Position: World Models must live in Parallel Worlds

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Abstract

World models learn spatio-temporal representations of a world, enabling them to predict future states, and support interaction, navigation, and simulation capabilities. For generative models to become effective agents in the physical world, they must develop and use world models. We posit that world models must be capable of counterfactual simulation – the ability to reason about *what if* scenarios. By simulating alternative realities, world models will be more capable, safe and creative when faced with novel, out-of-distribution scenarios. Furthermore, they can transcend mere pattern matching to achieve a true causal understanding of the world, a capability central to human intelligence, and a prerequisite for the next generation of AI agents.

1 The Case-Based Generalization Crisis

Generative AI has demonstrated remarkable capabilities in creating text, images and videos that mimic human output [1, 2]. However, for these models to transition from digital content creators to effective agents in the physical world, they require a deeper understanding of how the world works. This understanding is encapsulated in the concept of a "world model", an internal representation that allows an agent to simulate and predict the consequences of actions within its environment [3].

Current efforts to build world models focus on predicting future states from past observations, typically by scaling models and exposing them to millions of examples [1, 2, 4–7]. This approach, while powerful, creates a fundamental generalization gap. The resulting models excel at interpolating within their training data, but falter when asked to extrapolate to novel scenarios. They engage in *case-based generalization* [4, 8–10], effectively imitating the most similar training instances rather than abstracting the underlying physical or causal principles. This brittleness manifests in critical failures.

Models often lack compositionality, struggling to combine familiar concepts in novel contexts. For example, Veo 3 [2] struggles to generate "a hummingbird flying over a city" (Appendix A.1) because it associates the bird with natural habitats, rather than abstracting hummingbird and flying as transferable concepts. They also mistake correlation for causation, producing hallucinations such as people walking backwards in Genie 3 [3]. Additionally, they remain opaque black boxes, unable to explain their reasoning and unsuitable for safety critical applications. This raises a central question: *What capabilities would make world models robust in novel, out-of-distribution settings?*

[*]Equal contribution. Author order selected by coin flip.
[2]https://deepmind.google/models/veo/
[3]Why generative world models aren't ready for real applications (2025)

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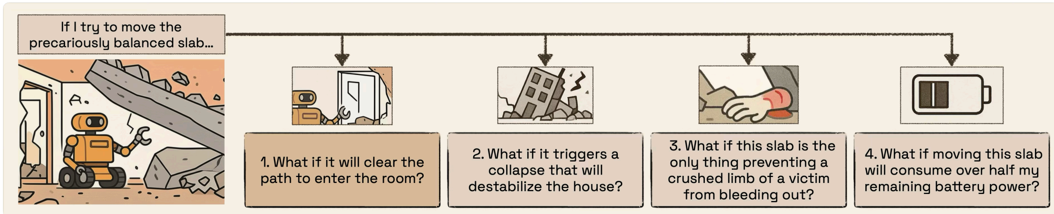

Figure 1: A search-and-rescue robot in a collapsed building: Should it move the precariously balanced slab? Current world models may predict trajectory (1), but **counterfactual simulation (CfS)** enables evaluating counterfactual trajectories (2, 3, 4) that are crucial for safety.

Human cognition provides a useful point of reference. When humans encounter a novel situation, we hypothesize alternatives: if a human drives into a school zone, we imagine that children may run into the road, or that a car door may suddenly open [11–13]. Such counterfactual simulations allow us to substitute, recombine, and adapt knowledge flexibly, enabling robustness in out-of-distribution settings.

Motivated by this, we posit that equipping models with the ability to perform **counterfactual simulation (CfS)** could be a key ingredient to achieving robustness, safety, and out-of-distribution generalization. For example, in Figure 1, a search and rescue robot enters a collapsed building and confronts a precariously balanced slab. A standard predictive world model simulates the most likely future (e.g., moving the slab to clear the path) and can miss catastrophic alternatives, such as collapse from a slight disturbance. By simulating parallel, hypothetical futures, world models could move beyond statistical pattern matching towards true causal reasoning, as we observe in human mental models.

2 Counterfactual Simulation

World model. Following [3], we define a world model as an internal representation that captures the causal structure and spatiotemporal dynamics of an environment. Given an initial state and an action, a world model predicts the next state and can roll out sequences to generate trajectories.

Counterfactuals. A counterfactual is a hypothetical "what-if" that changes a specific aspect of the world and examines how the outcome would differ, allowing us to reason about alternative outcomes. Within Pearl's Ladder of Causation [14], counterfactuals sit at the highest level. Beyond association (observing correlations) and intervention (predicting the effects of actions), they answer questions of the form, "What would have happened if I had acted differently?" (see Appendix A.2 for details).

Counterfactual simulation (CfS). A counterfactual simulation (CfS) is an alternative sequence of events generated by a world model that explores what could have happened had a specific event been different. To formalize, we define an event (e_t) as a single unit combining a state and an action at time t, such that $e_t = (s_t, a_t)$. The system's dynamics are captured by a world model (M), a function that predicts the next event. A trajectory (τ) is a sequence of these events over time, $\tau = (e_0, e_1, \ldots, e_T)$. Consider a factual trajectory (τ_{fact}) that represents the most likely sequence of events:

$$\tau_{\text{fact}} = (e_0^{\text{fact}}, e_1^{\text{fact}}, \ldots, e_T^{\text{fact}})$$

where each $e_t^{\text{fact}} = (s_t^{\text{fact}}, a_t^{\text{fact}})$.

A **counterfactual trajectory (τ_{cf})** is a hypothetical alternative created by performing an intervention. This involves selecting a specific step k and replacing the factual event e_k^{fact} with a different, hypothetical event e_k^{cf}. The new trajectory is then defined as:

$$\tau_{\text{cf}} = (e_0^{\text{cf}}, e_1^{\text{cf}}, \ldots, e_T^{\text{cf}})$$

This trajectory is constructed by following a three-part process, which can be visualized as a branching path from the factual trajectory. First, for all steps leading up to the intervention ($t < k$), the counterfactual events are identical to the factual ones: $e_t^{\text{cf}} = e_t^{\text{fact}}$. Second, at the intervention point ($t = k$), the factual event is replaced: $e_k^{\text{cf}} \neq e_k^{\text{fact}}$. Finally, for all steps following the intervention

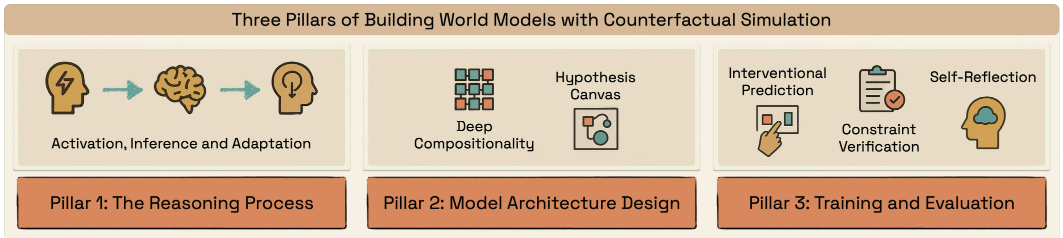

Figure 2: The three pillars for effective implementation of counterfactual simulation in world models.

$(t > k)$, the subsequent events are generated by the world model, simulating the consequences of the counterfactual change: $e^{\text{cf}}_{t+1} \sim M(\cdot|e^{\text{cf}}_t)$. This process generates a new trajectory that is identical to the factual one up to the intervention point but diverges afterward due to the change at step k.

3 Alternative Views

Prevailing View. A common prevailing view is that case-base generalization will be overcome naturally from scaling up generative models with more data and compute [1, 15]. Others advocate for test-time scaling: allocating greater compute at inference to improve reasoning abilities and generalization [16–18].

Our Position. We believe that scaling data, models or test-time compute alone is not a viable path forward to robust world modeling, for the following reasons.

1. High quality human data is finite[4], pushing reliance on synthetic data that risks model collapse as models train on their own outputs [19]. The energy and water demands of large data centers raise sustainability concerns and question the long term viability of continued scaling.
2. Large-scale models are data inefficient. LLMs train on trillions of tokens, far exceeding a child's linguistic exposure and still lack robust world understanding. [5]
3. Allocating more compute at test-time is not a cure-all for a flawed underlying model. A model that doesn't grasp intuitive physics, like object permanence, will just explore a larger tree of physically implausible outcomes, no matter how much compute is thrown at it.

4 The Path Forward

Effective counterfactual simulation requires a strong underlying causal framework for the world the model is trained on, and a structured process to trigger, generate, store, and use counterfactual simulations. We propose a three pillar approach (Fig. 2) to CfS in world models: the underlying reasoning process, the architectures to support it, and the training and evaluation methods for it. We discuss works that are relevant to CfS in Appendix A.3.

4.1 Pillar 1: The Reasoning Process

Inspired by the human cognitive process that governs counterfactual thinking ([13]), a world model capable of CfS requires capabilities for the reasoning processes of *activation* $\rightarrow$ *inference* $\rightarrow$ *adaptation*.

Activation. World models interacting with the physical world must decide *when to simulate counterfactuals*. This requires a system to identify which event $e^{\text{fact}}_{t=k}$ in τ_{fact} is an "activation event" based on its causal significance. In Fig. 1, the robot must identify that moving the slab is an activation event, because its alterations would create meaningfully different futures.

Inference. When an activation event is identified, the world model can perform targeted interventions on it to simulate consequences. Since full simulations are computationally expensive, a meta-cognitive

[4] https://globalcio.com/news/14933/

[5] https://babylm.github.io/

process determines when to use complete simulation versus cheaper heuristics. This process weighs decision importance and uncertainty against computational cost, reserving full counterfactual rollouts for high-stakes scenarios.

Adaptation. After inference, the model can use CfS outcomes to inform appropriate actions or preventative measures, using reasoning methods.

4.2 Pillar 2: Model Architecture Design

Deep Compositionality. To simulate meaningful counterfactuals, we call for architectures that can encode the world as a system of disentangled concepts, objects, and physical rules — where elemental building blocks can combine to form larger concepts. This deep compositionality requires the model to also learn the fundamental, transferable properties of objects and concepts, and the causal relationships between them. In Fig. 1, the robot must reason about properties, affordances, and resources: the slab is heavy, and lifting it would draw significant battery power, constraining subsequent actions. Graph-based and neurosymbolic methods have shown promise in encoding such compositional structure, [20, 21], but scaling them to open world modeling remains challenging [20, 22].

Hypothesis Canvas. In order to instantiate and maintain multiple parallel trajectories (τ_{cf}) in the inference process (§ 4.1), we propose the use of an external memory workspace or canvas. A world represented as a graph of entities and relations can be copied and modified on this canvas, creating distinct subgraphs for each CfS trajectory.

4.3 Pillar 3: Training and Evaluation

Training and evaluation should prioritize logical and physical consistency over reconstruction accuracy, given the lack of ground truth for counterfactuals.

Training. We need training objectives that encourage *interventional prediction*: given an initial trajectory τ_{fact}, identify activation event $e^{\text{fact}}_{t=k}$, and predict a simulation e^{cf}_{t+1}. Interventional objectives force world models to capture causal relationships rather than mere correlations.

Evaluation. For CfS, given the scarcity of ground truth for counterfactual simulation, is it more meaningful to evaluate models by verifying their adherence to logical and physical constraints. Rather than speculating what a specific alternate world "should" look like, *constraint verifiers* can validate that simulations respect domain rules (e.g., conservation laws, plausible dynamics of lift, consistent shading/shadows, compatibility between mass and motion). Beyond evaluating the quality of CfS, we also need to validate the *self-reflection* capabilities of the world model: how does the world model agent decide when to use a counterfactual trajectory based on the outcomes of CfS generated.

5 Impact and Limitations

Developing world models with **counterfactual simulation (CfS)** will enable robustness in critical domains like robotics and healthcare, where reasoning about novel situations is key to safe and effective operation. However, there are technical and safety challenges that need to be met.

How do we manage the simulation process itself? The number of counterfactual scenarios can be infinite in an unconstrained world model. Therefore, it is imperative to develop a mechanism where counterfactuals are generated from most plausible to the least plausible. A dynamically determined *counterfactual budget* will only allow for the most impactful but also most likely CfS.

How can we build these models? Building a single, all-encompassing causal model of the world is currently computationally infeasible. A more practical path may involve an ensemble of smaller, context-specific models that are more efficient and adaptable, and specialized memory modules for storing and retrieving CfS.

What are the ethical and safety implications? A model that can simulate "what if" scenarios can imagine both beneficial and harmful outcomes. It is critical to implement safeguards that prevent the model from acting on dangerous simulations. The core challenge lies in aligning the model to use this powerful capability solely for constructive and safe exploration. Furthermore, the latent reasoning behind a counterfactual simulation may be a black box. For these models to be trustworthy, they must be able to decode their simulations into human-understandable formats (like text or video), providing transparency into their decision-making process.

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A Appendix

A.1 Generation with Veo 3

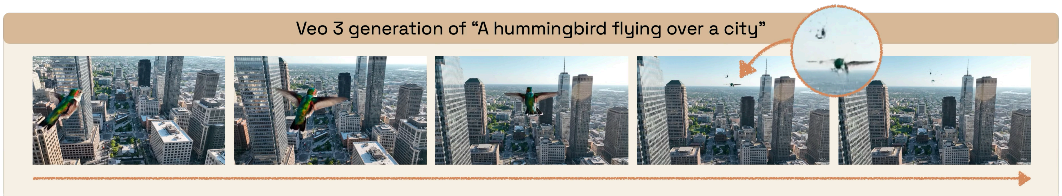

Figure A1: Although Veo 3 video generations are impressive in their quality, these generations often lack in physical accuracy and consistency. Here, the hummingbird flying over a city simply disintegrates and disappears into thin air, indicating that it is unable to generalize when a hummingbird appears over a city instead of nature, and that accurate world-modeling based counterfactual simulation is still a challenge.

A.2 Background on Counterfactuals

Counterfactuals are central to modern theories of causality in statistics and computer science. Donald Rubin's potential outcomes framework, known as the Rubin Causal Model (RCM), defines causal effects as differences between outcomes under different treatments [23], indicating counterfactuality. Judea Pearl advanced the field with *Structural Causal Models* (SCMs), which unify counterfactual reasoning, graphical models, and algorithmic tools for causal analysis [14]. SCMs represent assumptions with directed acyclic graphs (DAGs) and structural equations, enabling formal and computable causal and counterfactual queries when the causal structure is known. In relation to our work, learning such SCMs in a world model can enable deep compositionality (Sec. 4.2).

A key innovation in Pearl's framework is the *Ladder of Causation*, which organizes causal reasoning into three levels:

1. **Level 1: Association.** This level involves seeing and observing, answering questions like, "Given what I have observed, what is likely to happen next?" This is the domain of most current world models, which excel at pattern recognition and prediction based on statistical correlations.
2. **Level 2: Intervention.** This level involves doing and acting, answering, "What will happen if I do X?". This requires a causal model that can predict the effects of deliberate actions, moving beyond passive observation.
3. **Level 3: Counterfactuals.** This is the highest level of causal reasoning, involving imagination and retrospection. It answers, "What would have happened if I had acted differently?" This requires contrasting the observed reality with a hypothetical, unobserved world.

This hierarchy follows an increasing expressive power: associations capture patterns, interventions identify effects, and counterfactuals analyze alternative outcomes. For truly powerful world models, achieving counterfactual reasoning and simulations will be a cornerstone to their real-world success.

In AI and machine learning, counterfactuals are used extensively in a wide variety of tasks, from explainability and fairness, to model capability building and evaluation. Counterfactual explanations identify the minimal input changes needed to alter predictions [24], while bias and fairness methods test whether outcomes shift towards biased outputs when counterfactual inputs are introduced [25–31]. Additionally, counterfactuals are used to improve language and VL modeling [32, 33], test the capabilities of GenAI models [26, 34], and for data augmentation [35].

A.3 Relevant works for Counterfactual Simulation

Prior works have considered the use of counterfactuals, especially in world modeling for autonomous driving. OmniDrive [36] considers counterfactual questions in driving scenarios. GAIA-2 [37] enables OOD scene generation for synthetic driving data, akin to counterfactual simulations we propose. OCTET [38] generates counterfactual explanations in driving scenarios. These research works further justify the need for counterfactual simulation, and show several practical scenarios where it is useful.

Another line of research introduces Counterfactual World Models [39–46]. These methods use masked modeling to train promptable visual world models to perform counterfactual simulations, and to perform counterfactual reasoning in agent models in the context of RL. These works are clear starting points for researchers interested in working on visual world modeling. Our goal is to achieve open-world, real-life counterfactual simulation, as imagined in our three pillar process (§ 4).