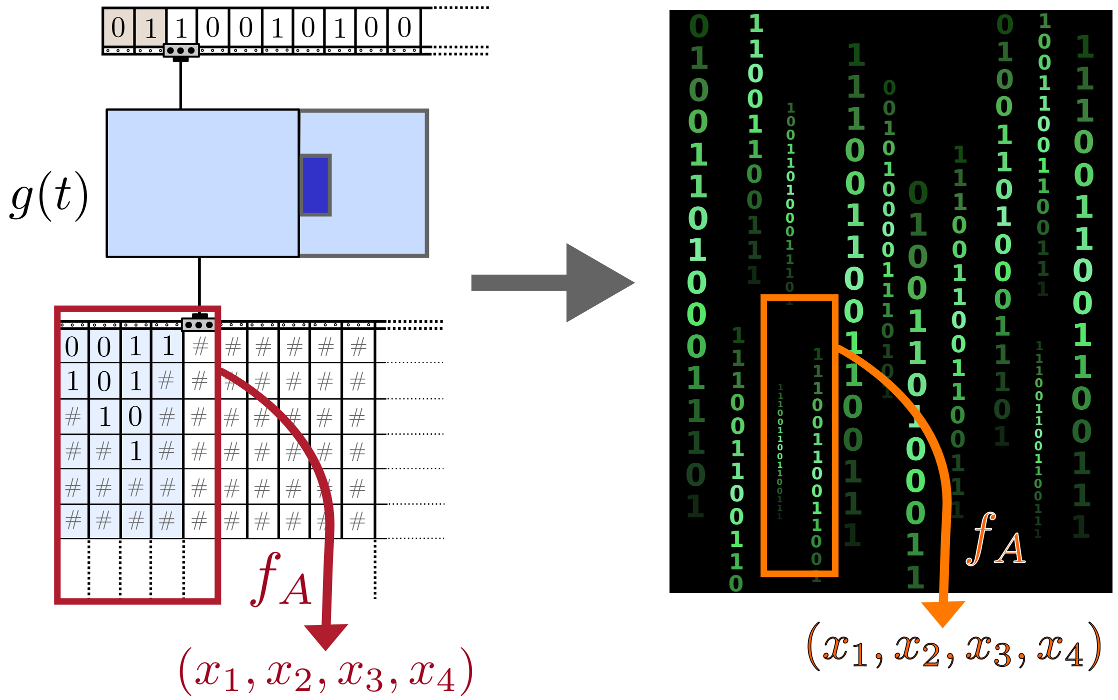

Abstract process (not even necessarily discrete in a naive sense).

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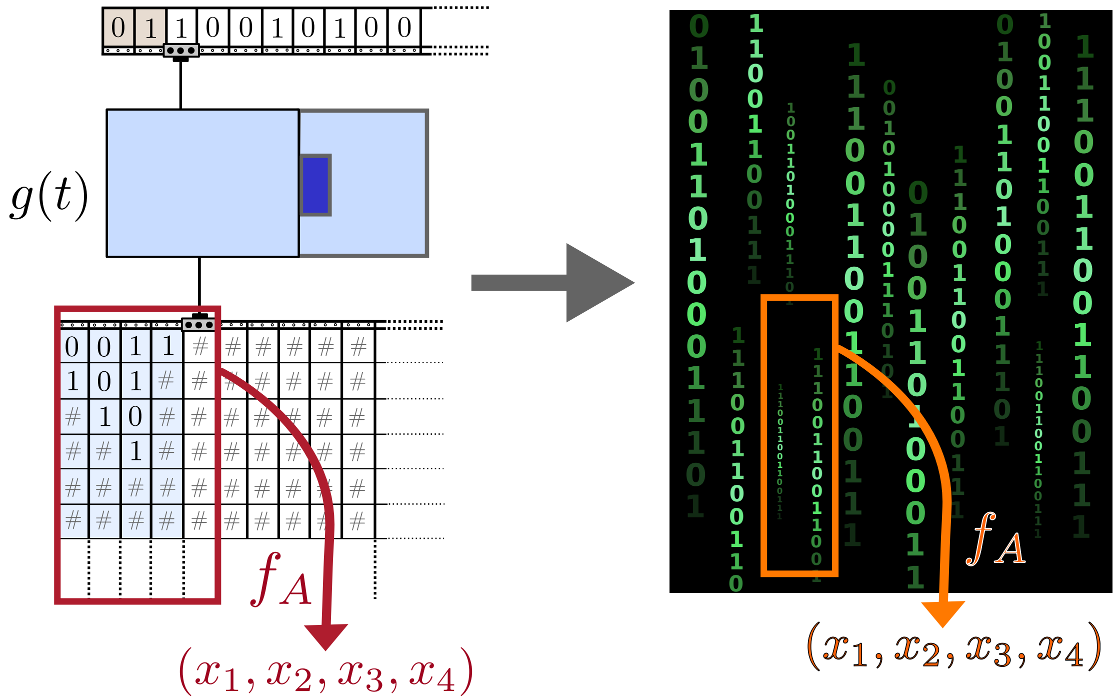

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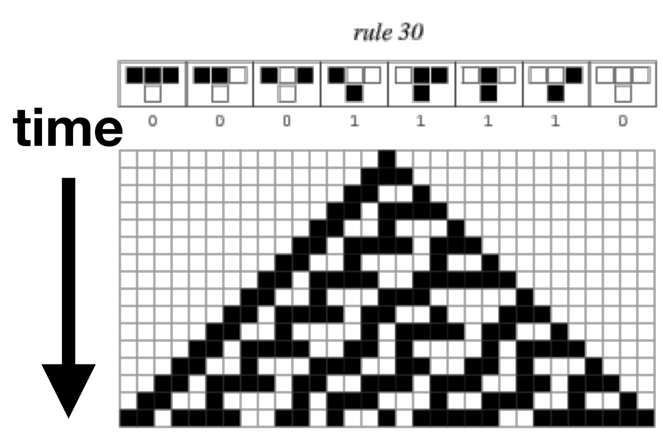

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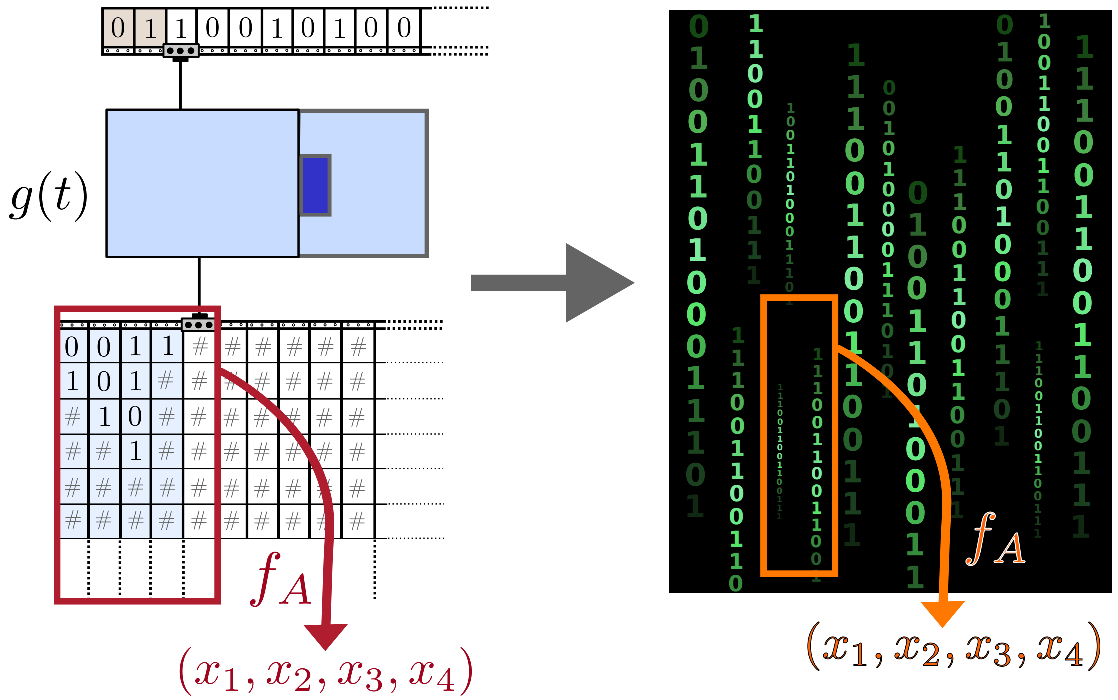

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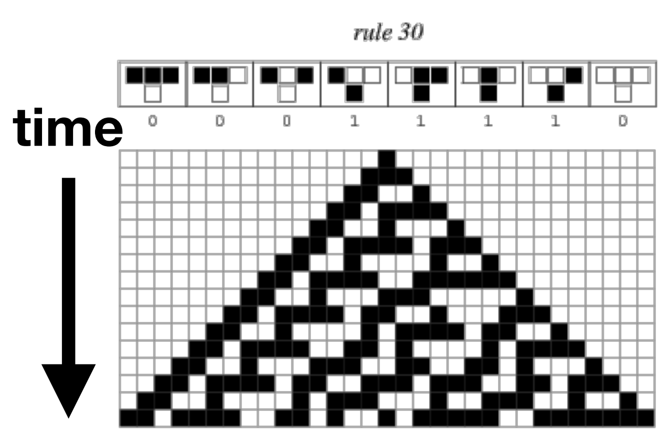

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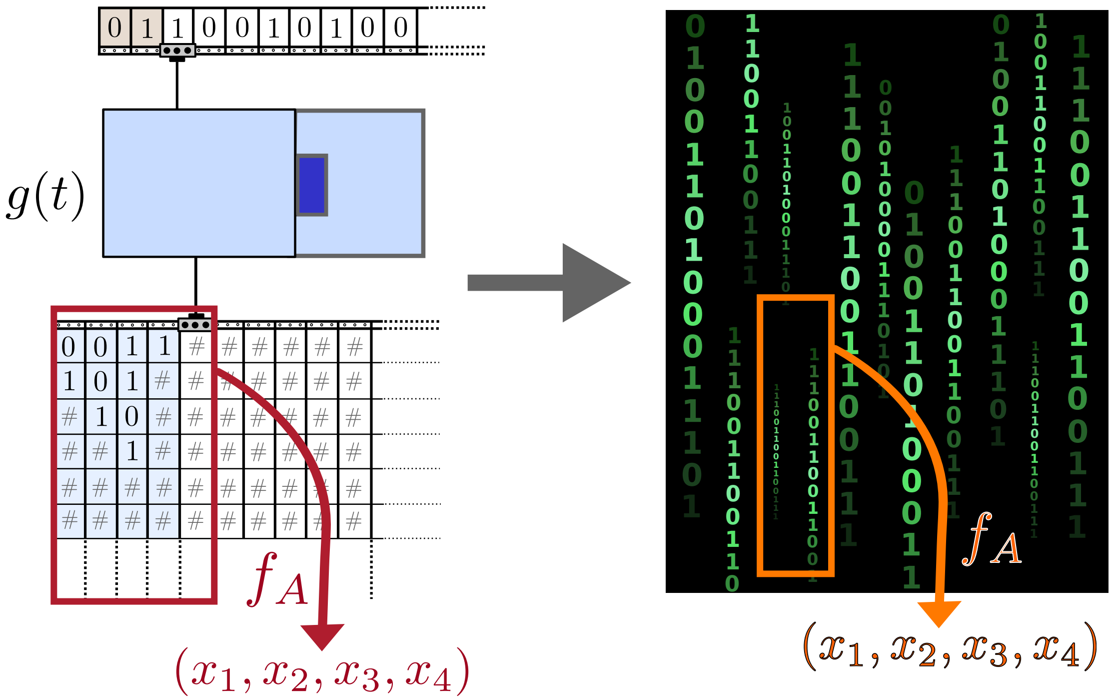

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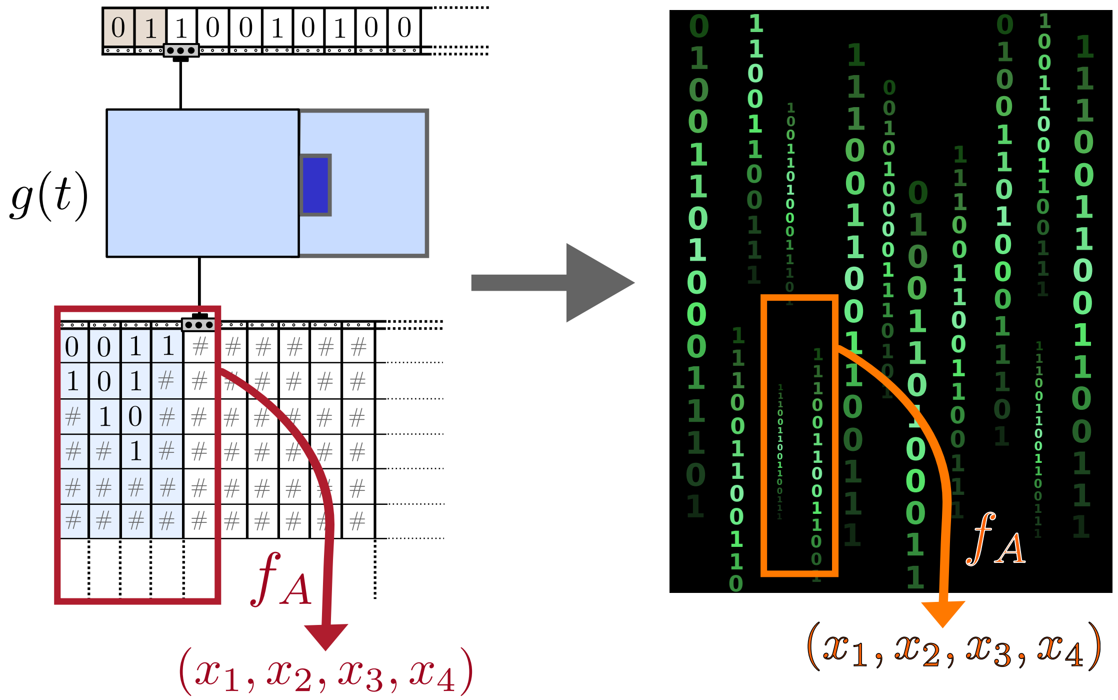

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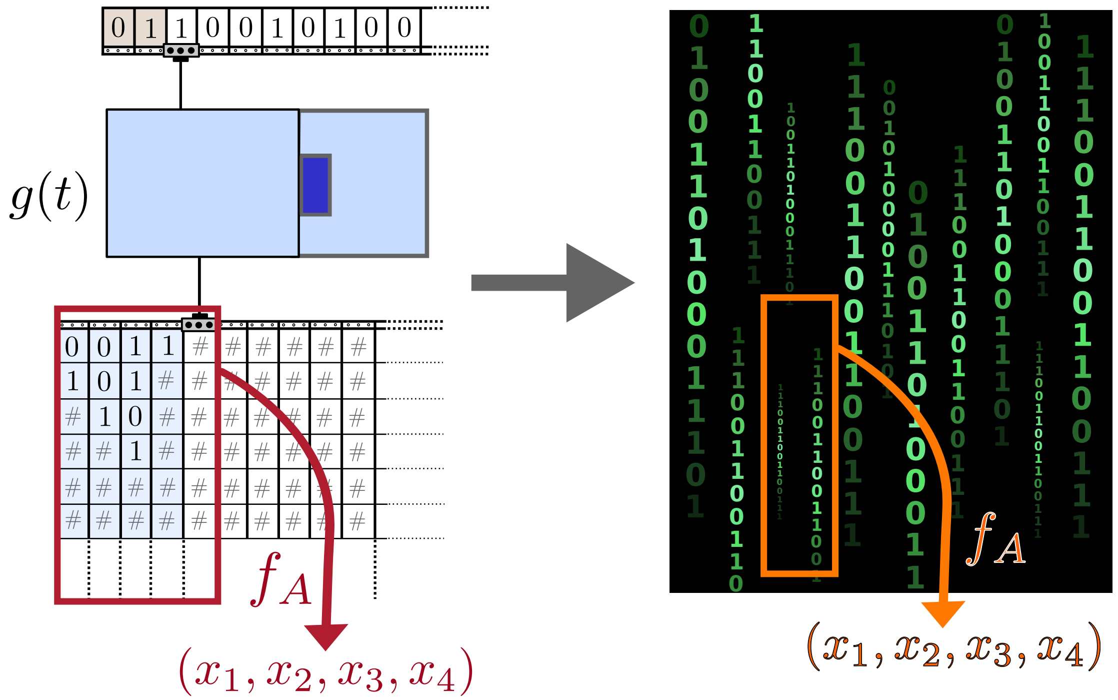

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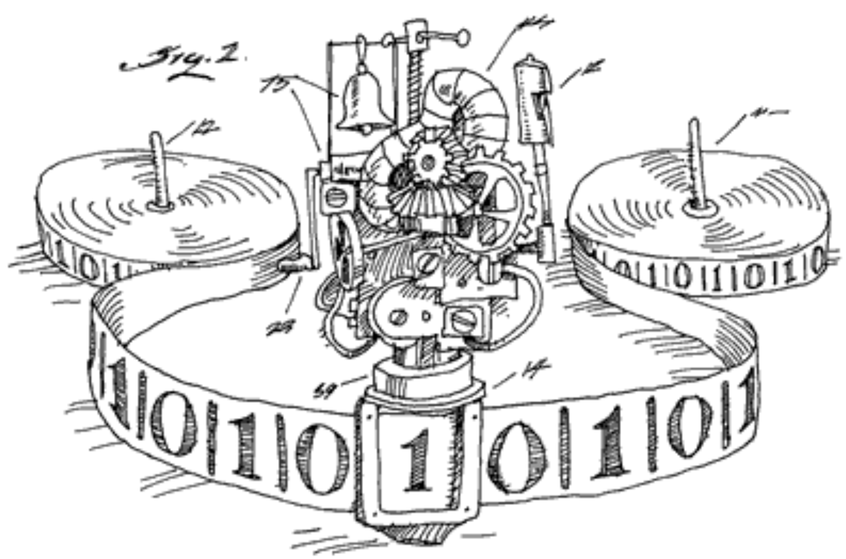

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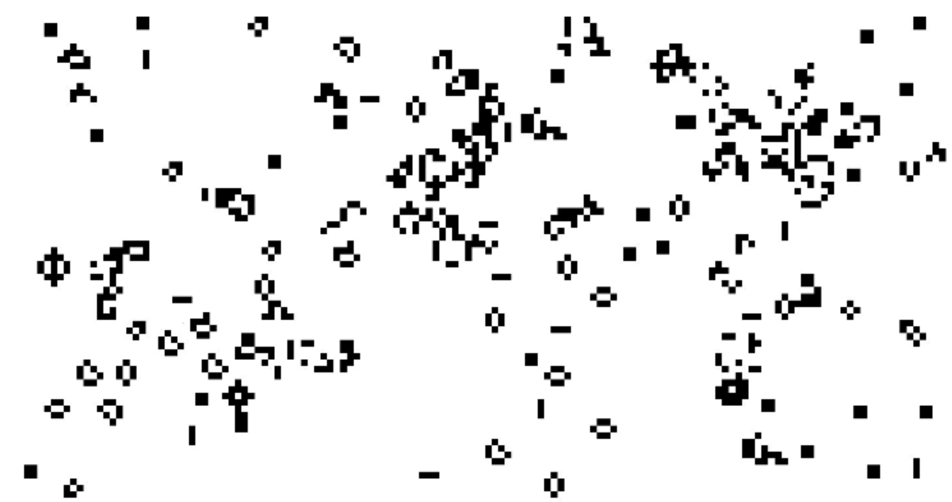

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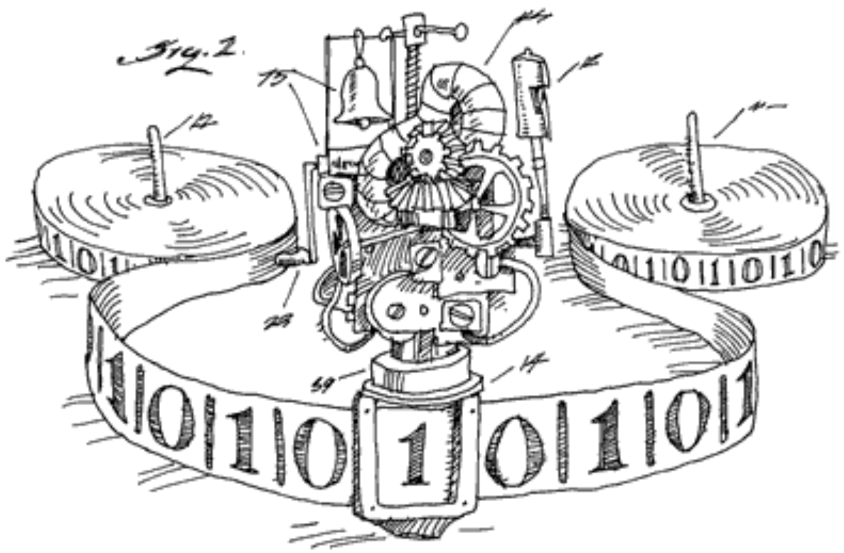

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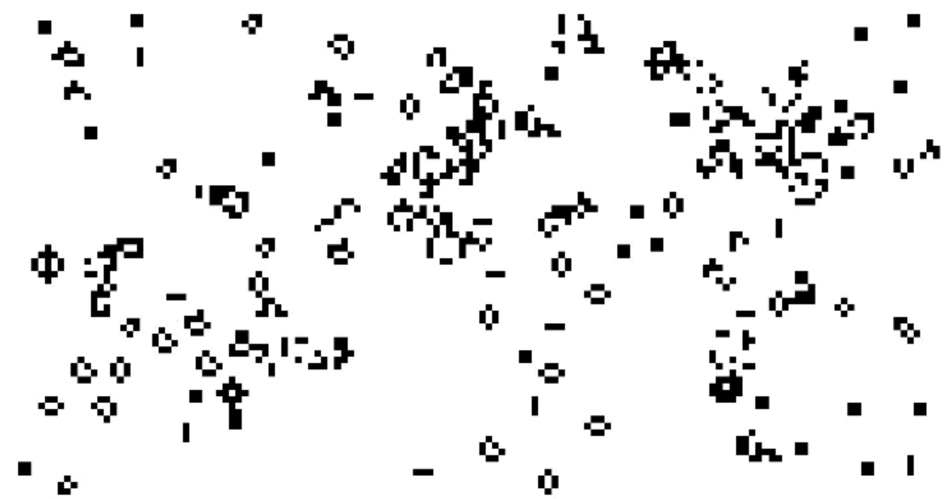
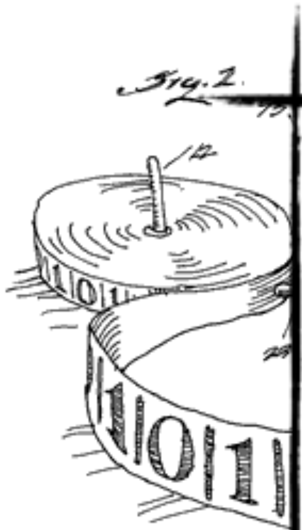


Comparison with physics that we observe:

- Generically, (simple) computations start in **simple initial state**, and then evolve with increasing algorithmic entropy.
- Time evolution is in principle **simulatable by a (short) Turing machine program** (but not necessarily efficiently!).
- Process is **fundamentally probabilistic**, but TM not necessarily the most natural model of computation to represent the process.

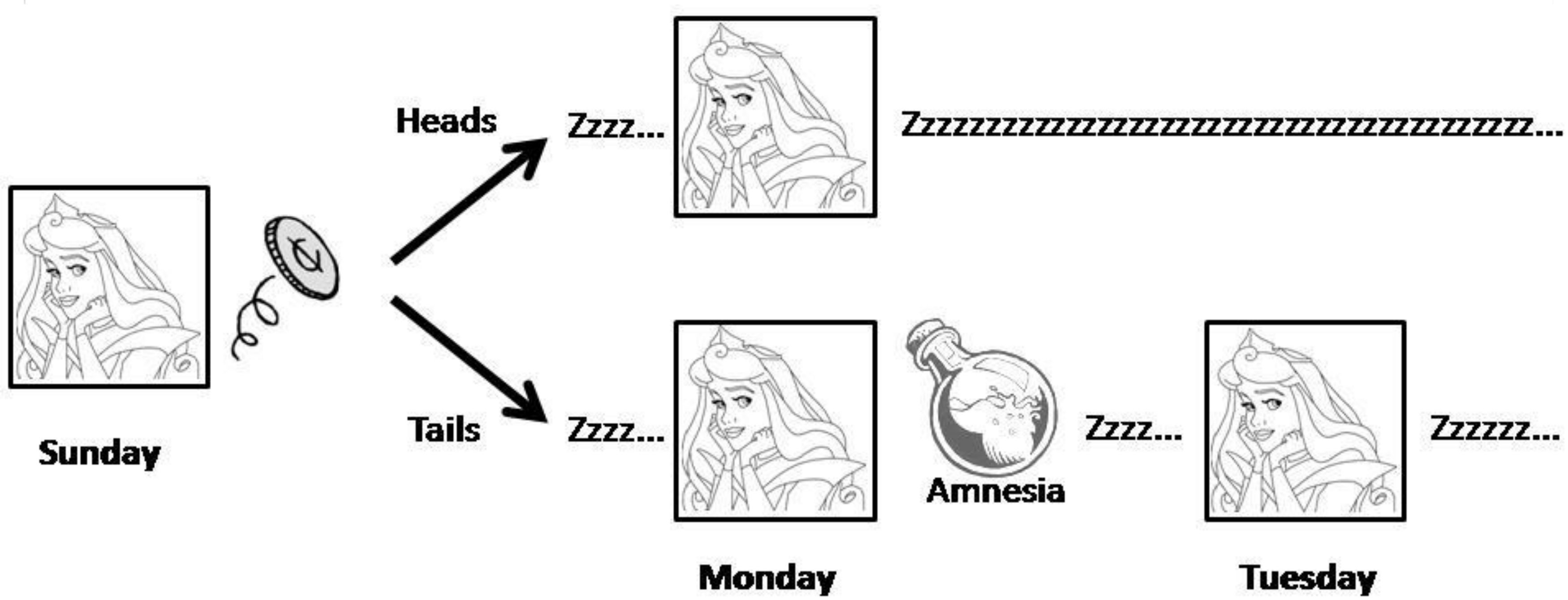
Prediction 2: **Simple, computable, probabilistic "world"**



is not

In fact, **violation of Bell inequalities and no-signalling** (wrt. computational causal structure) generic predictions, assuming that the open problem from further above can be solved.

http://pirsa.org/displayFlash.php?id=18040080



Compari

- Gene ... **state**,
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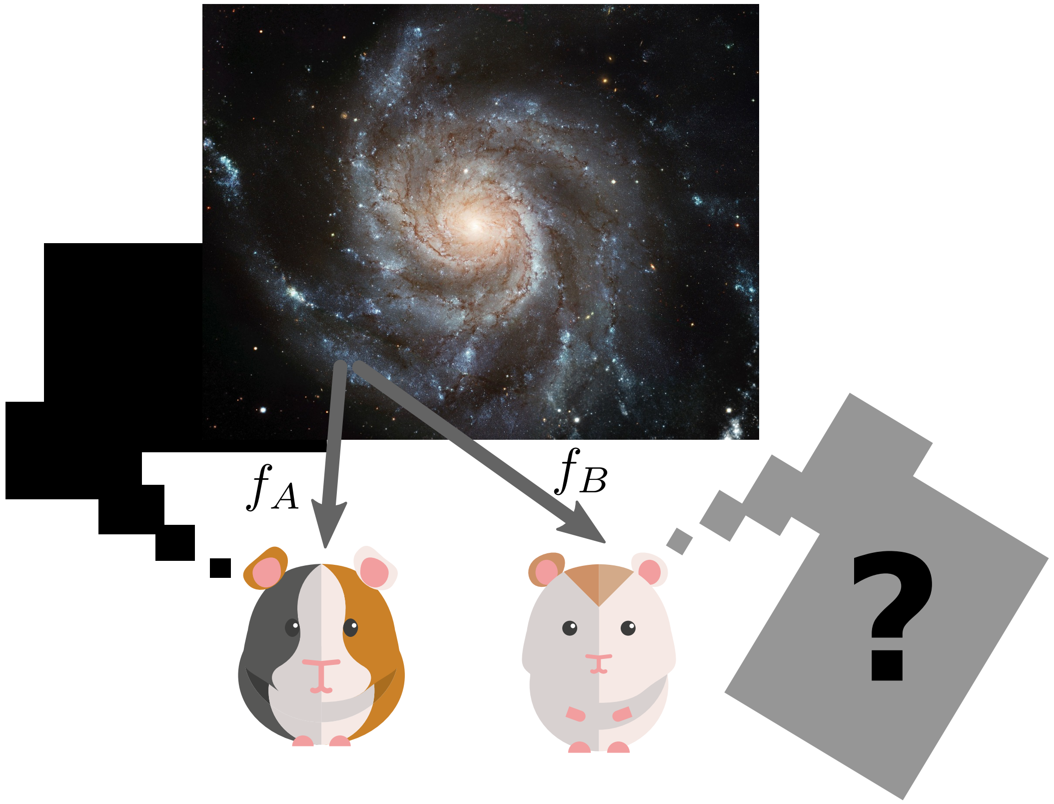
Outline



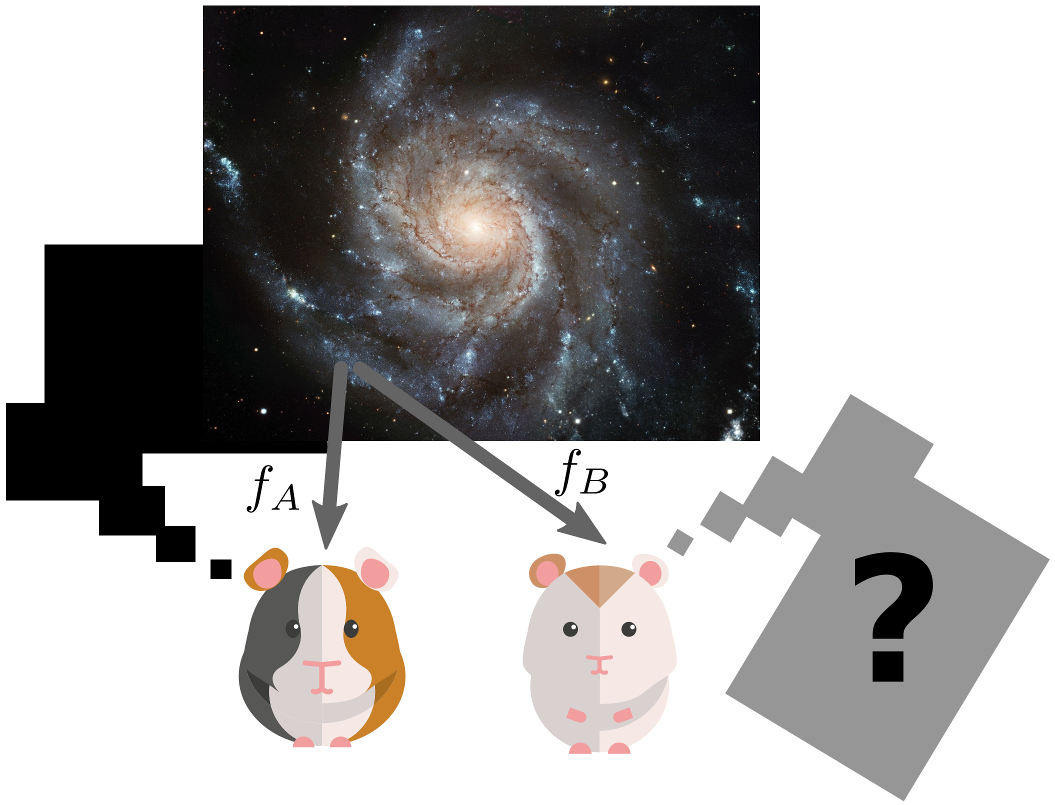
1. Motivation

2. Postulates of the theory

3. How does an external world emerge?

4. What about more than one observer?

Outline



1. Motivation

2. Postulates of the theory

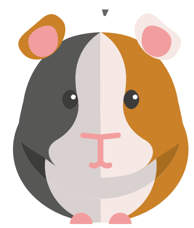
3. How does an external world emerge?

4. What about more than one observer?

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

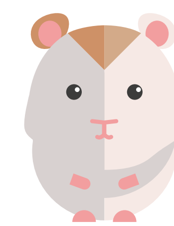
Apriori, different observers make their *own* "private" observations.

Abby



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

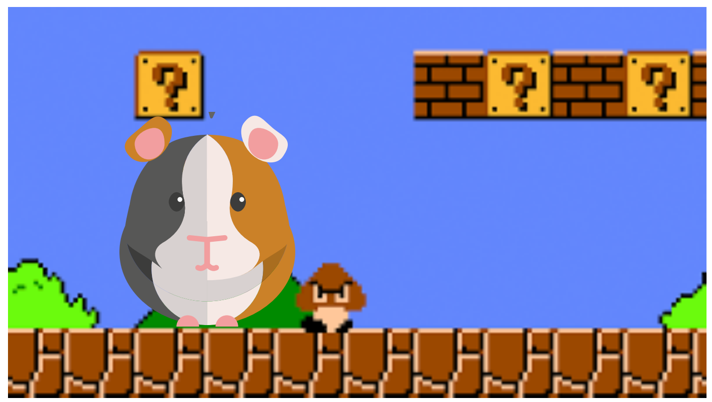
Bambi



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

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

Apriori, different observers make their *own* "private" observations. They are completely unrelated, and live in their own "external worlds".

A-world   **B**-world

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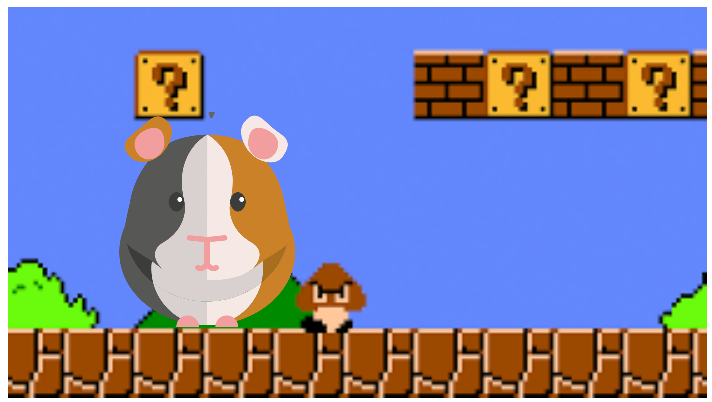
A-world   **B**-world

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

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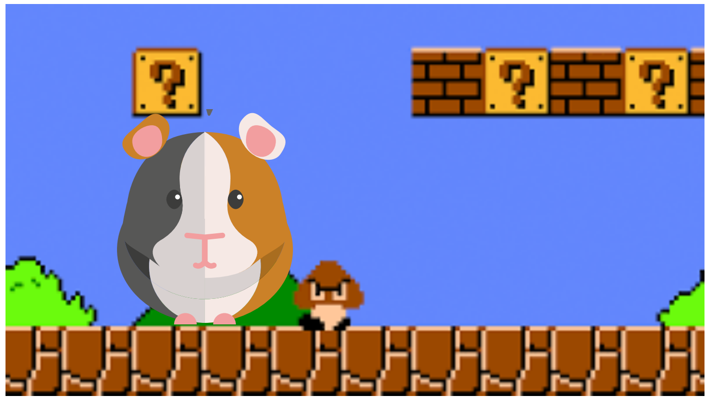

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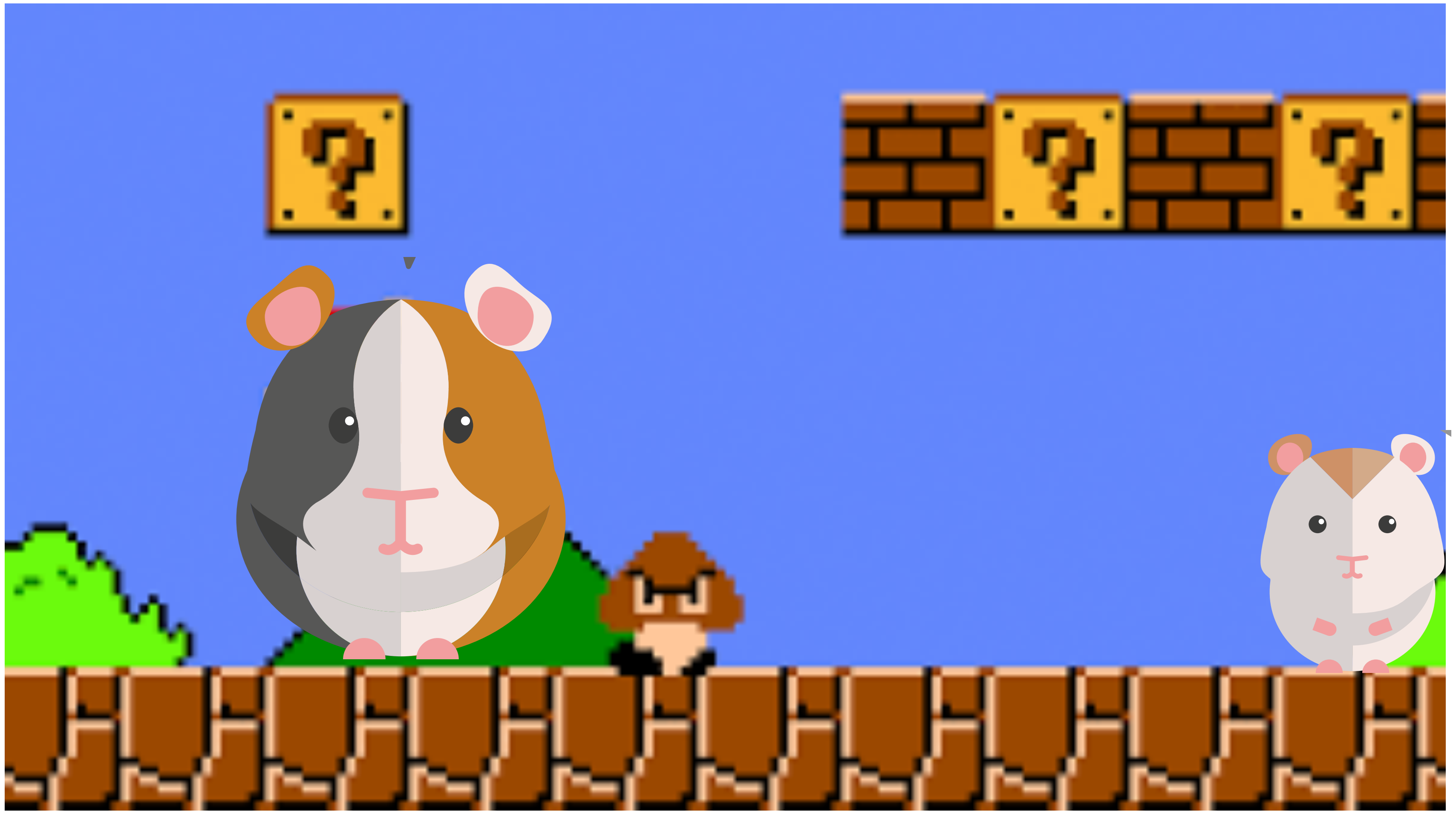

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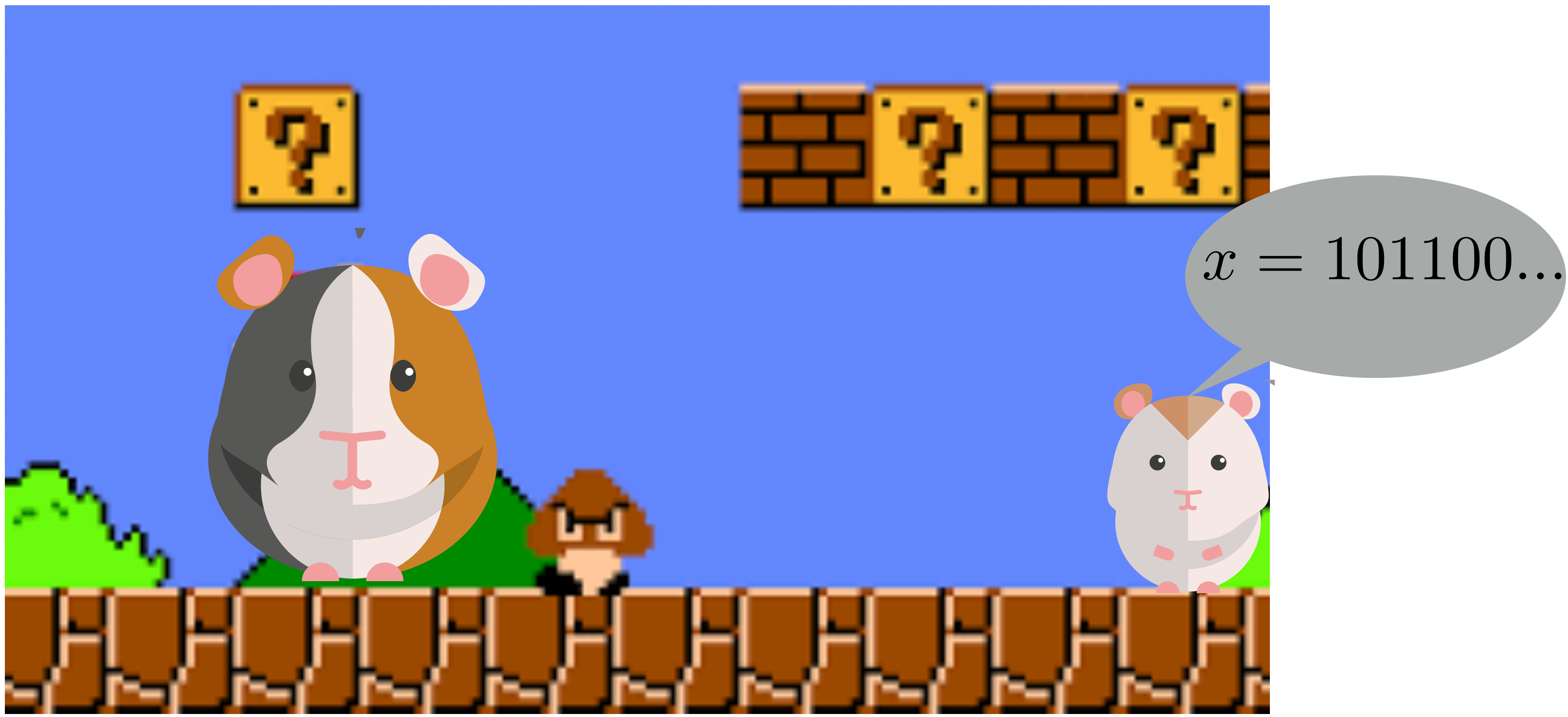

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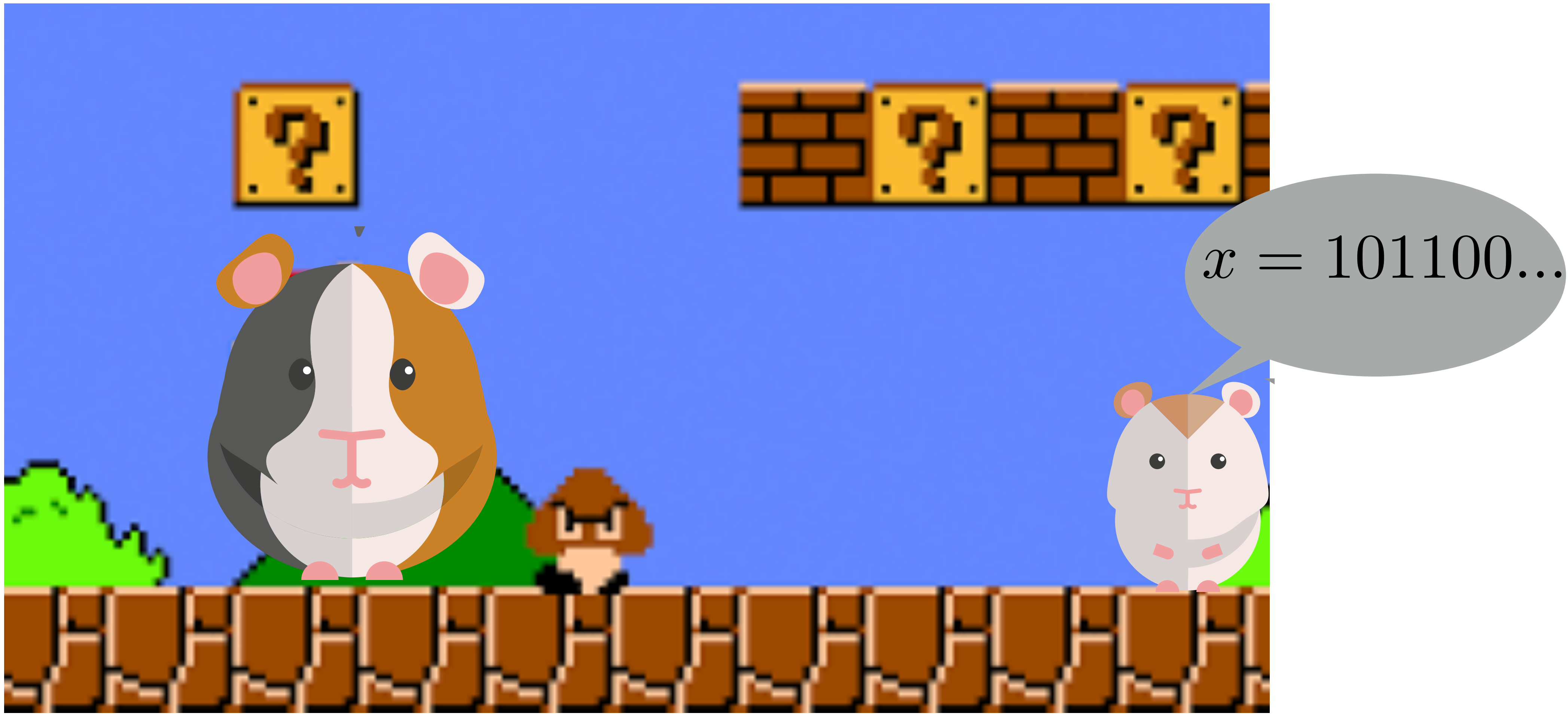


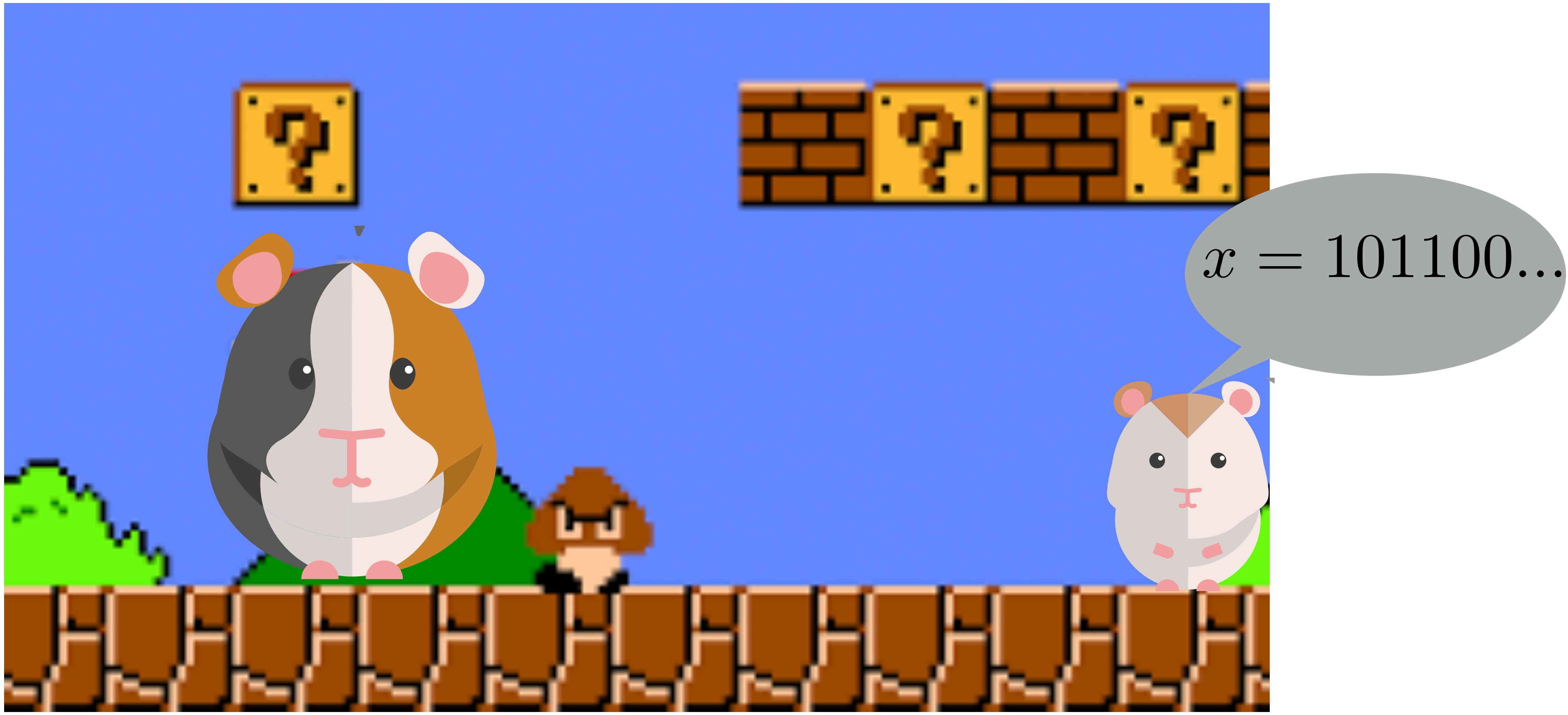
But suppose that **A** sees something in her external world that seems like another observer **B** to her...

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

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

How to formalize this:

A-world



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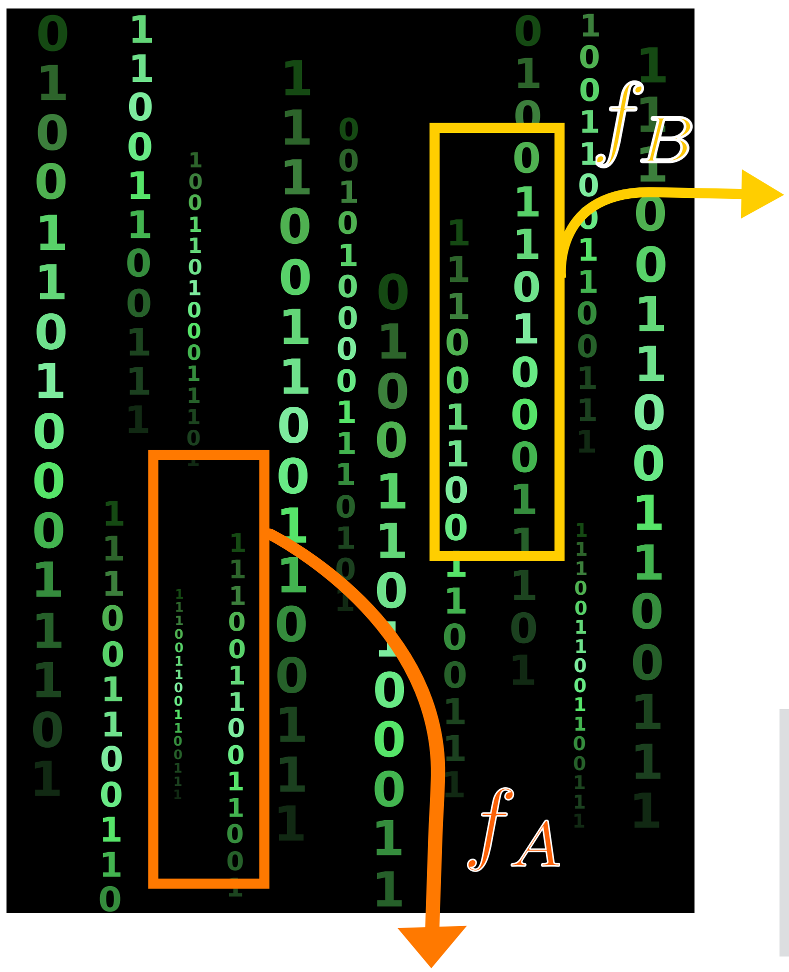

$x = 101100...$

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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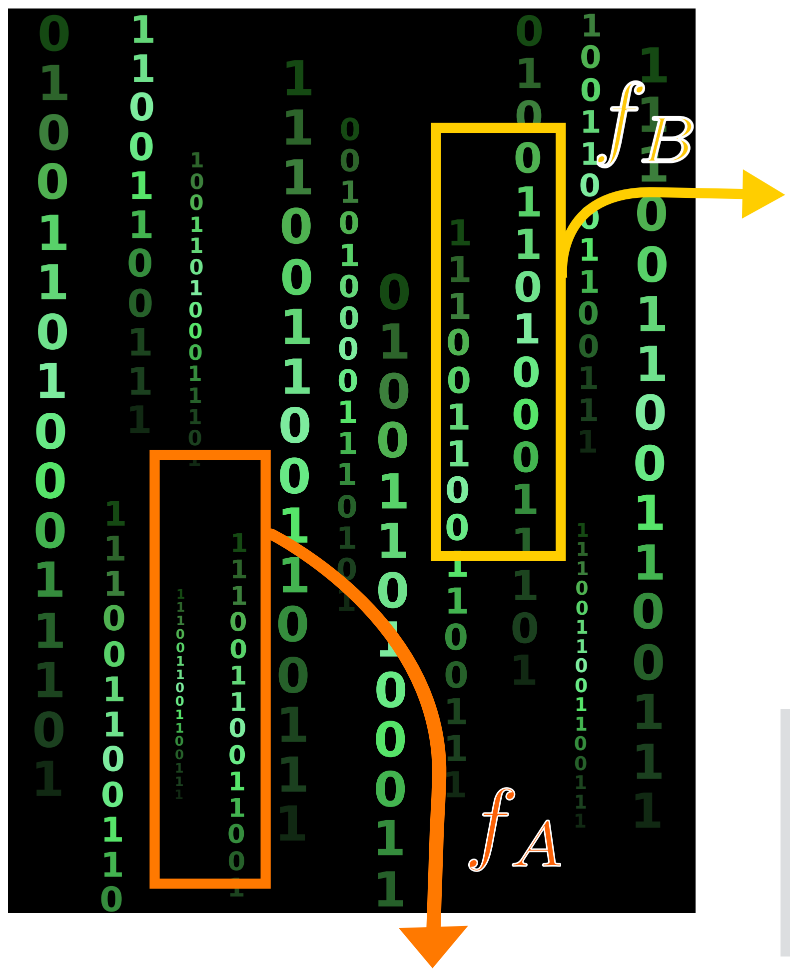

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Two probability distributions:

$\nu(x_1, x_2, \ldots, x_n) :=$ 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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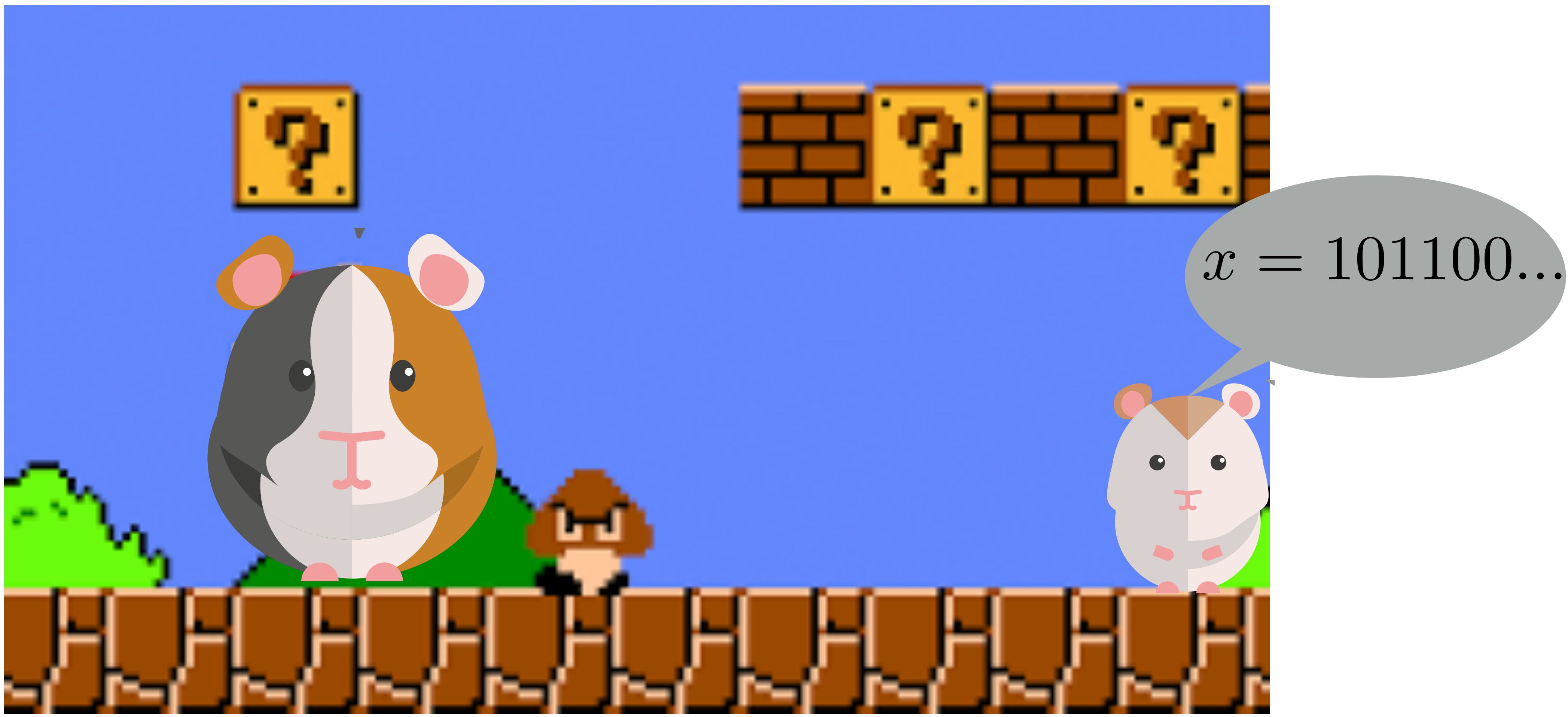

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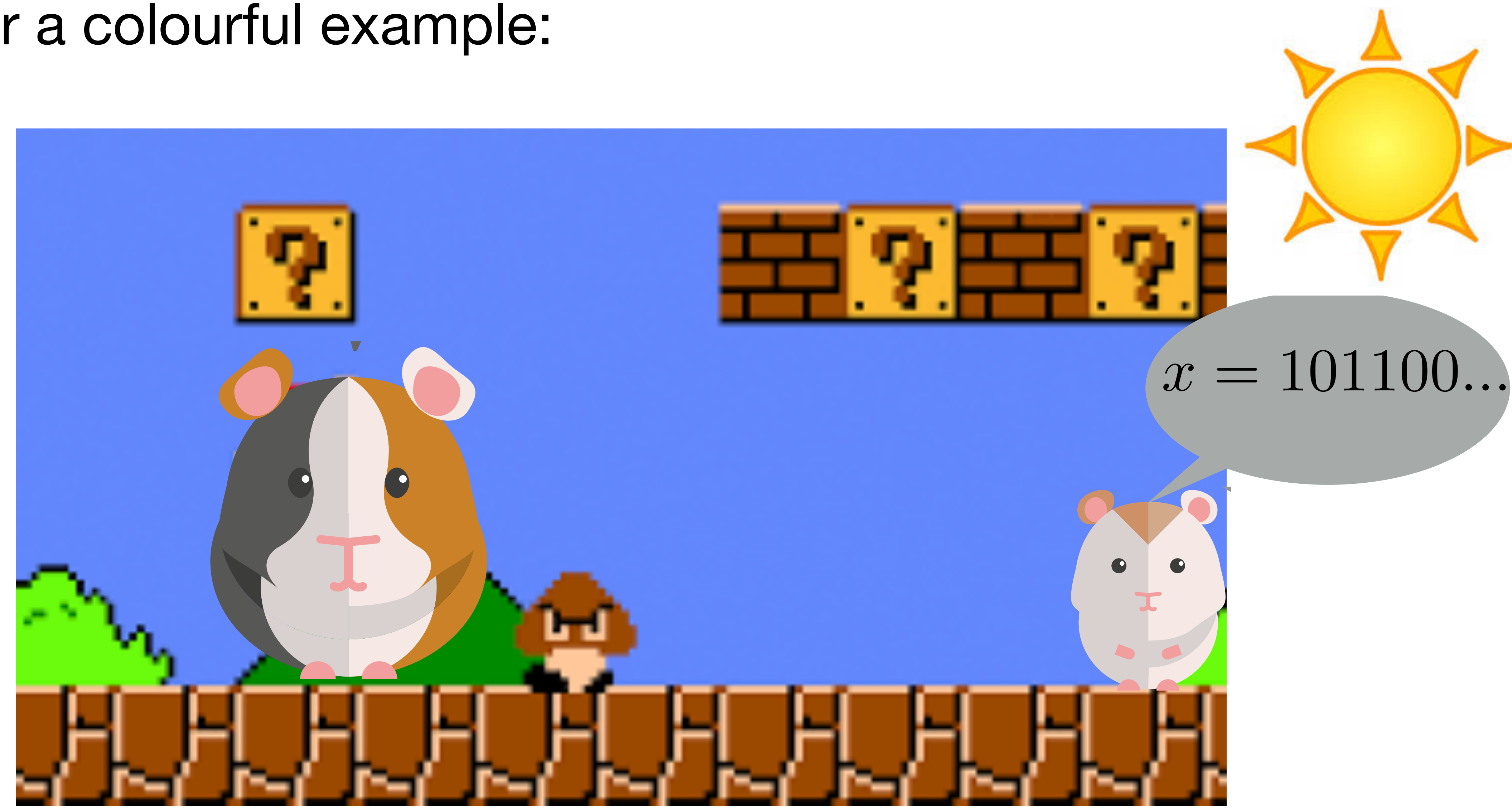
Let's consider a colourful example:

A-world



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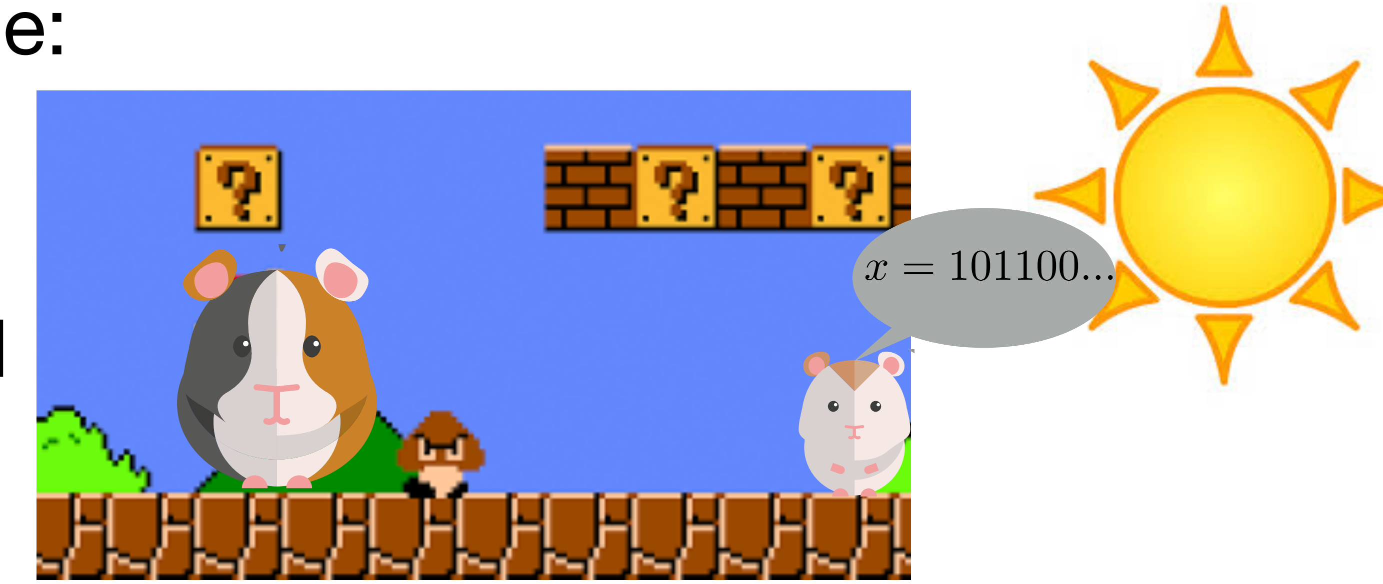

If Abby has a chance of about 100% of *seeing Bambi see the sun rise tomorrow*, then will Bambi have a chance of about 100% of seeing the sun rise tomorrow?

ν

$\mathbf{P}$

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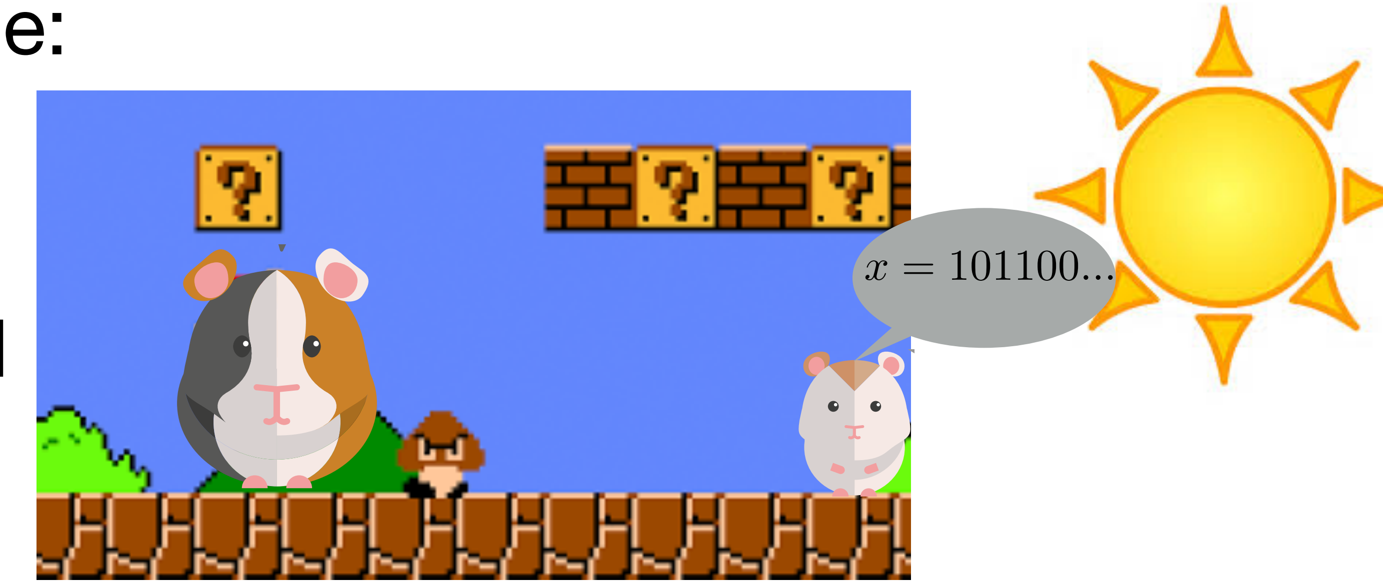

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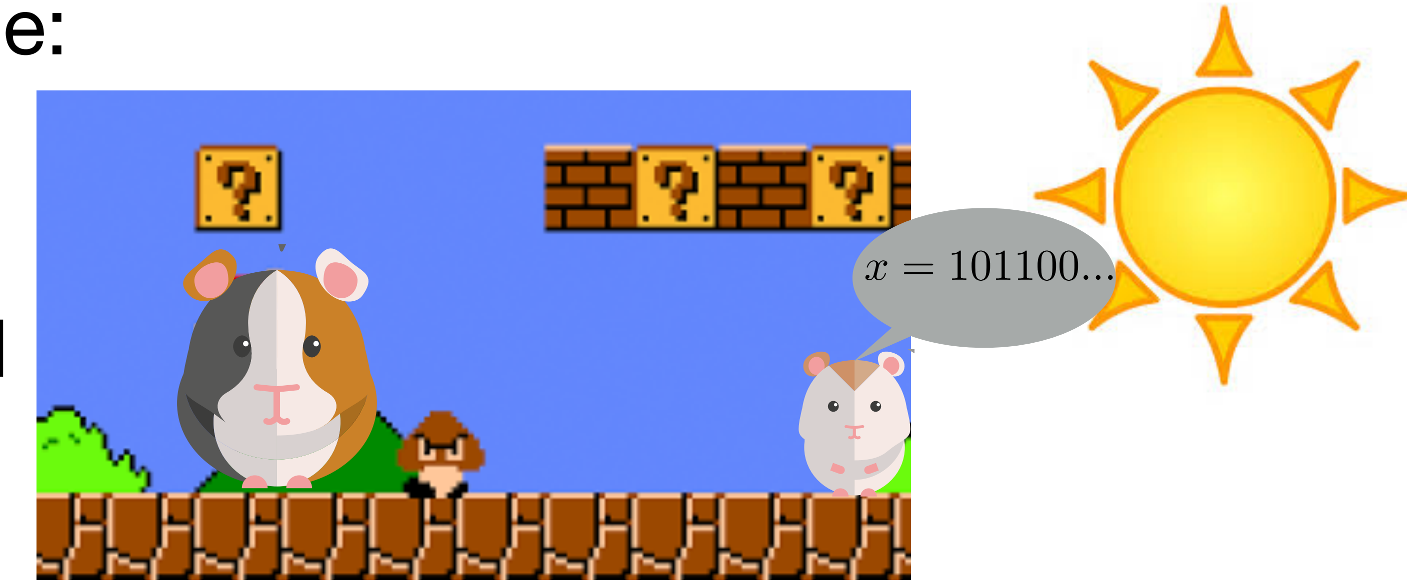

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Theorem: With ν-probability one,

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

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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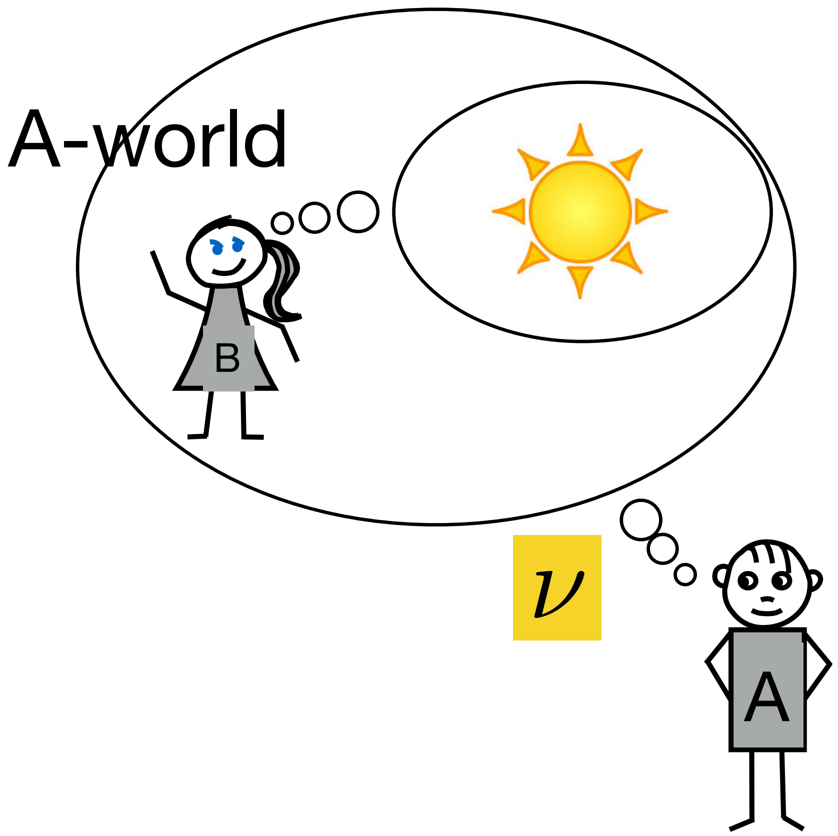
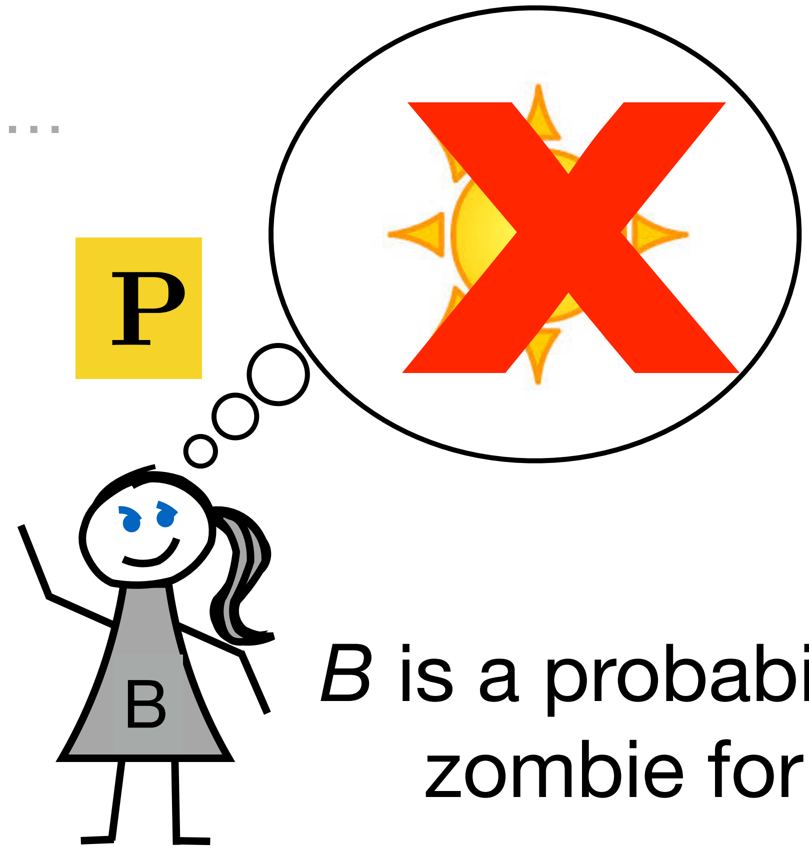


but



B is a probabilistic zombie for *A*.

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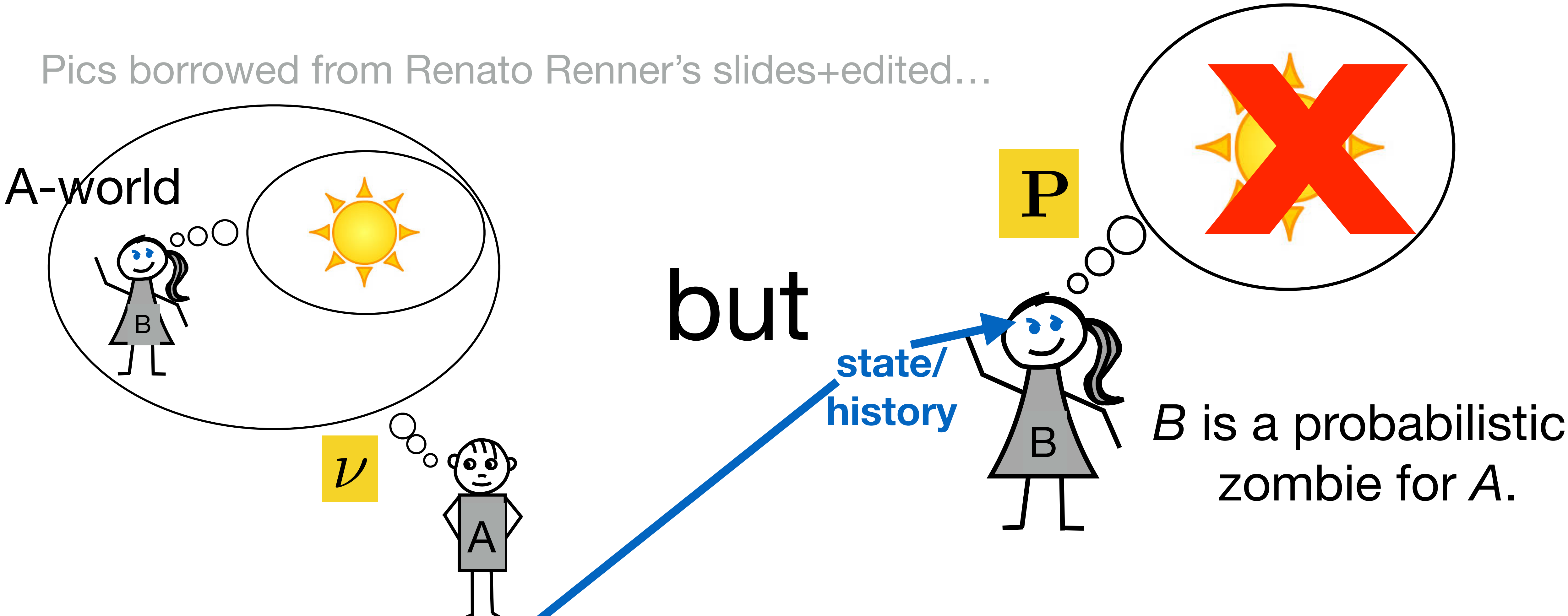

prob. of B's state according to A-world

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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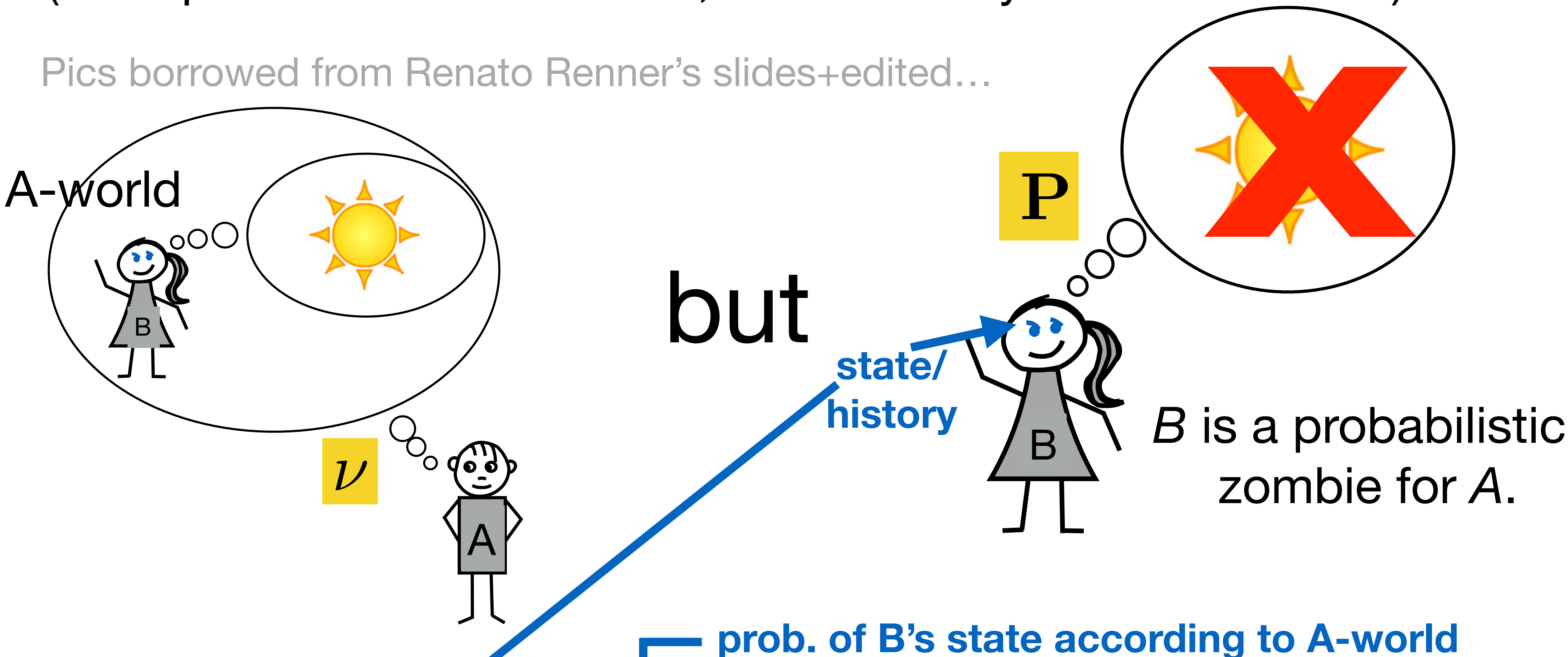

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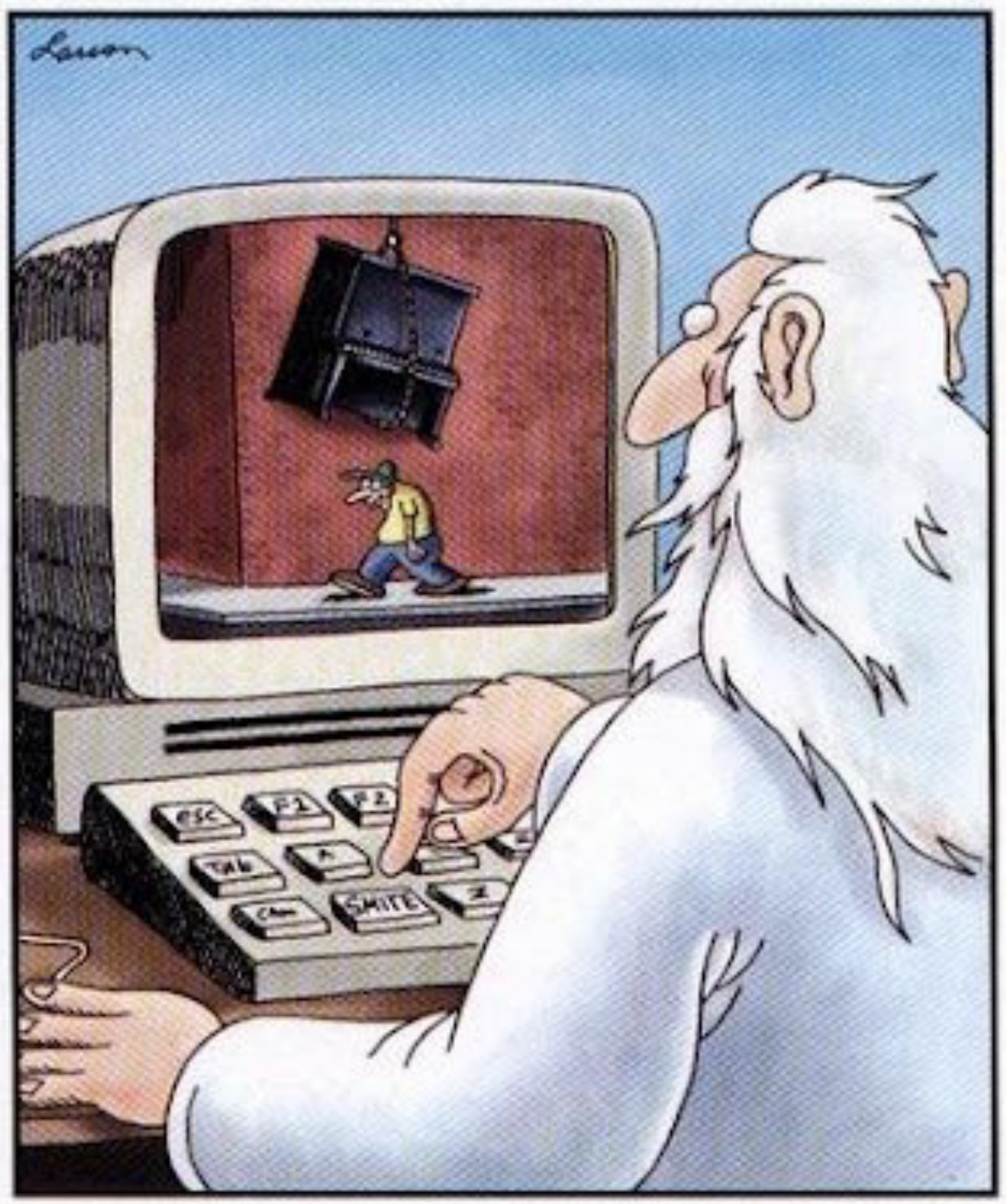

God at His computer

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.

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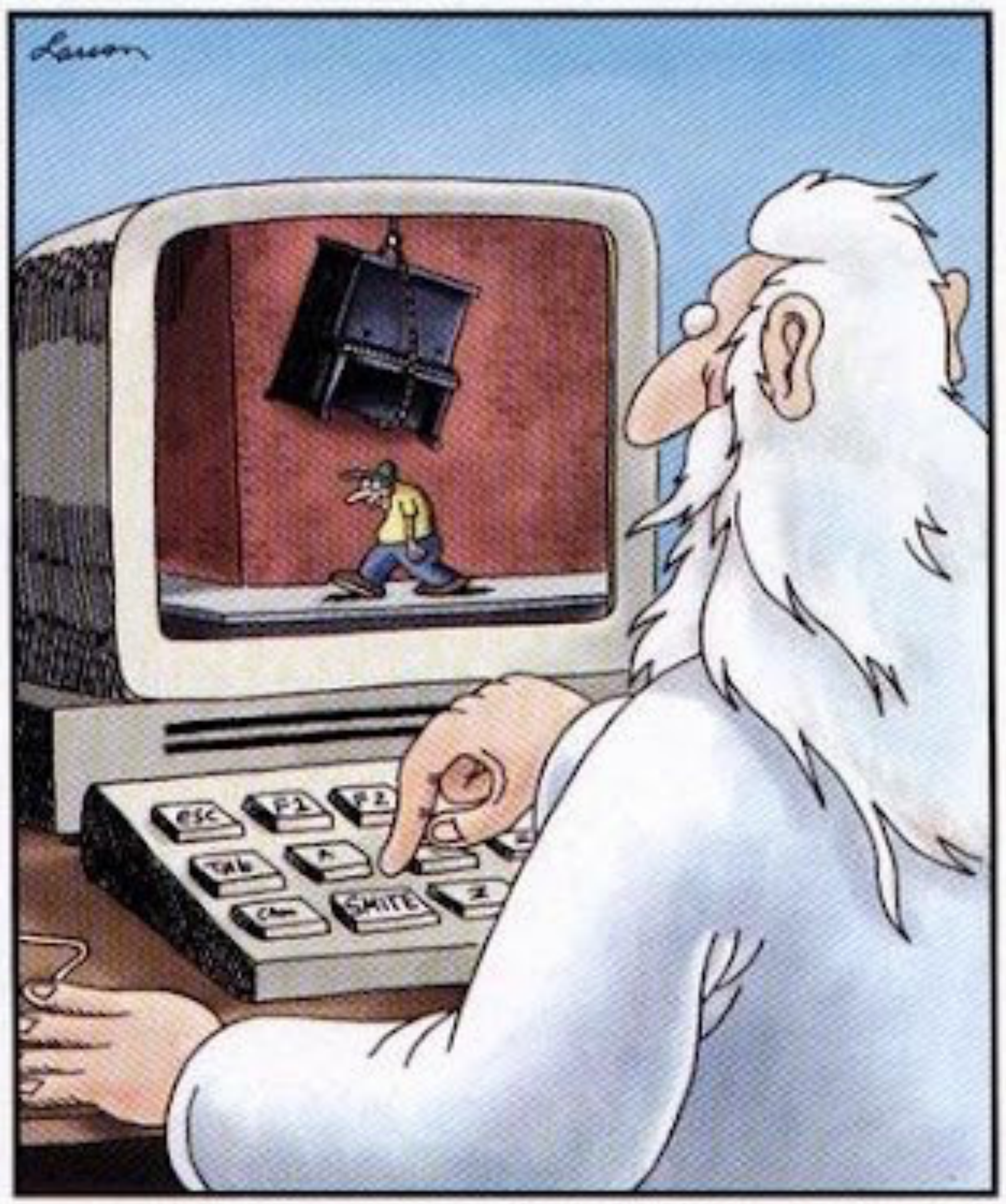

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Advantage: this theory also makes **(other) testable predictions** — maybe a reason to also trust its predictions in this "crazy" (untestable) regime.

Conclusions

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− Cannot use it for quantum gravity or cross sections or…………

O Proof of principle / **blueprint** of an “idealistic” predictive theory.

+ Many predictions / consequences from very simple assumptions.

- Existence of a simple computational probabilistic external world
- Emergence of objectivity (typically)
- Probabilistic zombies (in some cases)
- Resolves (versions of) the Boltzmann brain problem++
- No-signalling and Bell violation (**modulo an open problem**)
- Predictions for computer emulation of agents
- (Some sort of) subjective immortality, *but no possibility to use this for solving NP-complete problems in poly time*. (**But depends very much on details of the formulation.**)

Full version: **arXiv:1712.01826**
Short version (v2 soon): **arXiv:1712.01816**

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