DSC291: Machine Learning with Few Labels

World Model

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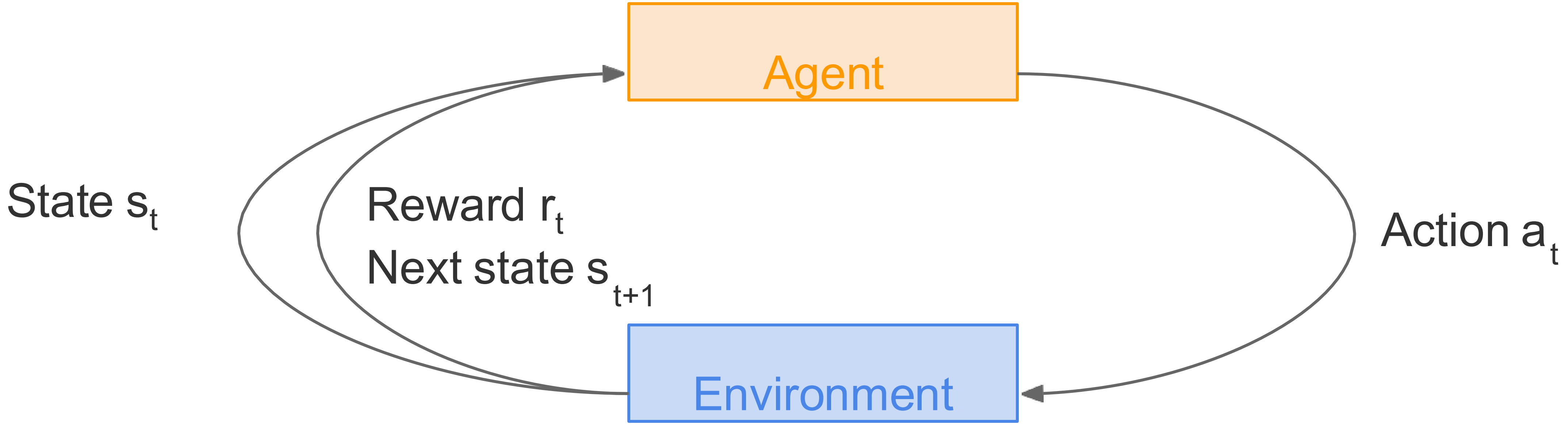
UC San Diego
HALICIOĞLU DATA SCIENCE INSTITUTE

Outline

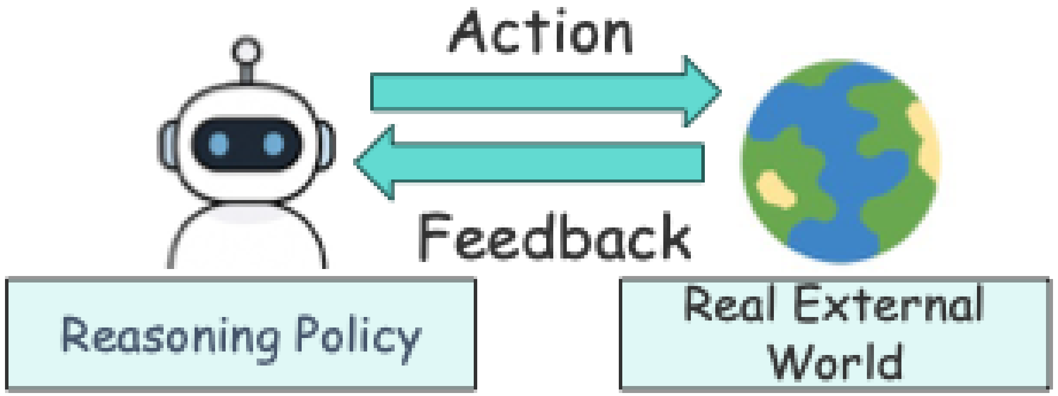
- World Model

- Paper presentation:
  - Sijin Lyu, Tianhao Zhou: "Improving noisy student training for low-resource languages in End-to-End ASR using CycleGAN and inter-domain losses”

Reinforcement Learning

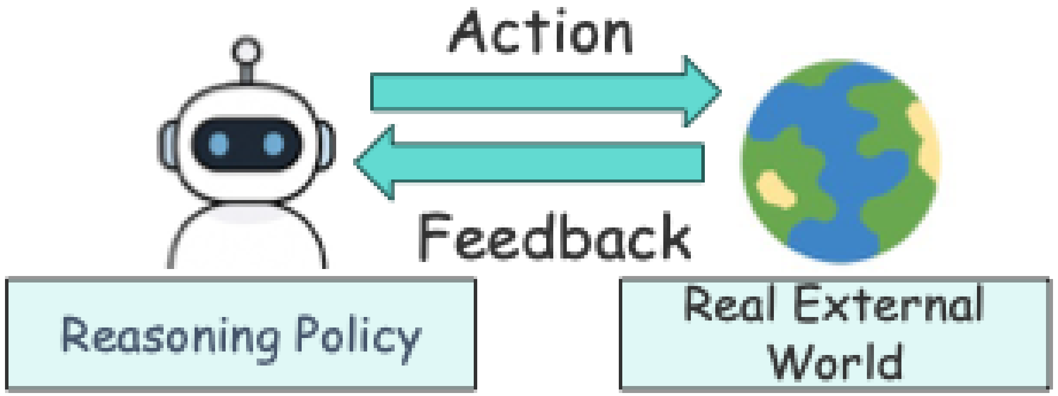


Reinforcement Learning



- Deployed in the real world
- Expensive, slow to get feedback

Reinforcement Learning



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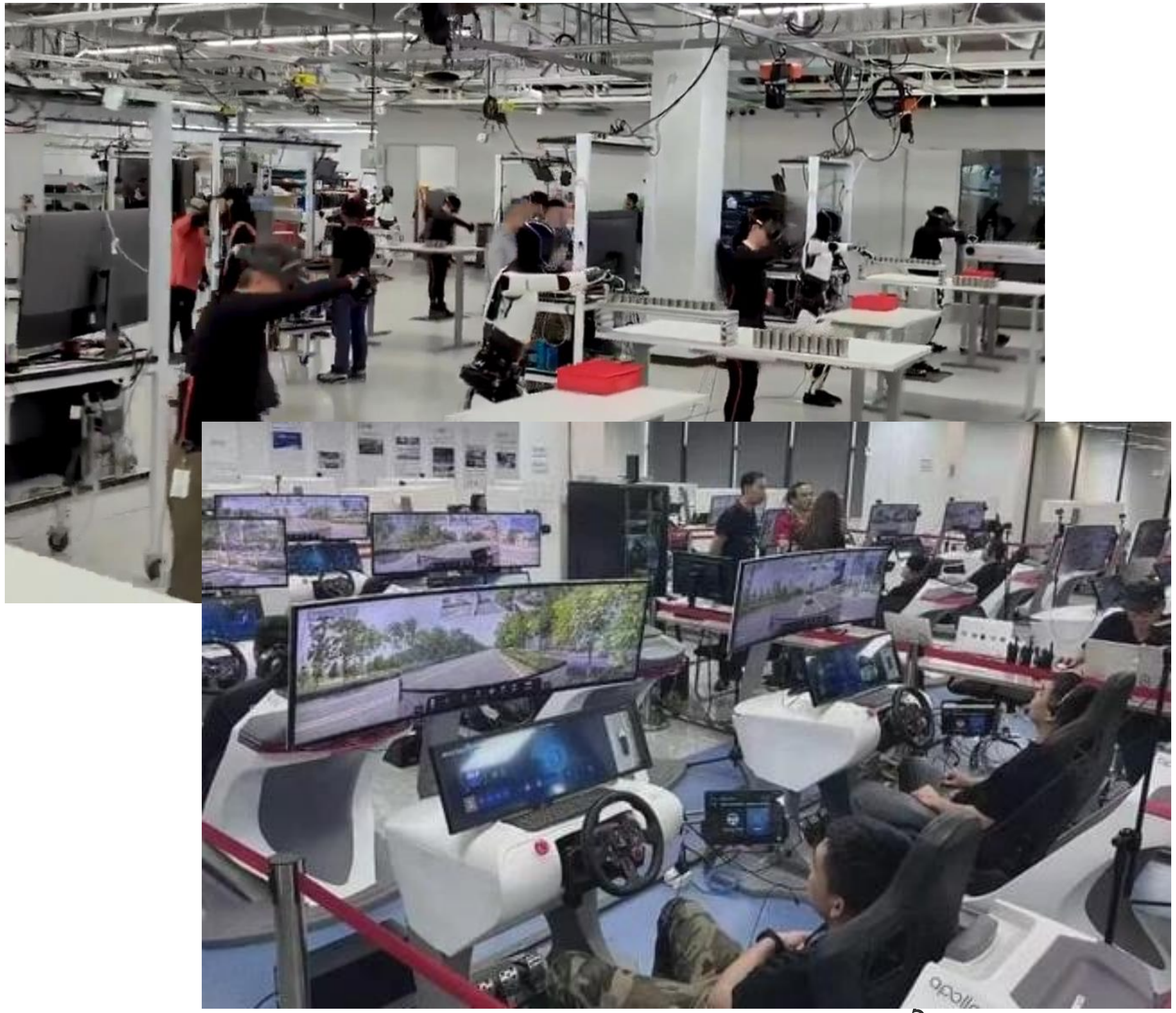
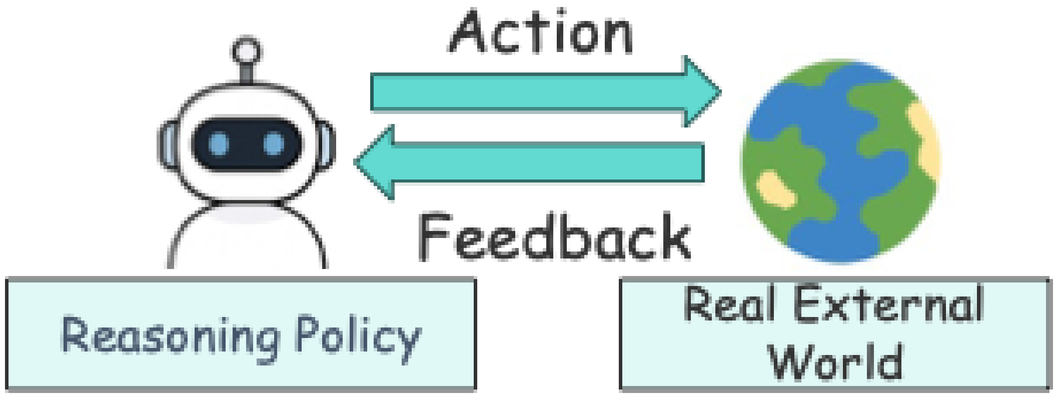
Human data collection farm



Reinforcement Learning

- Deployed in infinitely diverse simulated worlds
- Cheap, fast to get feedback



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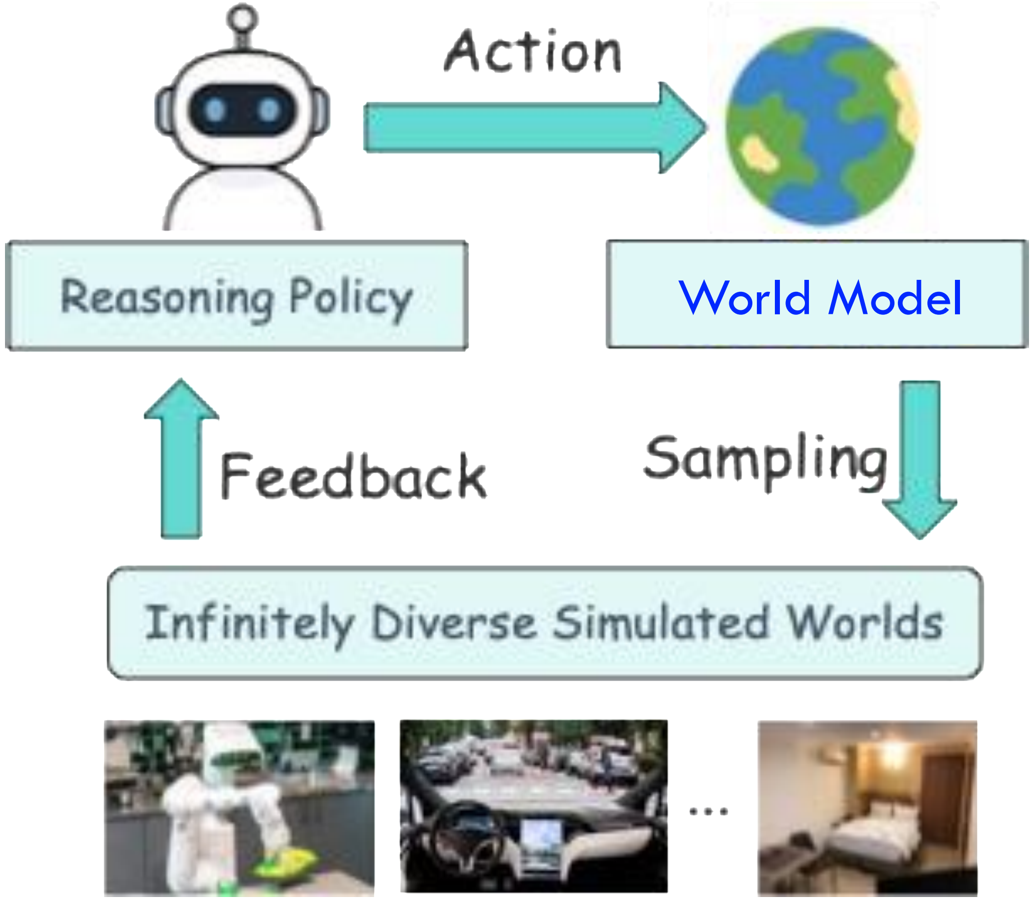


World model

- State transition probabilities
- Next “world” prediction

$$P(s'|s,a)$$

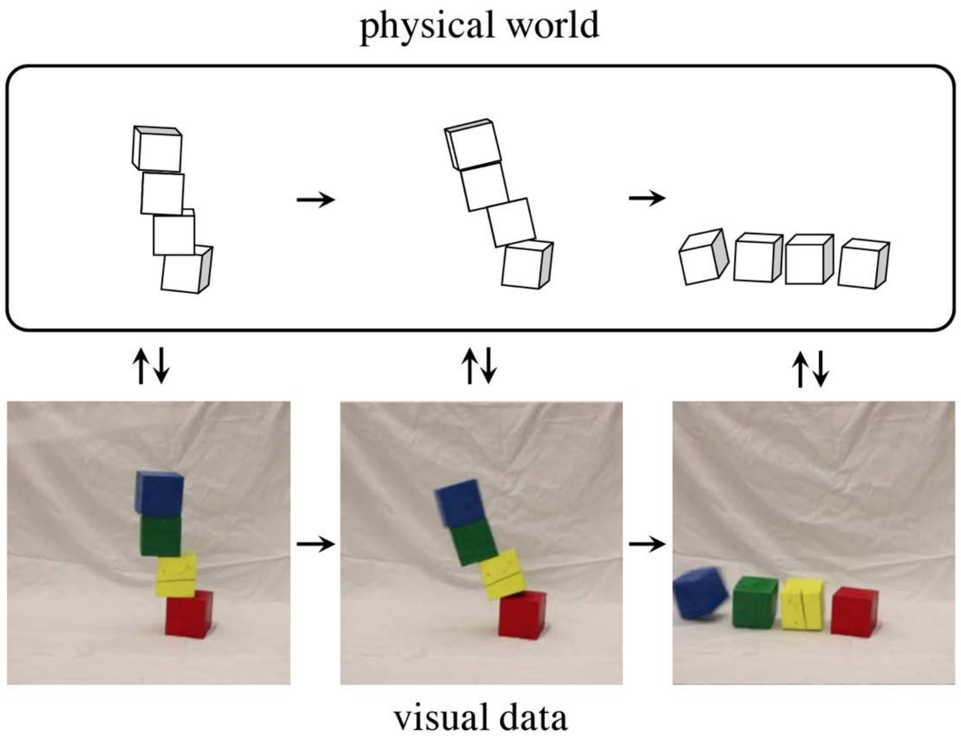
next state

current state

action

World model

- Next "world" prediction $P(s'|s,a)$
- Prior research built domain-specific world models
  - Primarily in robotics and embodied AI



(i) Computer vision: model-based physical scene understanding

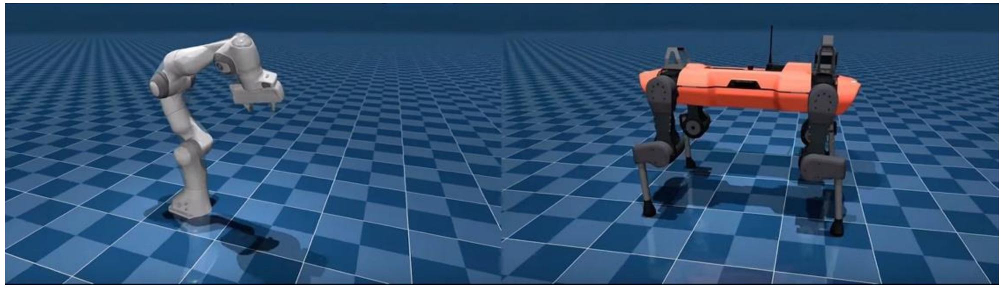
Wu et al. (2017)

World model

- Next "world" prediction $P(s'|s,a)$
- Prior research built domain-specific world models
  - Primarily in robotics and embodied AI

(ii) Physics engines / embodied simulators

MuJoCo



Todorov et al. (2012)

AI2-THOR

Kolve et al. (2017)

Habitat 2.0

Szot et al. (2021)

World model

- Next "world" prediction $P(s'|s,a)$
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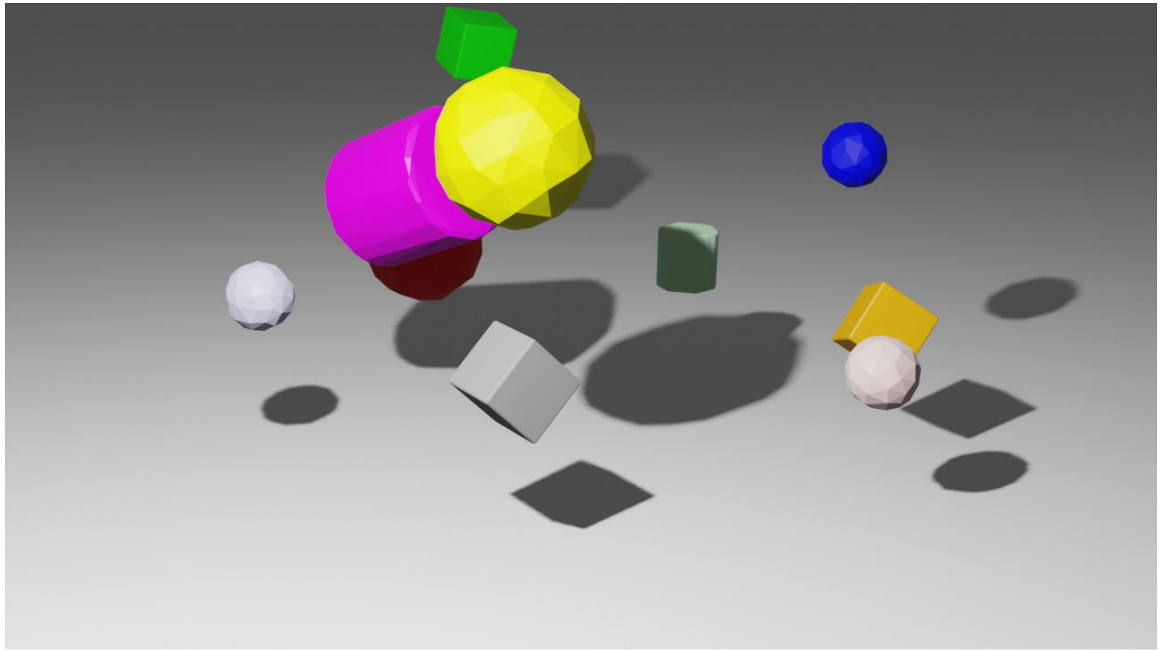
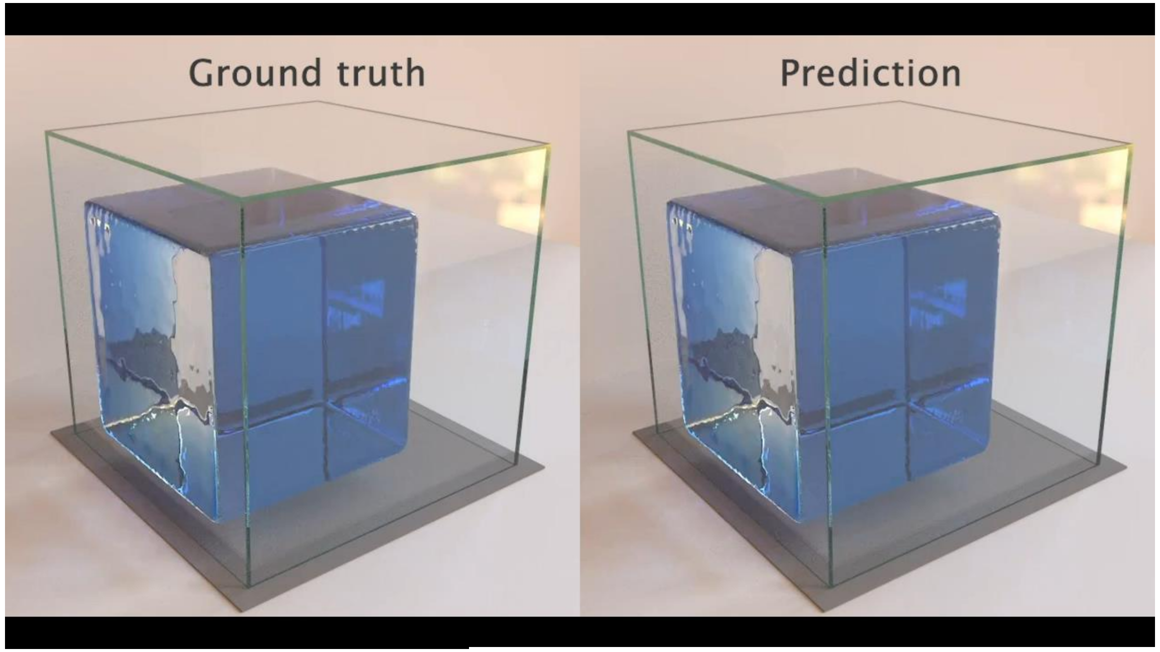
  - Primarily in robotics and embodied AI

(iii) Learned neural physics engines



Allen et al. (2023)



Sanchez-Gonzalez et al. (2020)

World model

- Next "world" prediction $P(s'|s, a)$
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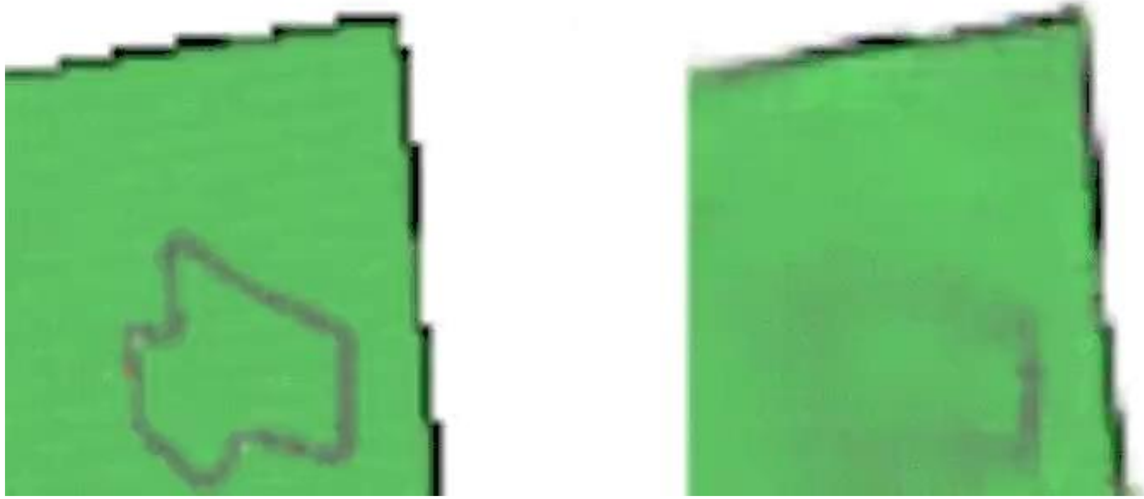
  - Primarily in robotics and embodied AI

(iv) Video prediction models

Ground-truth

Synthesis



Ha & Schmidhuber (2018)

World model

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(iv) Video prediction models

GAIA-1

World model

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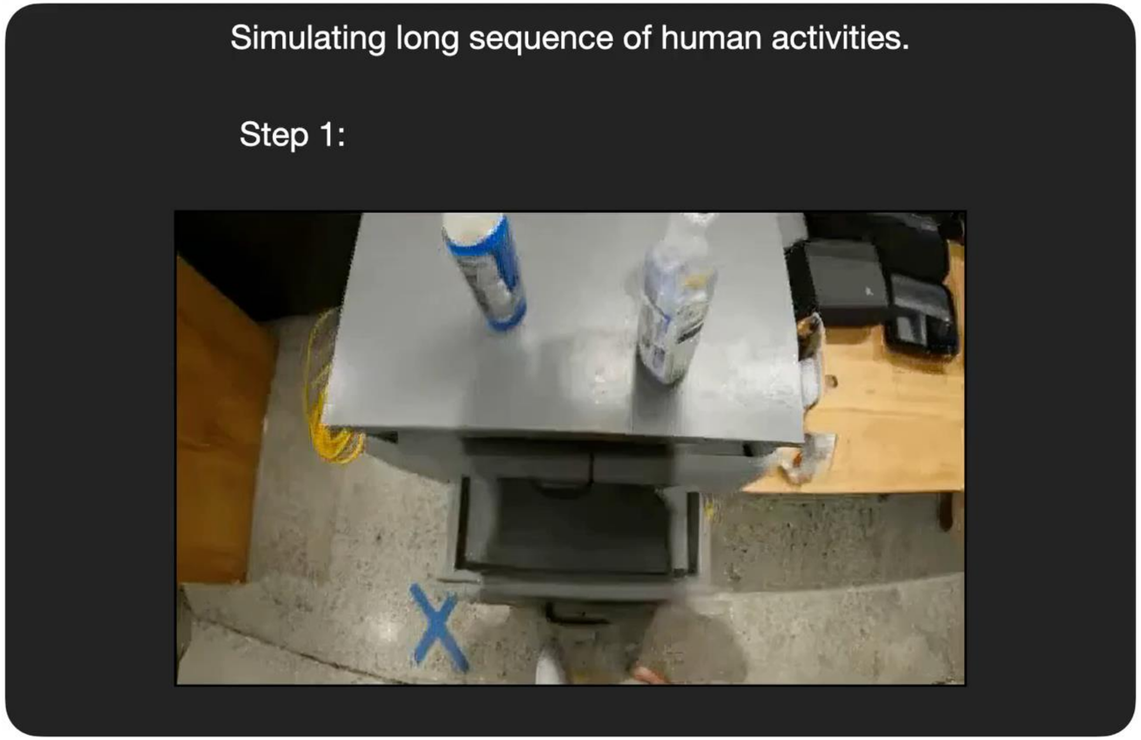
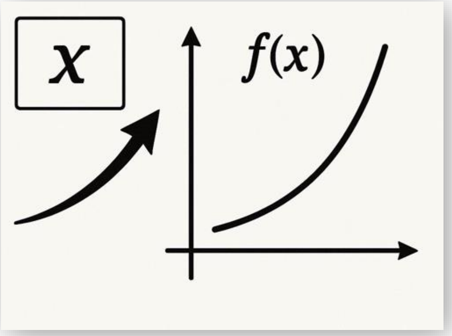


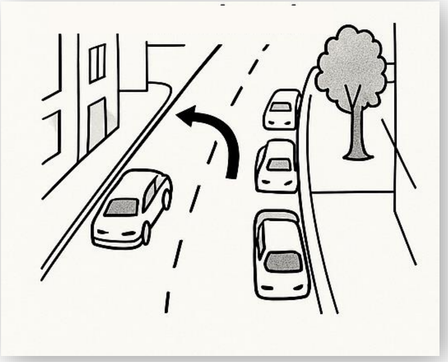
[Yang et al., 2023]

World model

- Next "world" prediction $P(s'|s,a)$
- Prior research built domain-specific world models
  - Primarily in robotics and embodied AI
- The scope of simulation defines the capability of reasoning
  - "More simulation, more intelligence"

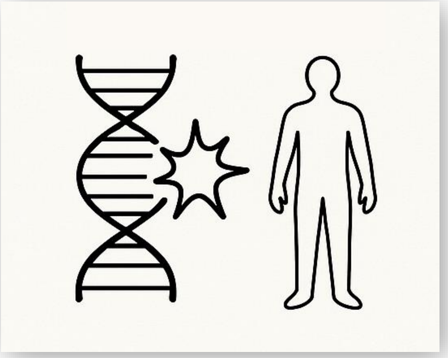


Would the value of a function increase if I changed this variable?



What would happen on the street if I turned the vehicle left

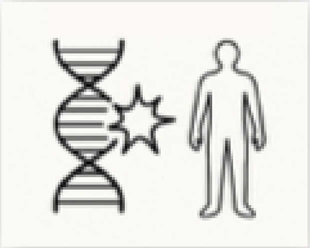
How might a business grow if a specific policy were applied



What biological effects would arise from a specific genetic mutation

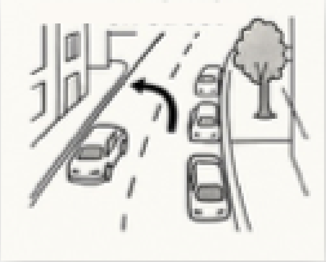
The scope of WM simulation
⇒ the capability of reasoning

Scientific reasoning
(drug discovery)

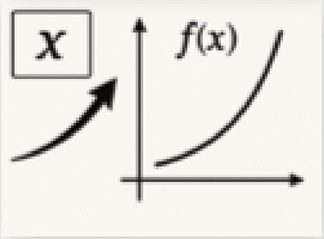


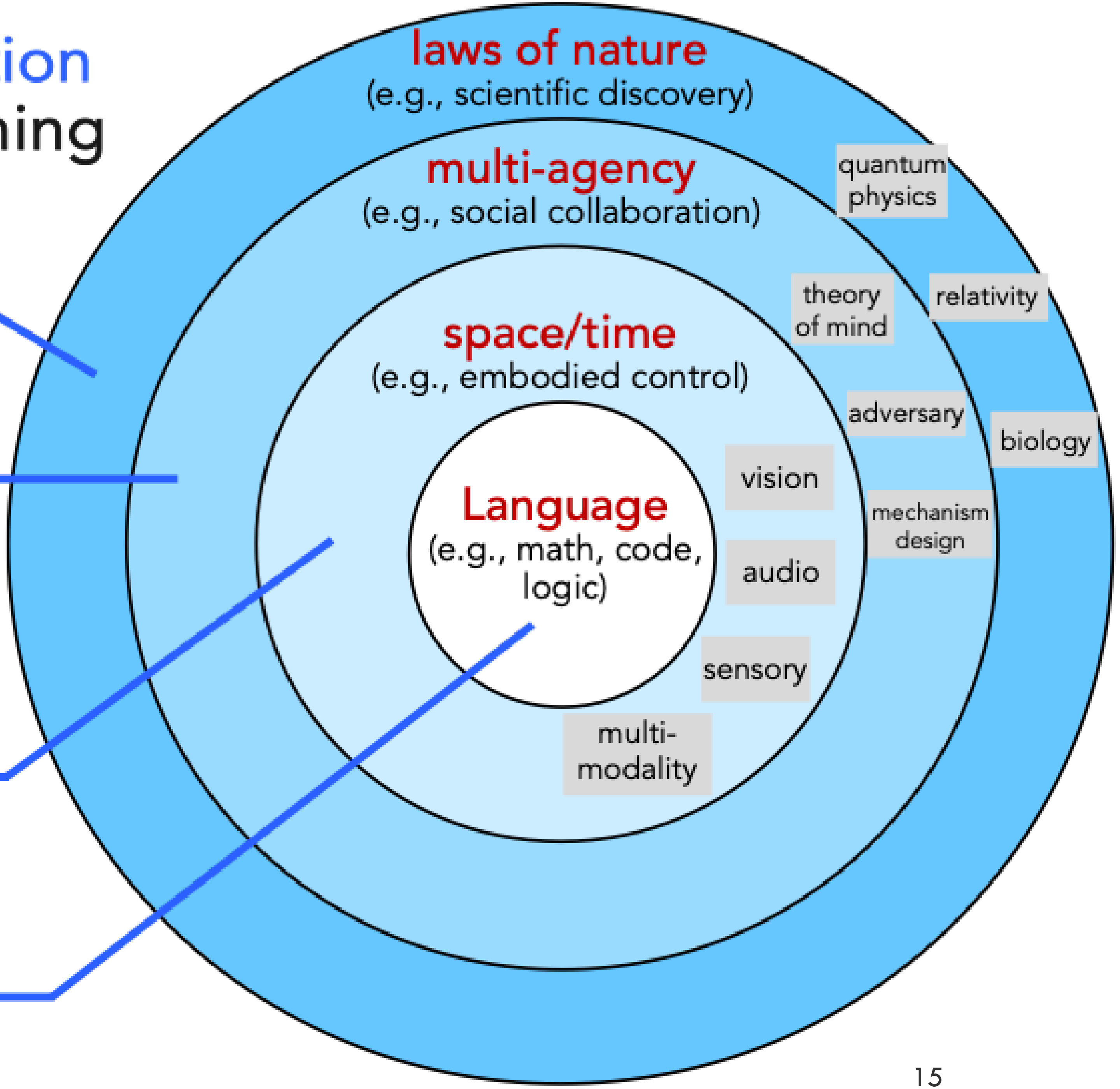
Social/business reasoning

Physical reasoning
(auto-driving, robot)



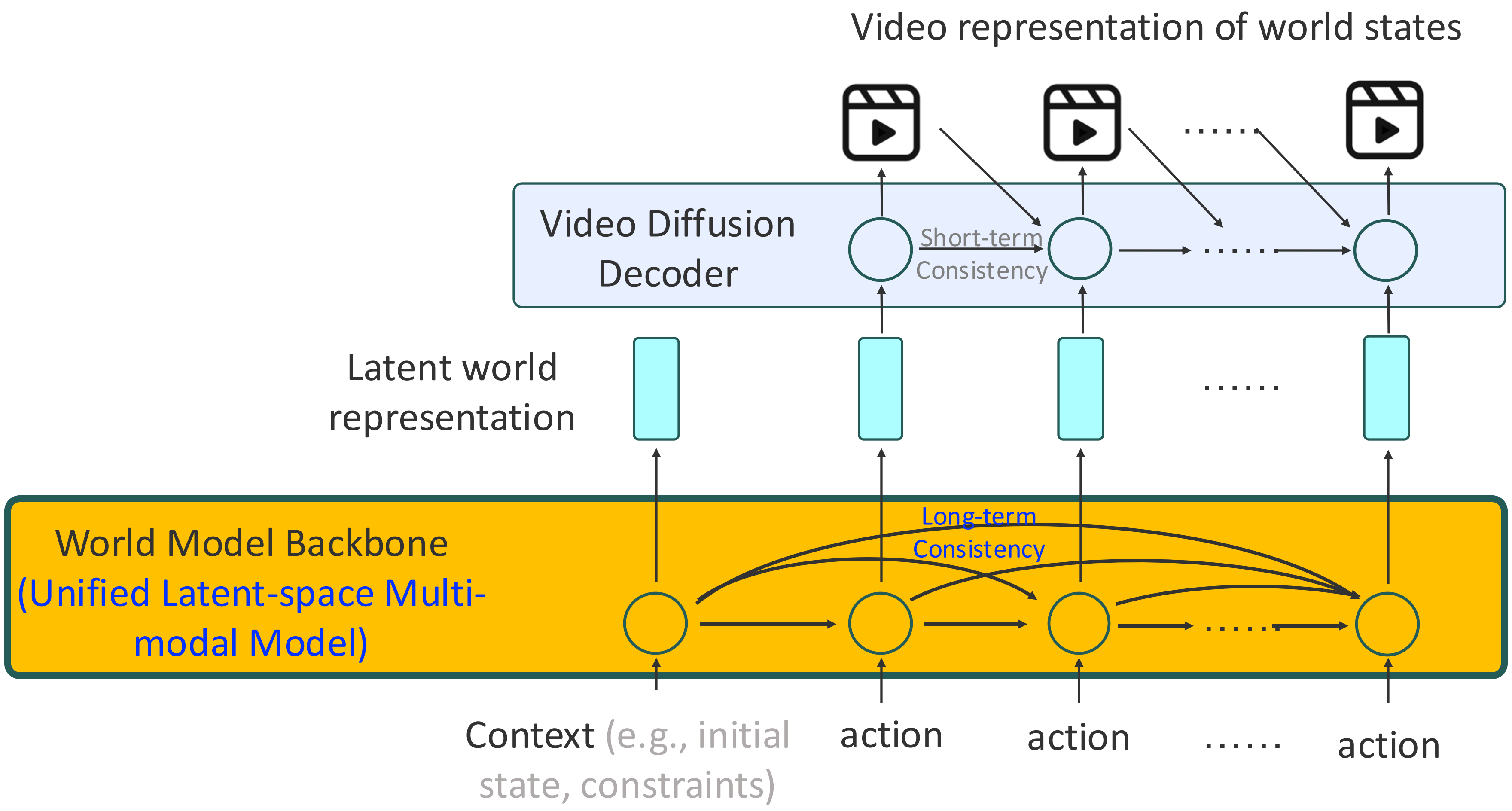
Symbolic reasoning
Computer use

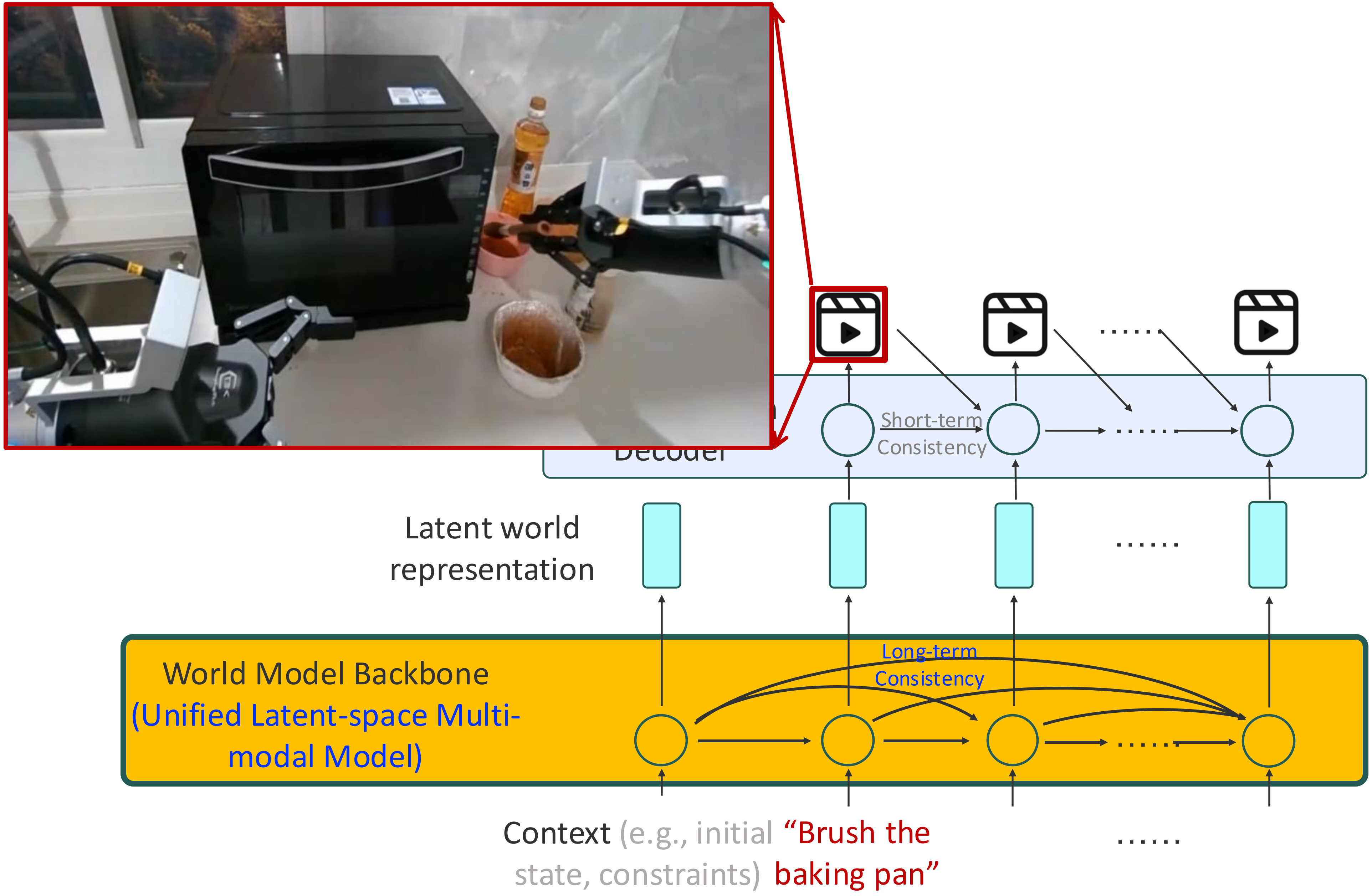


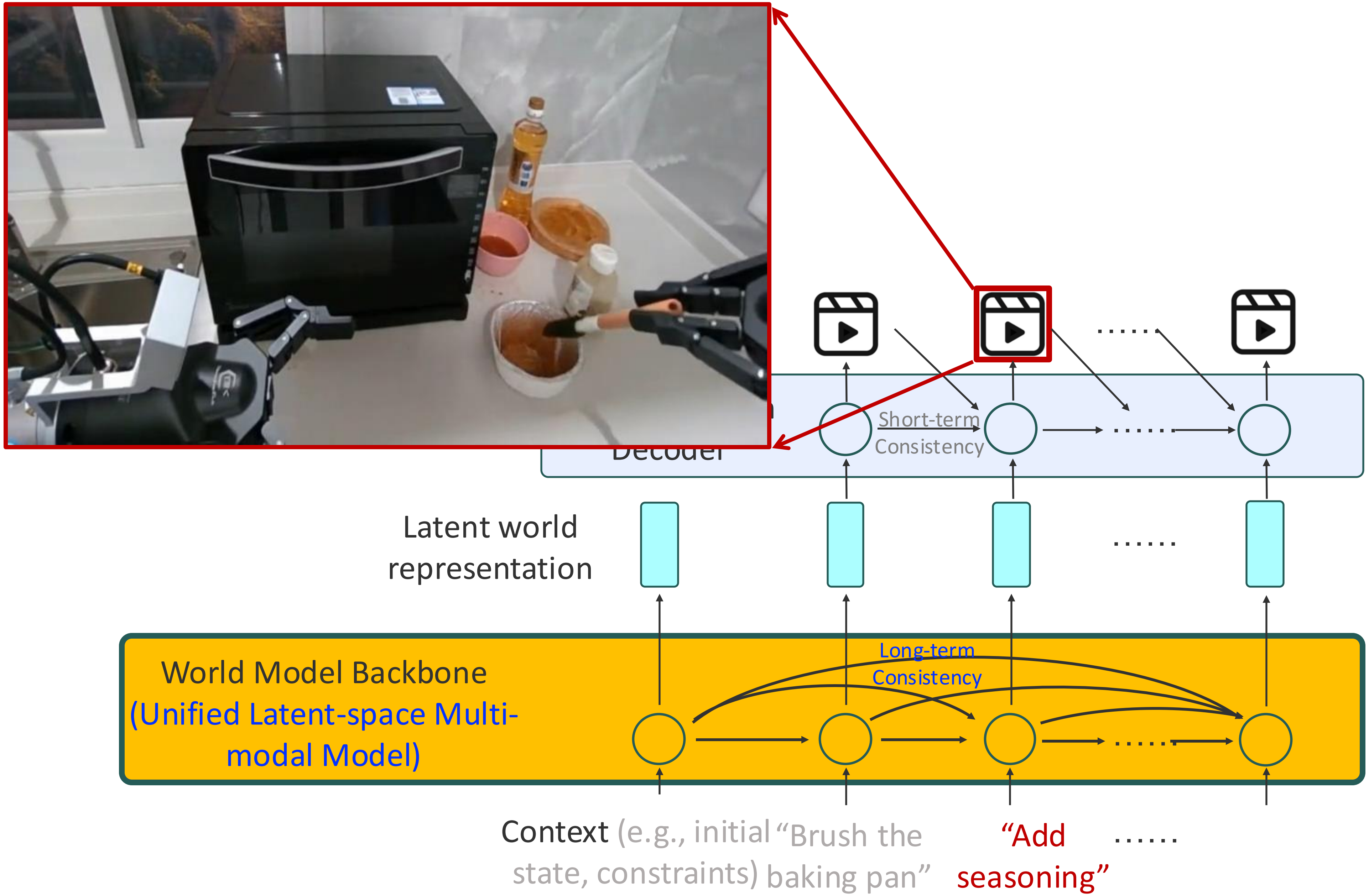


PAN World Model

(Physical, Agentic, Nested)




Decoder
Short-term
Consistency
......
Latent world representation
......
World Model Backbone
(Unified Latent-space Multi-modal Model)
Long-term
Consistency
......
Context (e.g., initial state, constraints)
"Brush the baking pan"
......


Short-term
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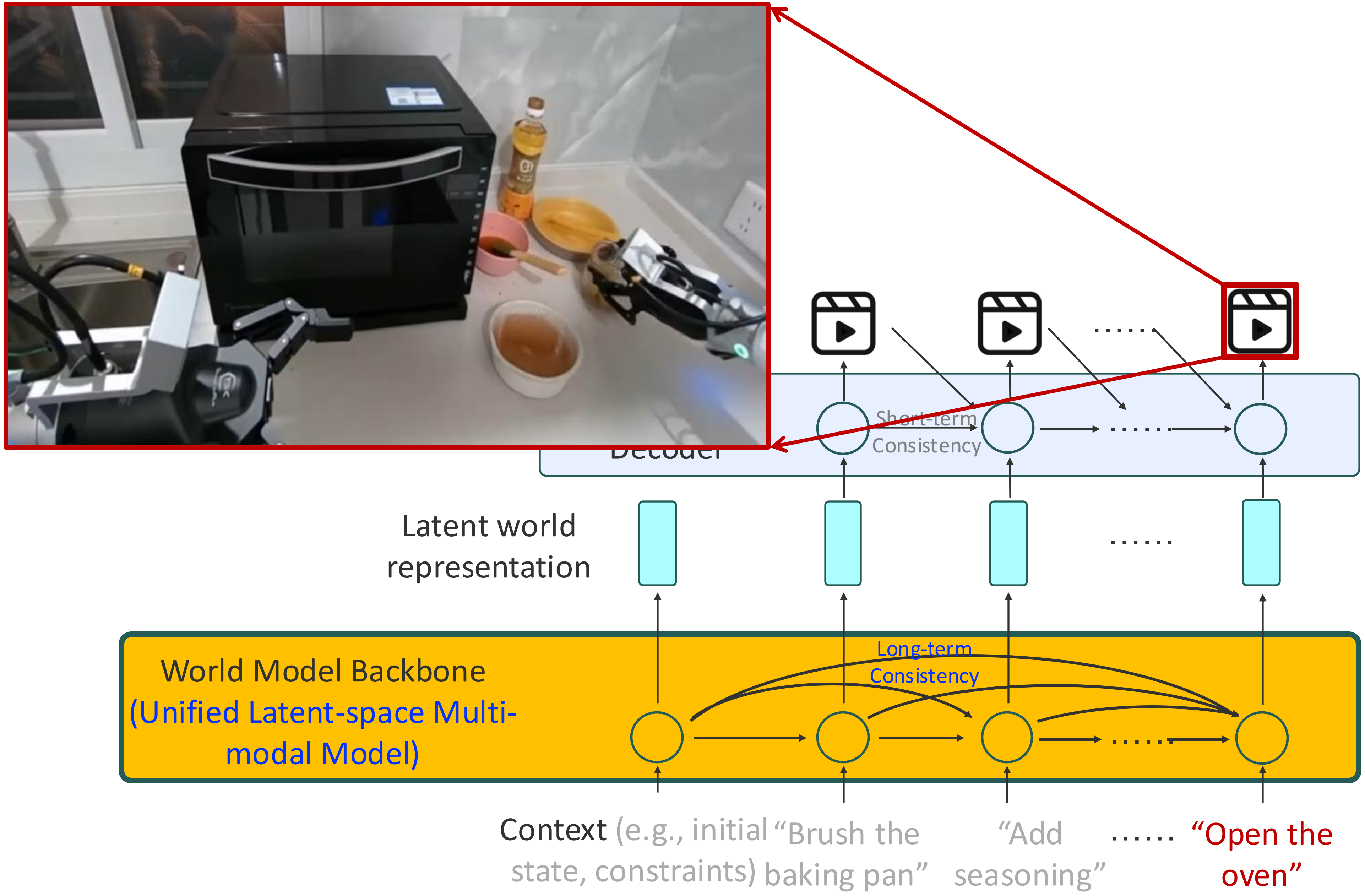
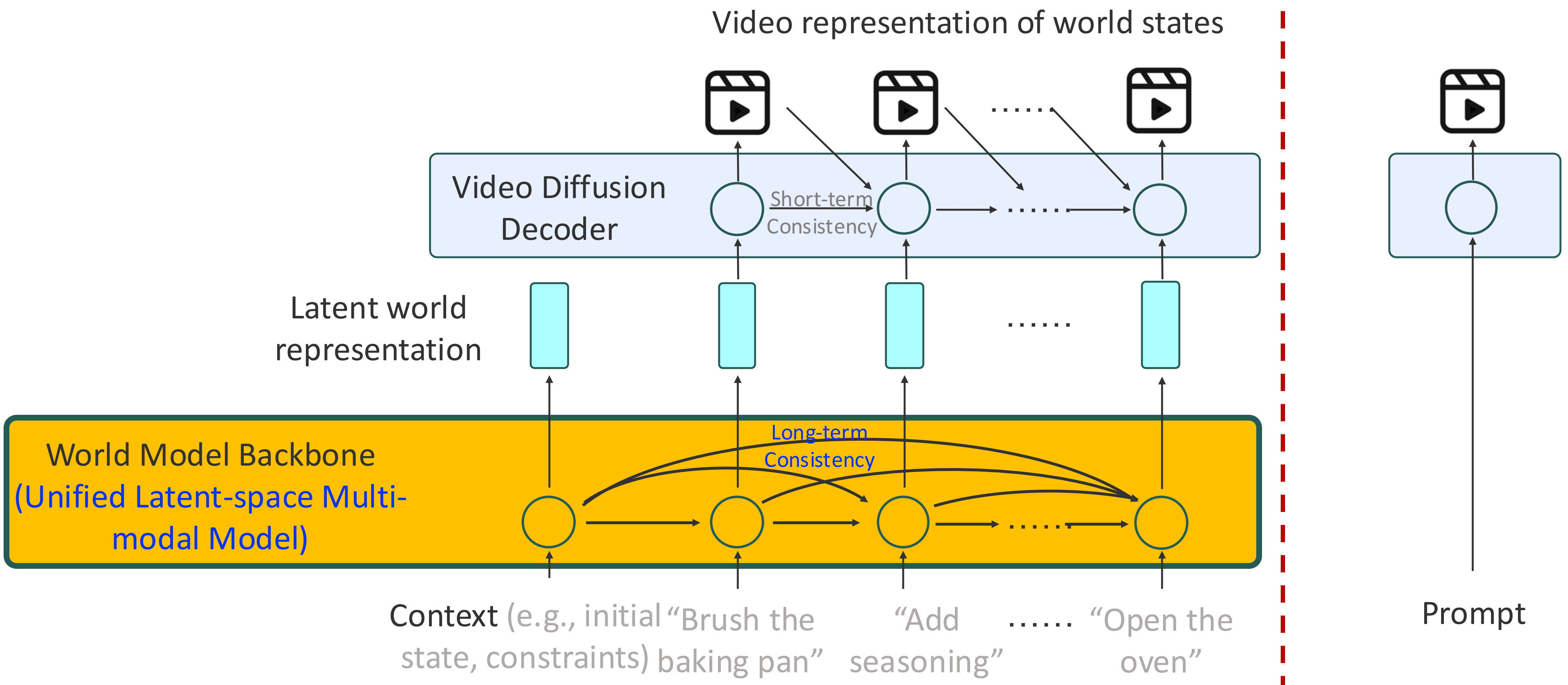
Consistency
Context (e.g., initial state, constraints)
"Brush the baking pan"
"Add seasoning"
......

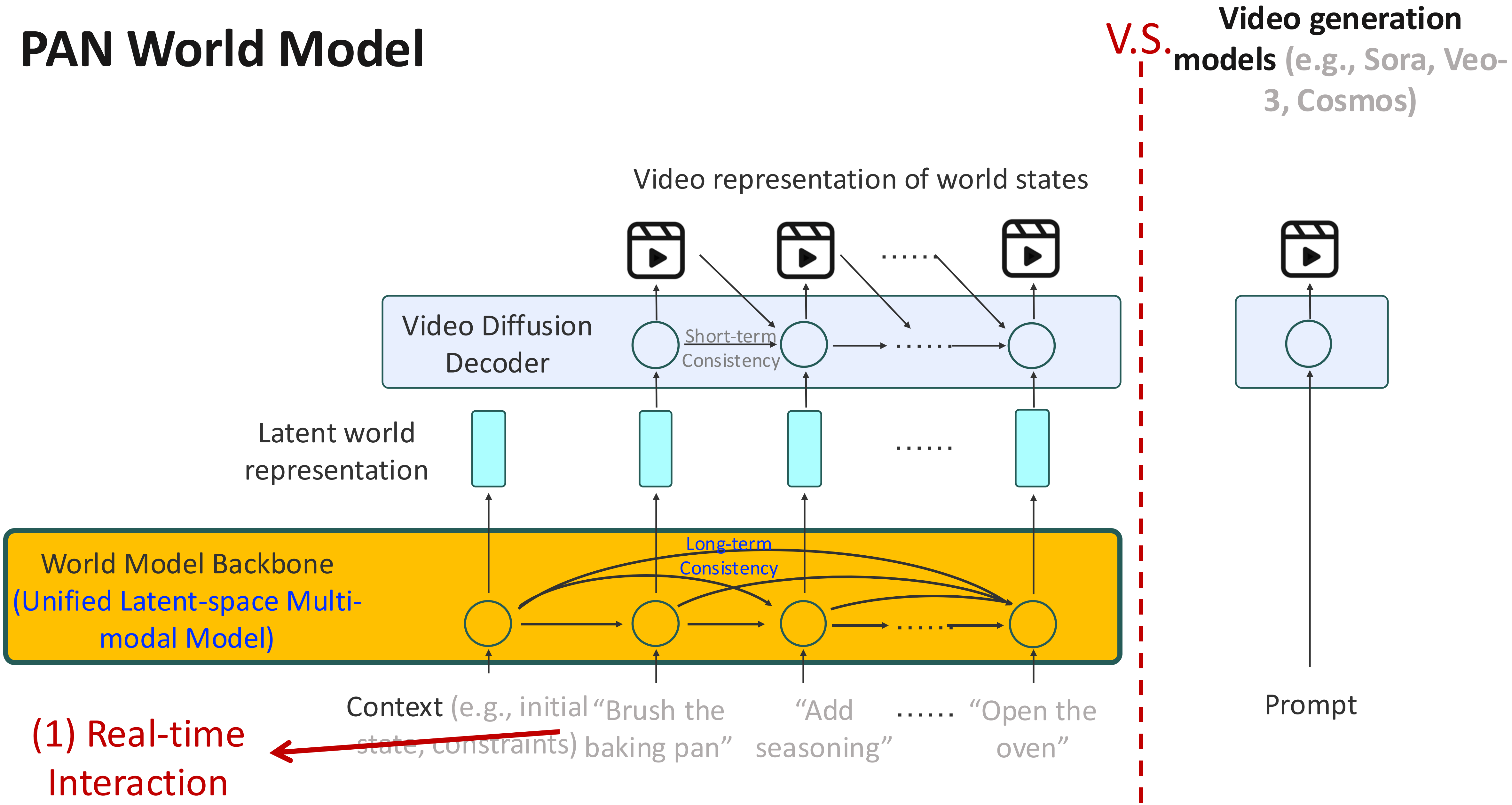

Short-term
Consistency
Decoder
Latent world
representation
World Model Backbone
(Unified Latent-space Multi-modal Model)
Long-term
Consistency
Context (e.g., initial state, constraints)
"Brush the baking pan"
"Add seasoning"
"Open the oven"

PAN World Model

V.S. **Video generation models** (e.g., Sora, Veo-3, Cosmos)



PAN World Model



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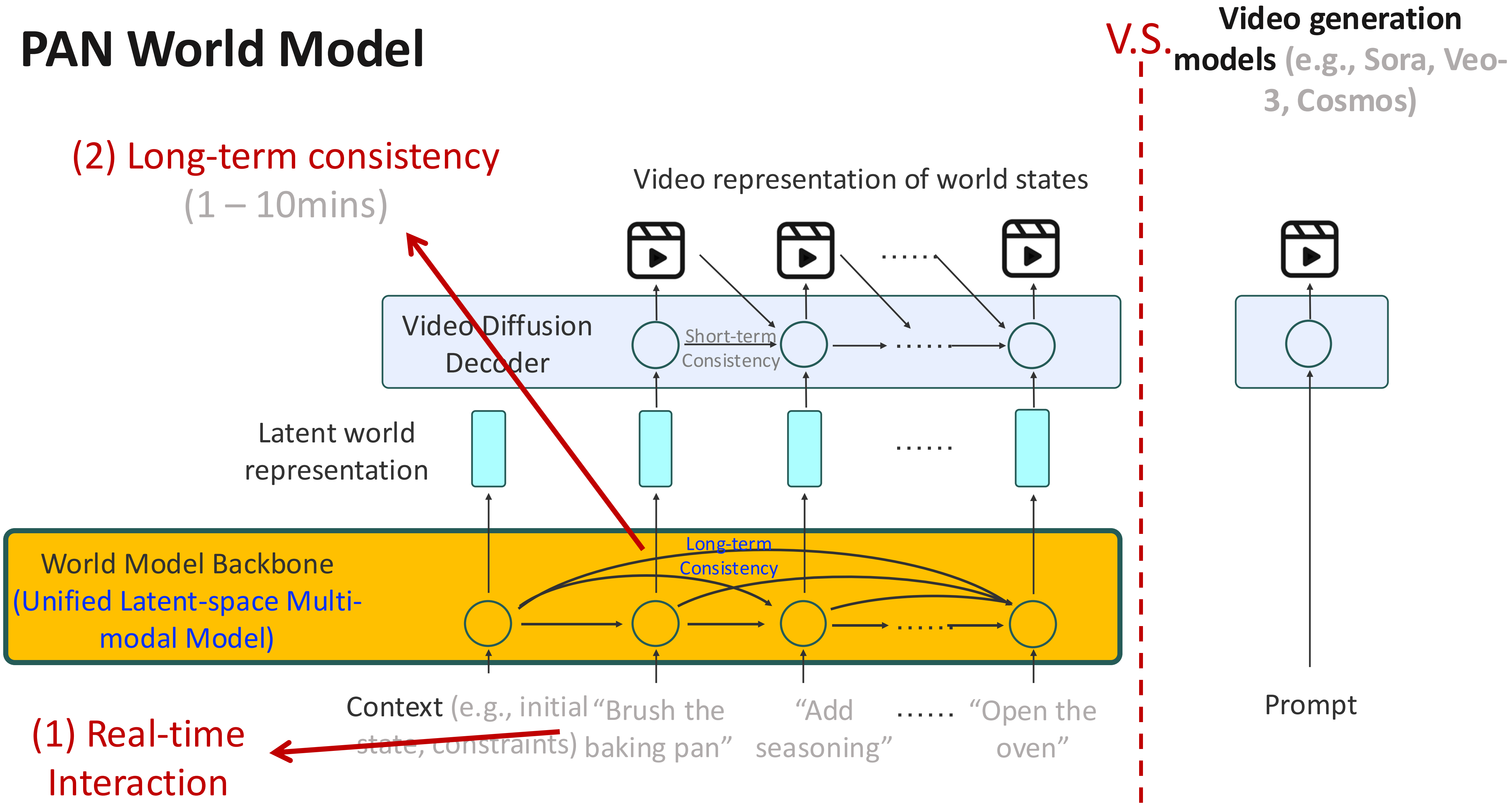

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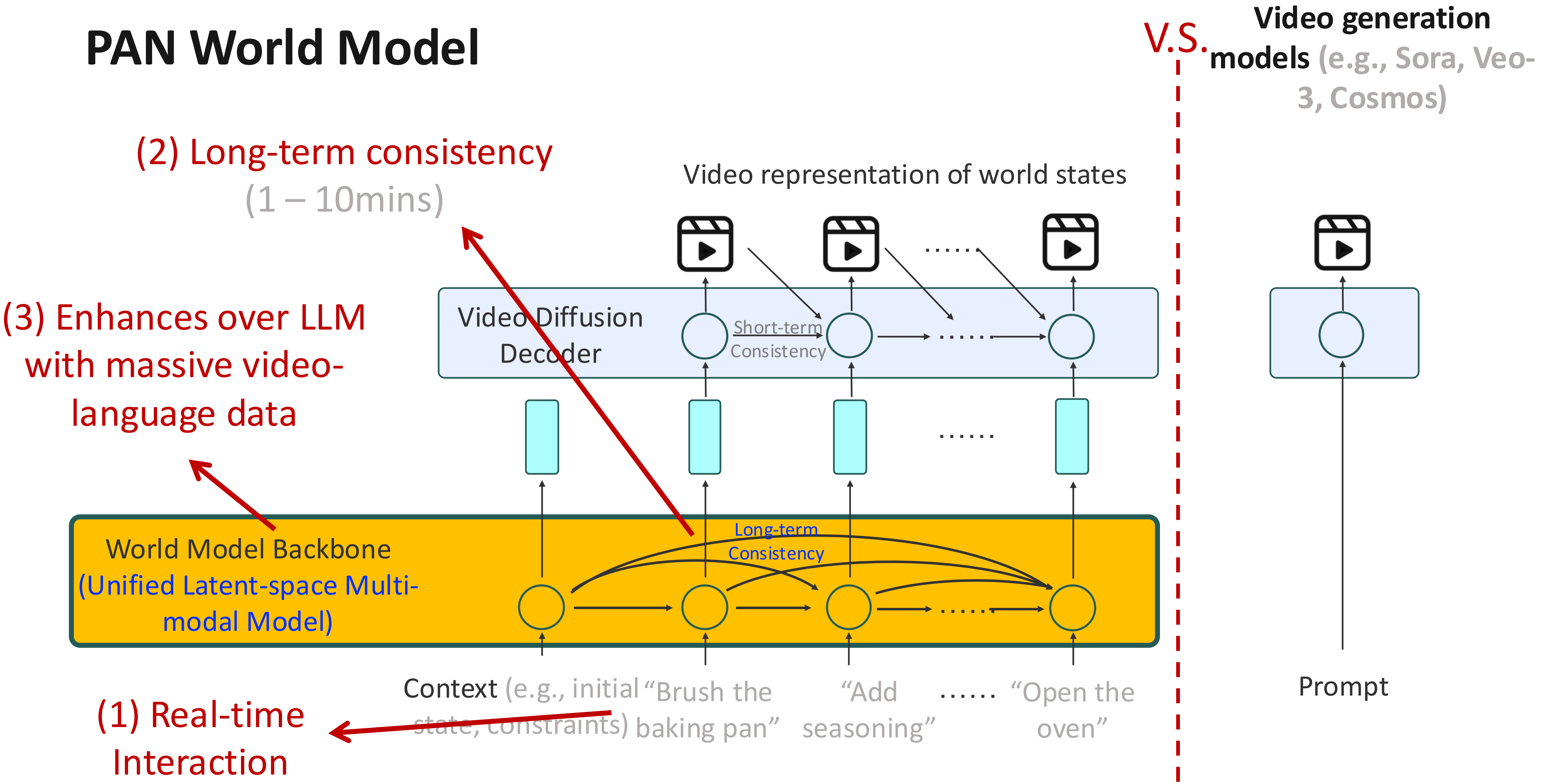
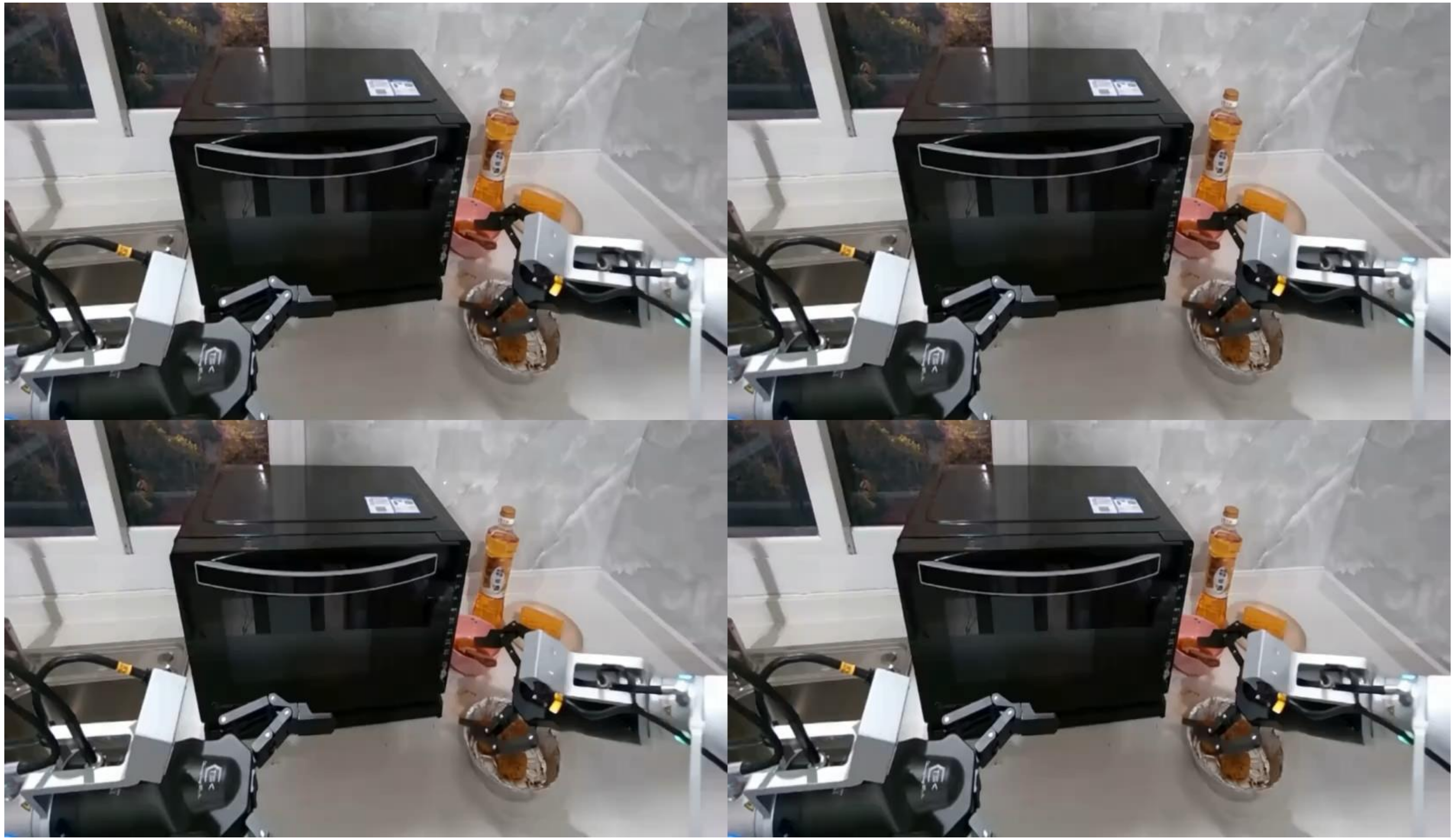


PAN World Model: Simulation Results

Robot: Complex manipulation

Locomotion



PAN World Model: Simulation Results

Robot: Complex manipulation

Locomotion

Input actions:

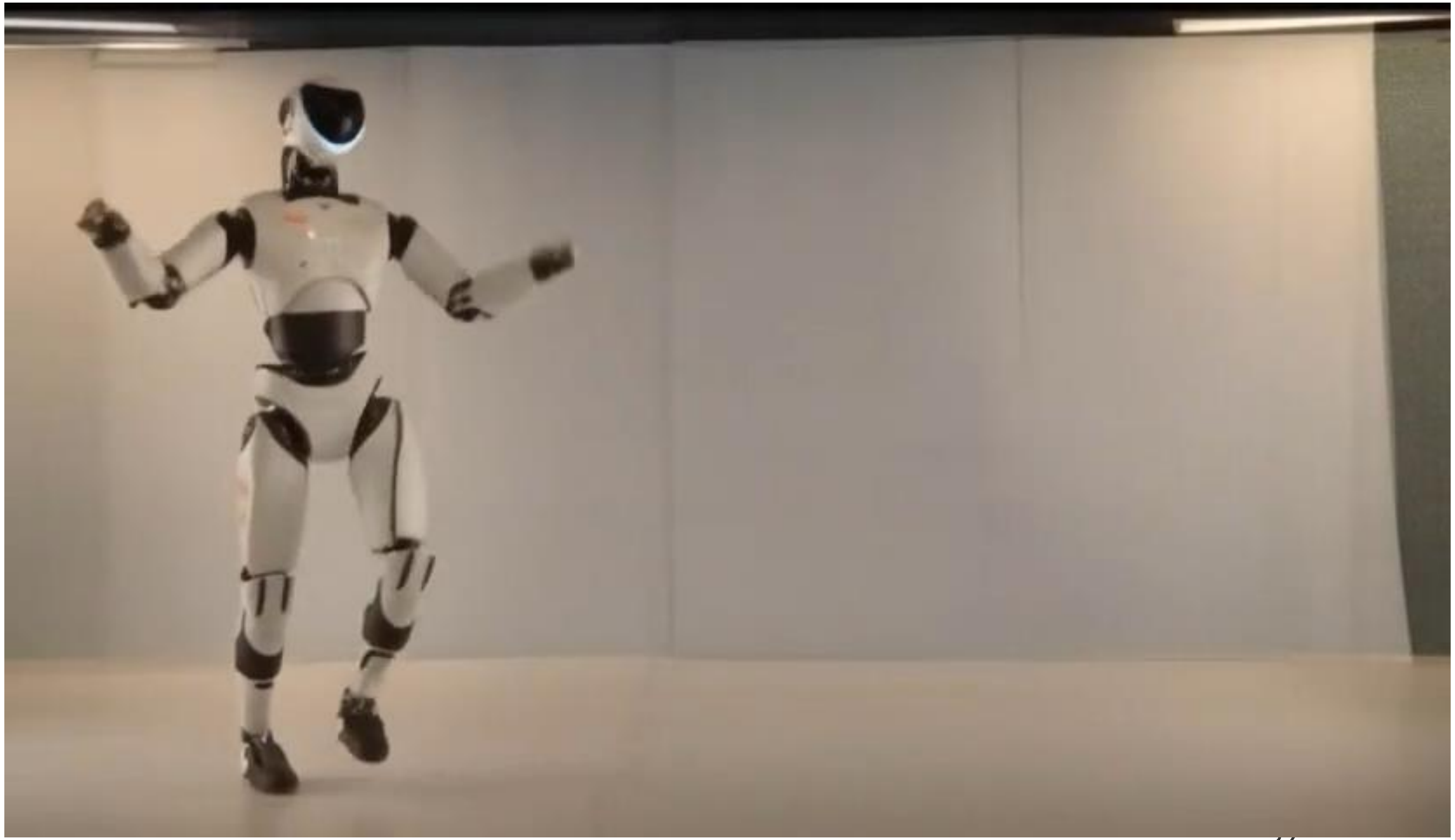
> Wave arms and jump

> Dance dance dance!

> Grasp a rose behind and show to the audience

> …

> Make a heart shape with hands



PAN World Model: Simulation Results

Driving: Dangerous situations

PAN World Model: Simulation Results

Complex environments in various styles

PAN World Model: Simulation Results

Complex environments in various styles

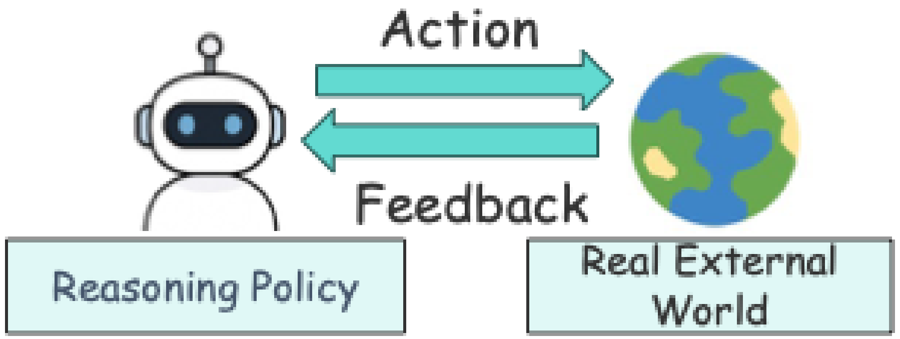
PAN World Model: Simulation Results

Complex environments in various styles

Summary so far

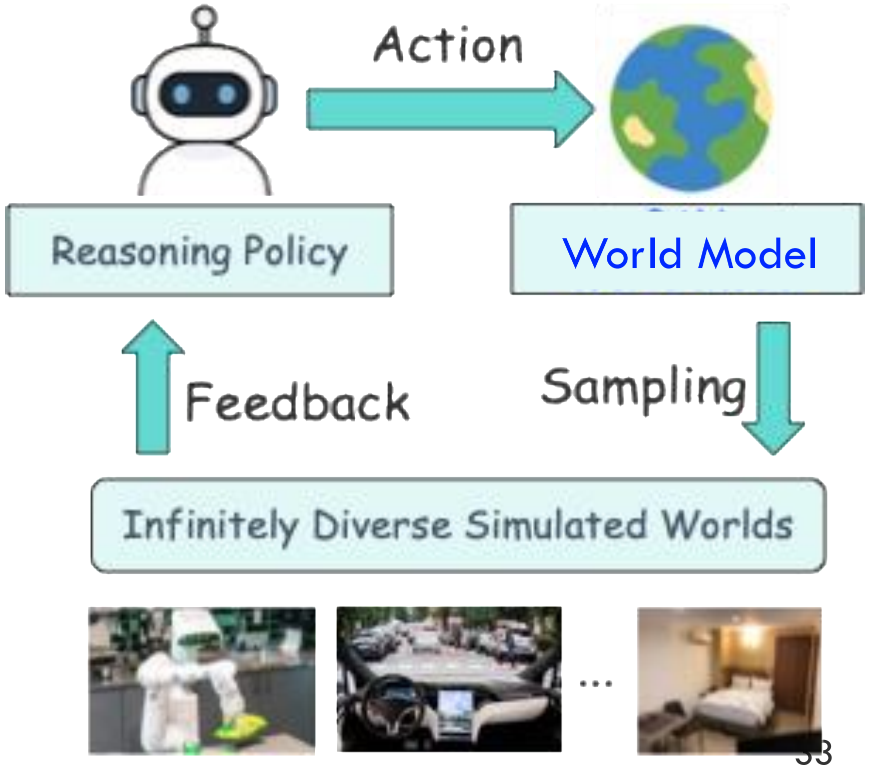
Traditional Reinforcement Learning

- Deployed in the real world
- Expensive, slow to get feedback

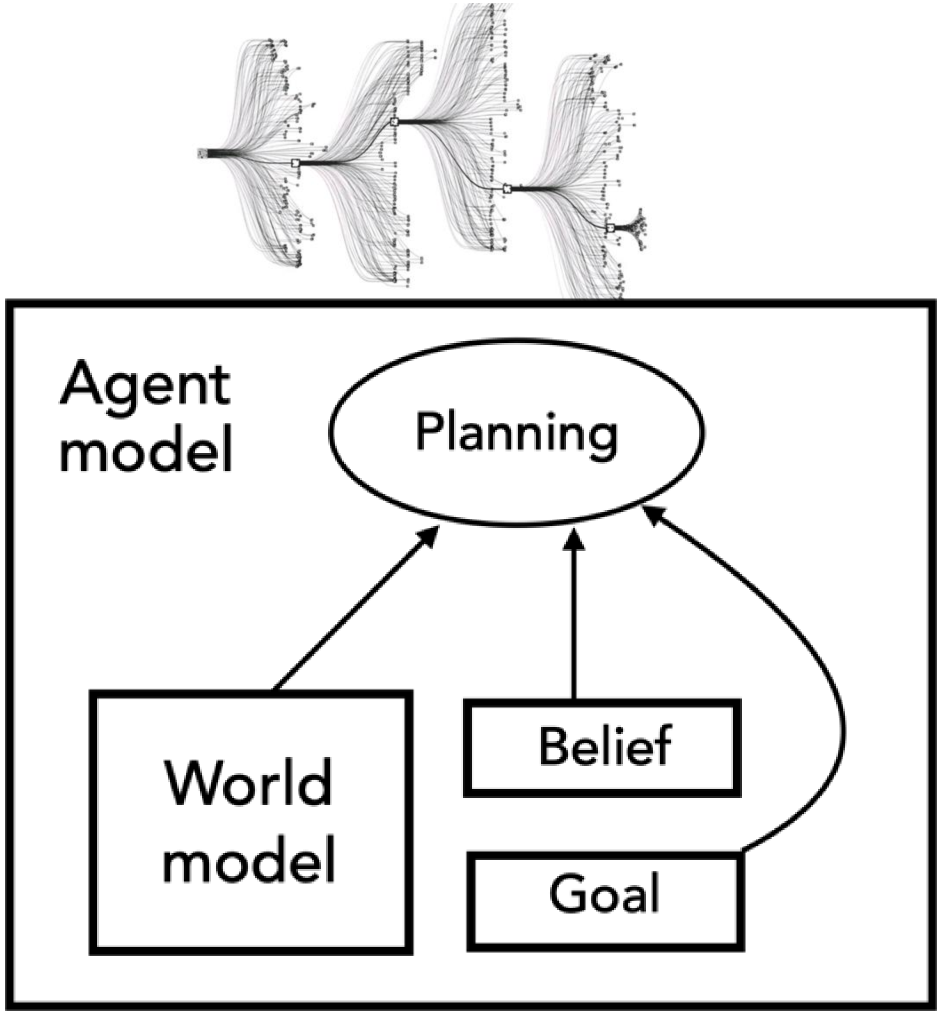


"Dream"-time learning

- Deployed in infinitely diverse simulated worlds
- Cheap, fast to get feedback

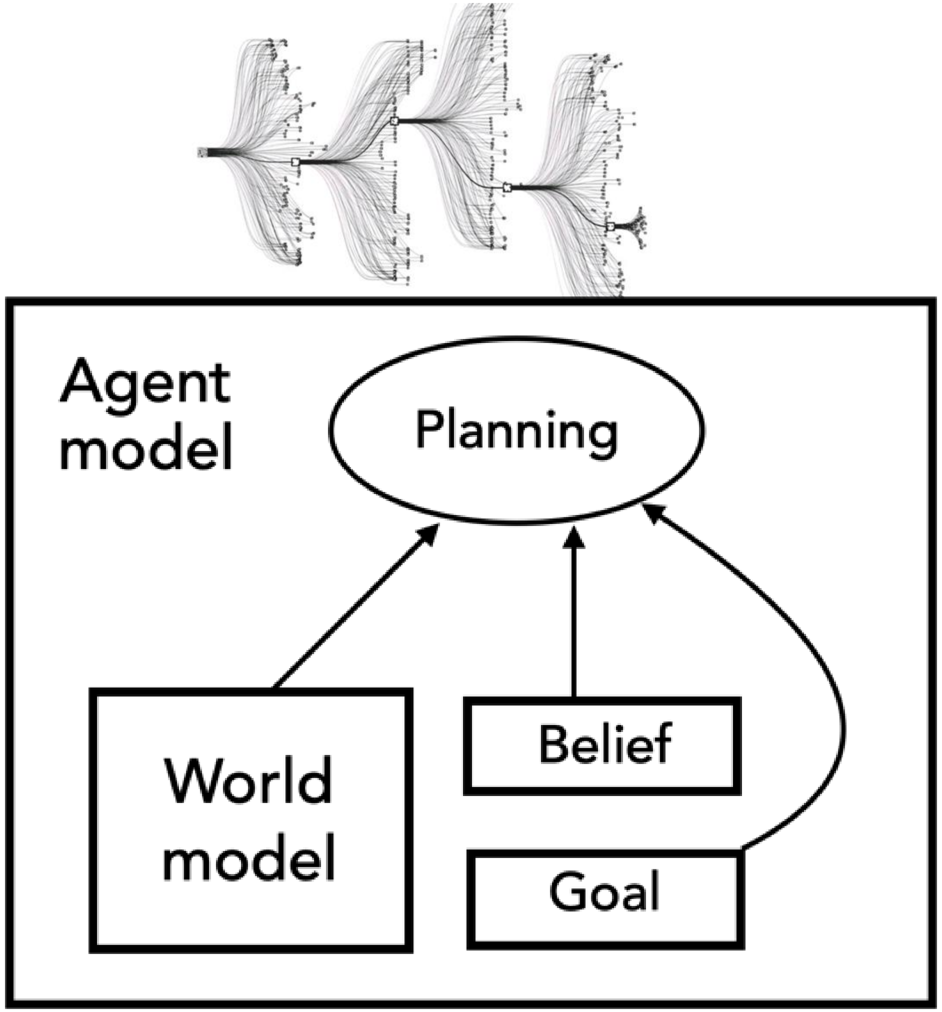


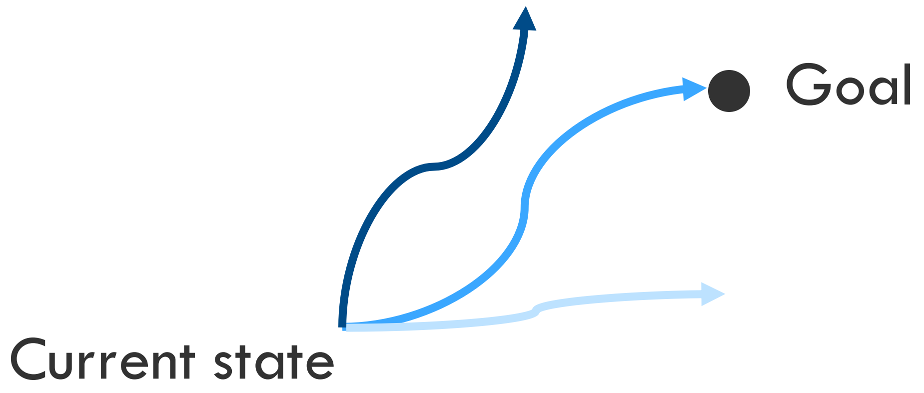
World Model for Inference-Time Planning



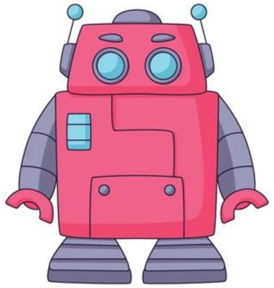
$$P(s'|s,a)$$

World Model for Inference-Time Planning





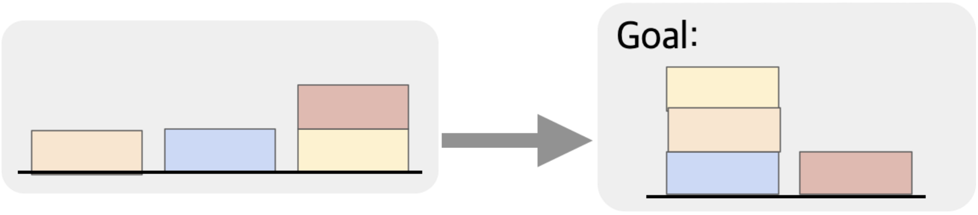
- Simulate plans with world model
- Choose the best plan



$$P(s'|s,a)$$

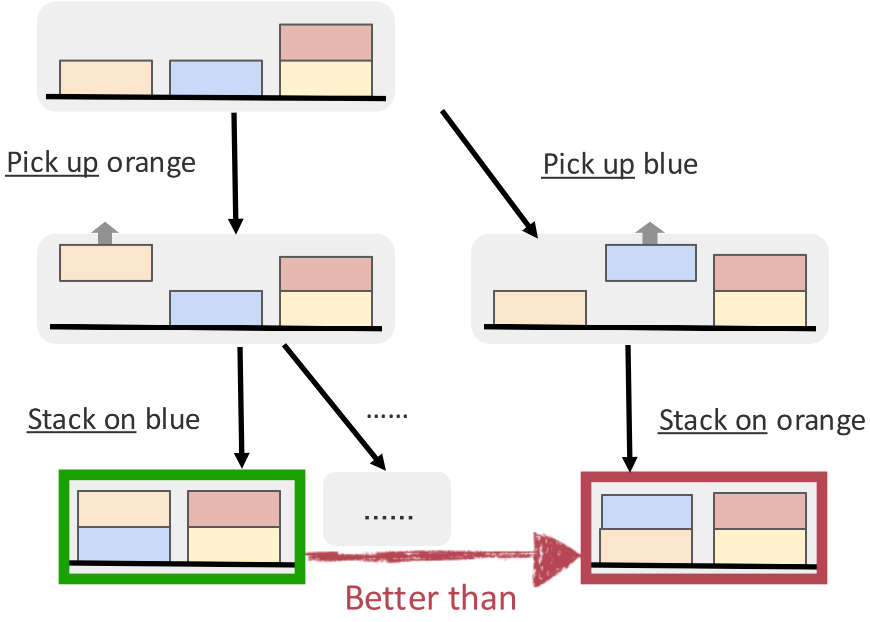
World Model for Inference-Time Planning

How to move the blocks to the goal state?



Human: strategic planning

- Internal world model to predict states
- Simulation of alternative plans
- Assess outcomes to refine/pick the best



LLMs: Autoregressive plan generation

GPT-4

1. Pick up the orange block.
2. Stack it on the blue block.
3. Pick up the yellow block. ✗
4. Stack it on the orange block.
5. Pick up the red block.
6. Put it on the table.

Invalid Action!
The yellow block is still under the red one.

How Nature Works

Simulates possibilities recursively; complexity emerges

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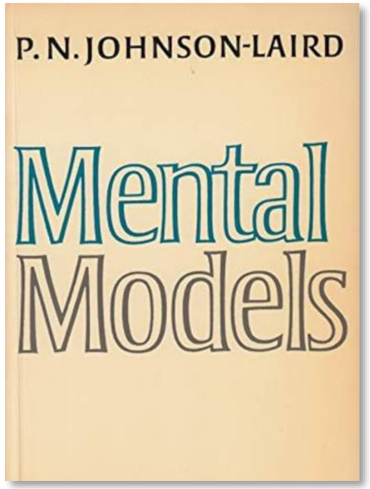
Simulates possibilities recursively; complexity emerges

Example 1: Human reasoning

- Humans "reason by thinking about what's possible"



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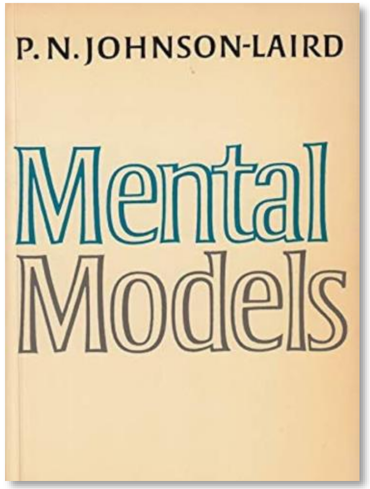

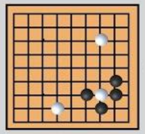

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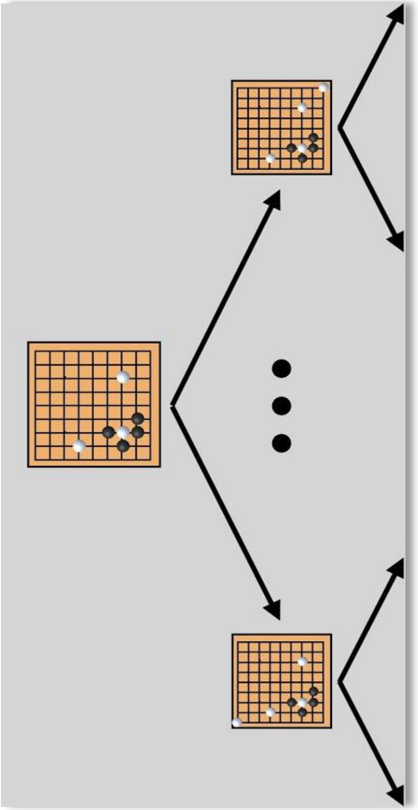

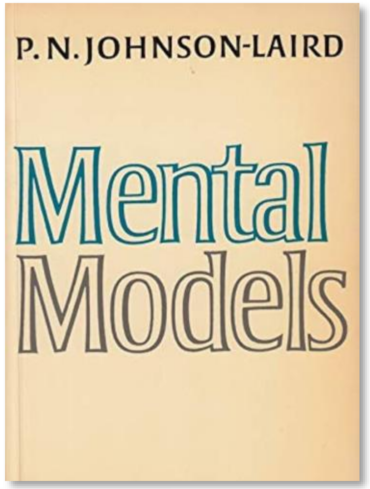

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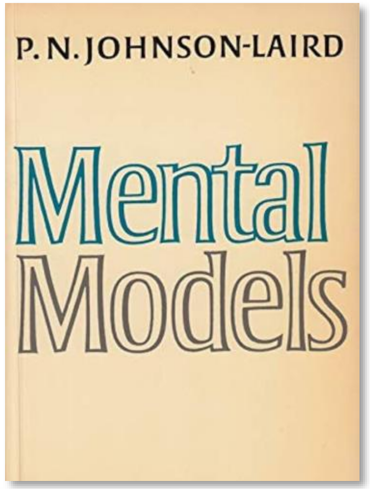

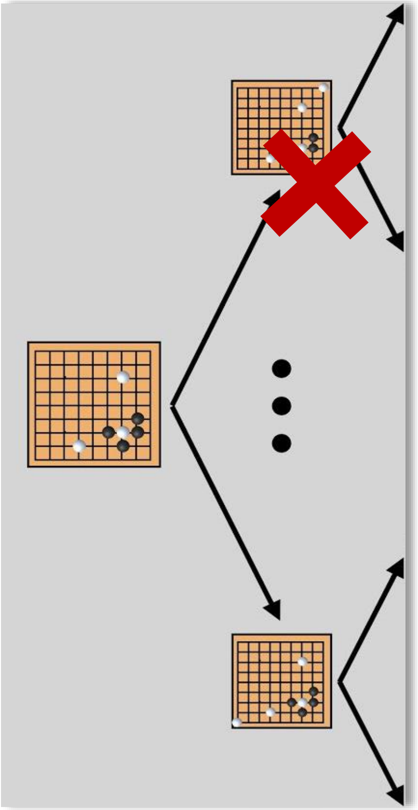

- Simulate alternative hypothetical worlds with **mental models**
- Rule out possibilities that do not fit context, knowledge, or goals

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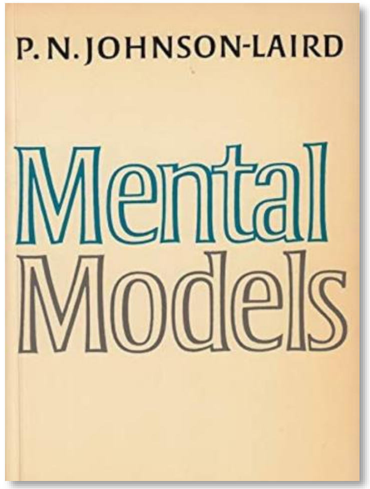

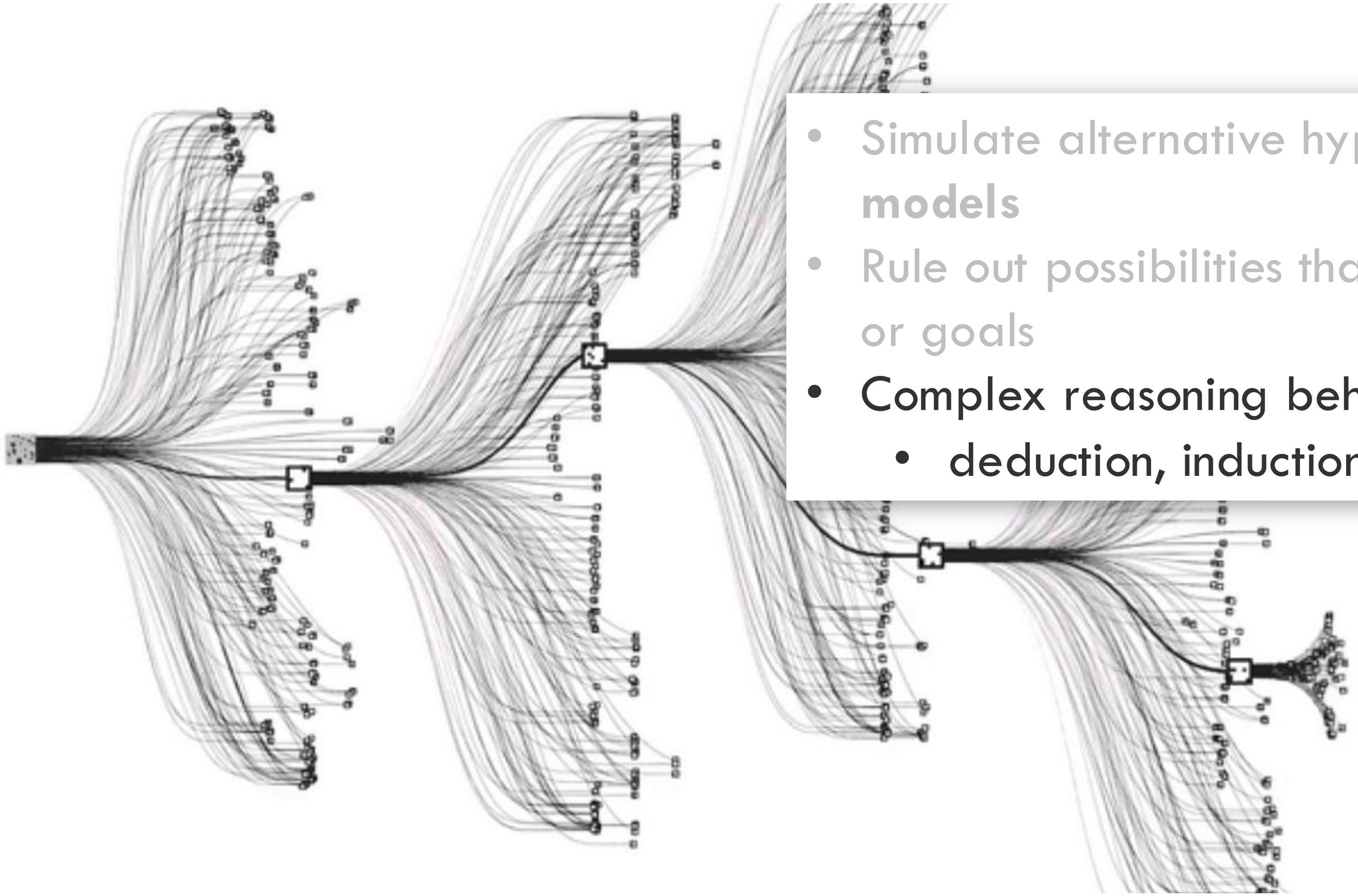

- Simulate alternative hypothetical worlds with **mental models**
- Rule out possibilities that do not fit context, knowledge, or goals
- Complex reasoning behaviors emerge
  - deduction, induction, abduction, …

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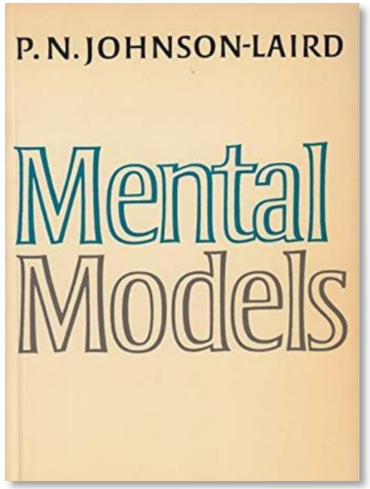

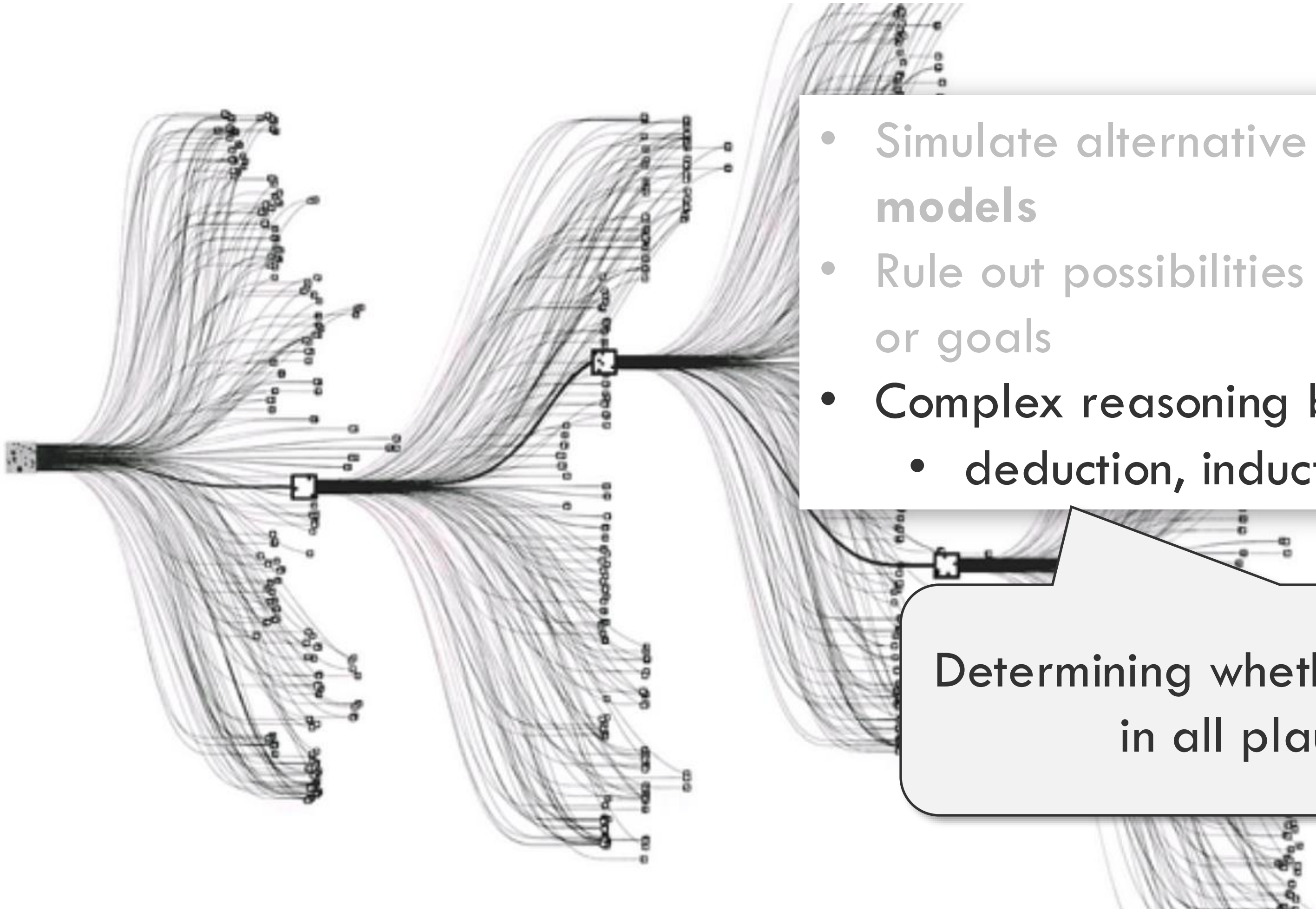

- Simulate alternative hypothetical worlds with **mental models**
- Rule out possibilities that do not fit context, knowledge, or goals
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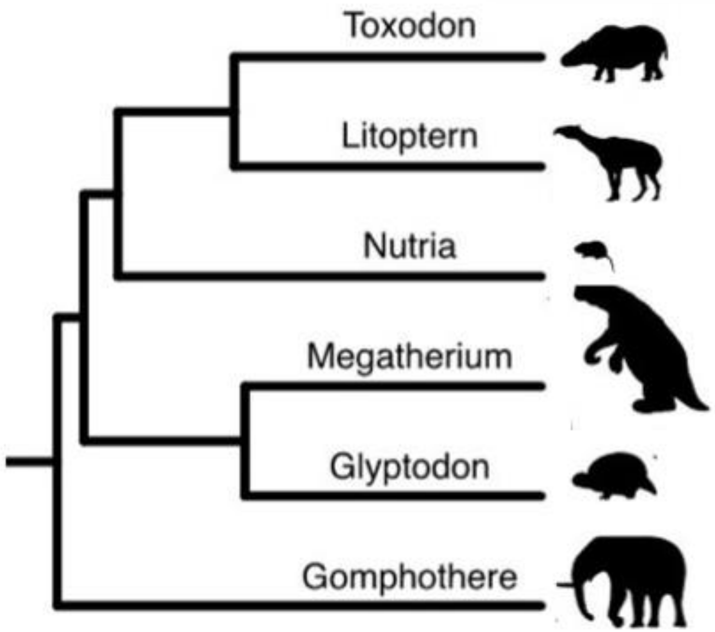
Determining whether a conclusion holds in all plausible worlds

How Nature Works

Simulates possibilities recursively; complexity emerges

Example 2: Natural evolution

- Generate mutations with molecular genetic mechanisms (genotype -> phenotype)



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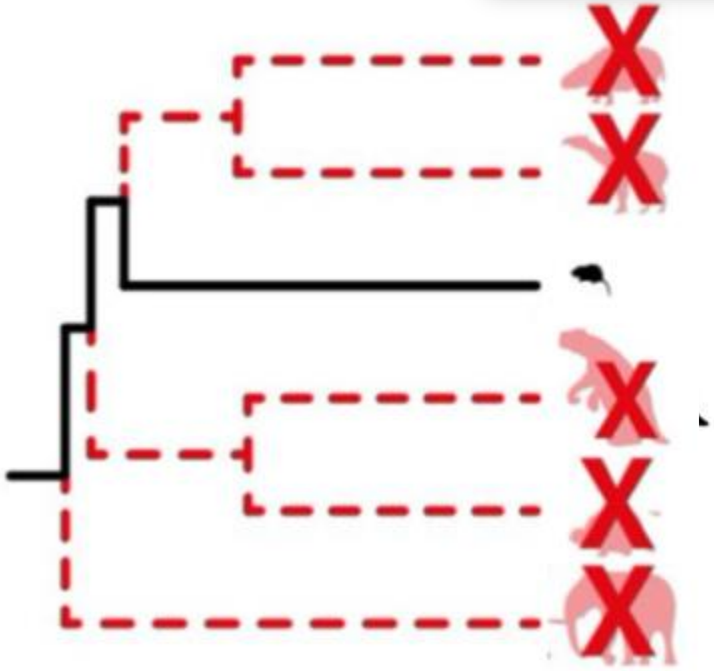

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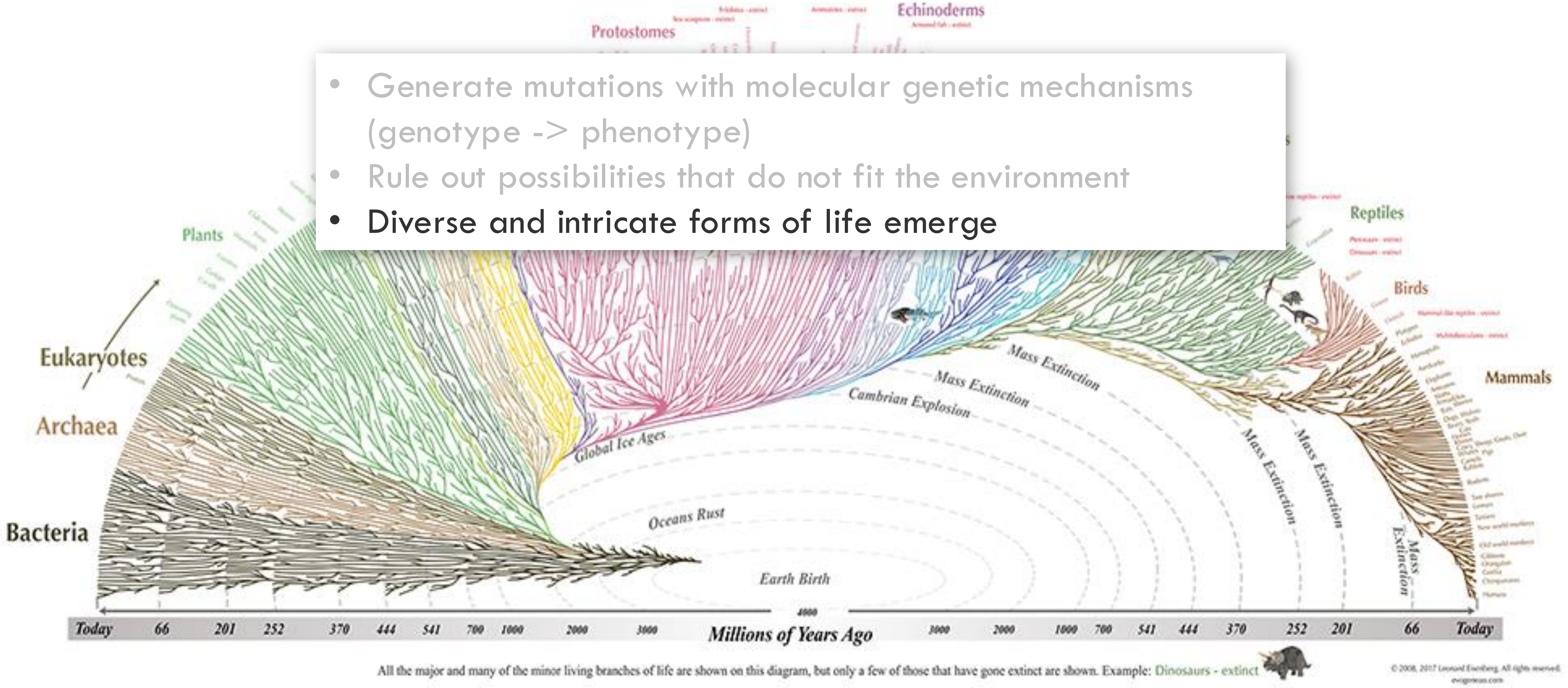
Example 2: Natural evolution

- Generate mutations with molecular genetic mechanisms (genotype -> phenotype)
- Rule out possibilities that do not fit the environment
- Diverse and intricate forms of life emerge



How Nature Works

Simulates possibilities recursively; complexity emerges

Human reasoning

Natural evolution

Mental models

Molecular genetic mechanisms

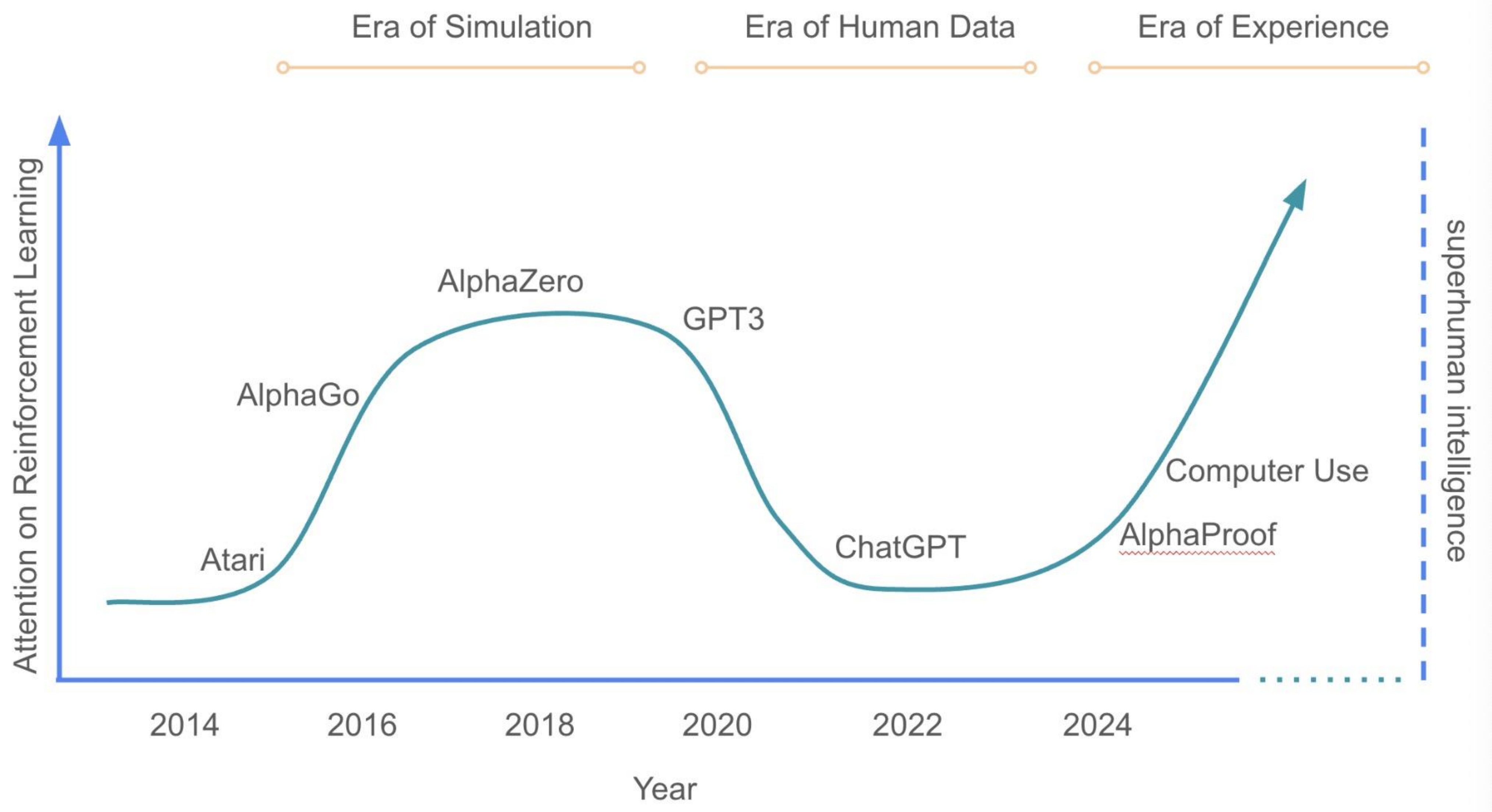
Simulating possible consequences of an action

$$P(s' | s, a)$$

→ "World Model"

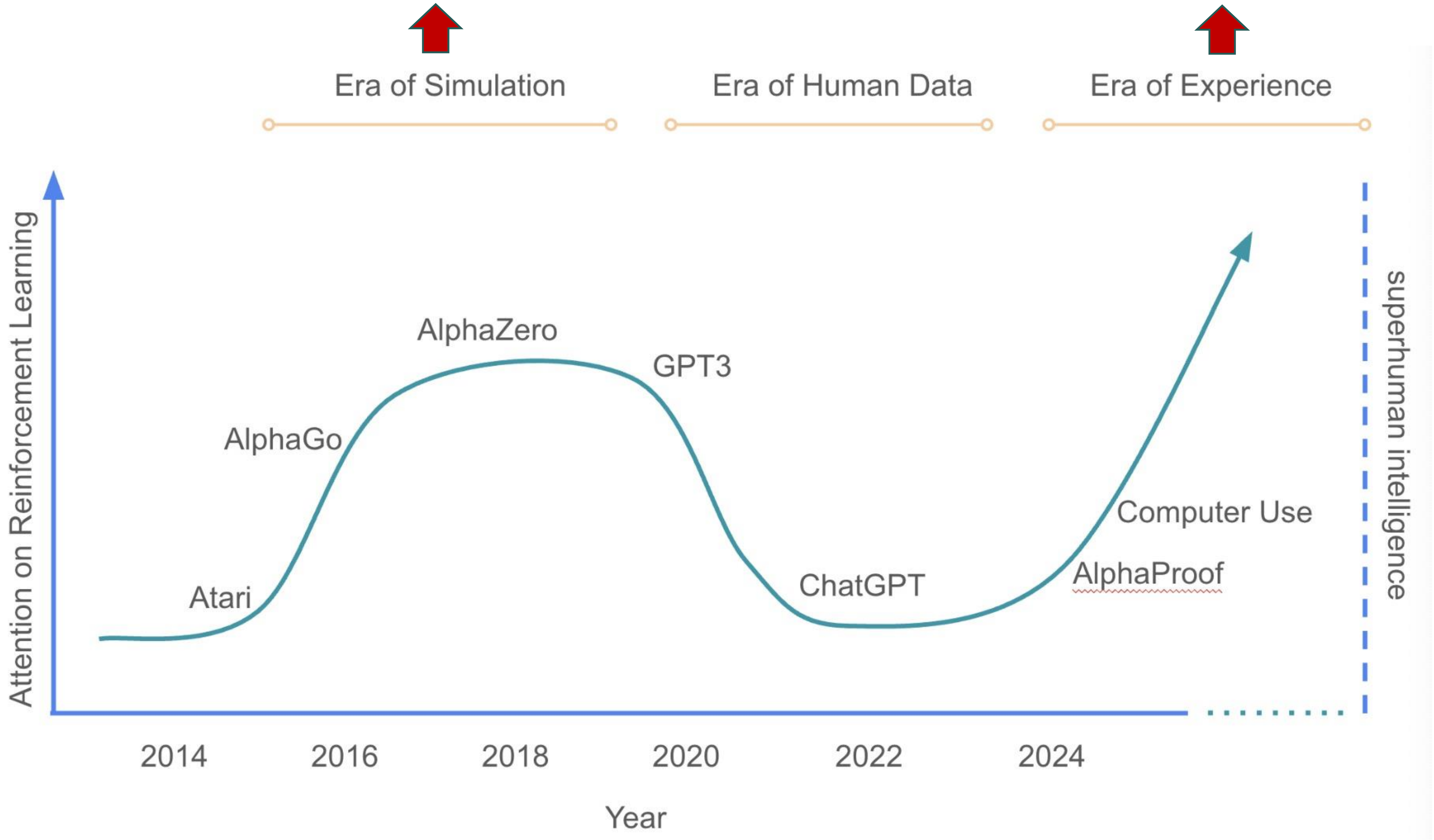
Welcome to the Era of Experience

David Silver, Richard S. Sutton*



Era of Symbolic Simulation

Era of World Model Simulation



Questions?