World Modeling, Simulation, and Embodied Intelligence: State of the Art and Future Directions

Bjørn Remseth
Email: la3lma@gmail.com
With much AI assistance

***Abstract*—Artificial intelligence has made great strides by leveraging models of the world, high-fidelity simulations, and embodied agents that perceive and act. This paper provides a comprehensive overview of the state of the art in world modeling, simulation, and embodied intelligence. We connect developments in academic research, open-source platforms, and industry applications. We review seminal models and systems, discussing their origins, mechanisms, evolution, and how they interrelate. Key topics include learned world models for prediction and planning, physics simulators and realistic virtual environments, and embodied AI agents that integrate perception, cognition, and action. We highlight how these components come together in modern AI—enabling advances in autonomous robots, intelligent vehicles, and virtual agents—and we speculate on upcoming trends such as differentiable simulations, foundation models for embodied intelligence, and the path toward artificial general intelligence in the physical world. All references to important papers and systems are provided with URLs when available for further exploration.**

***Index Terms*—world modeling, embodied intelligence, simulation, reinforcement learning, robotics, artificial general intelligence**

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I. Introduction

Intelligent agents that can model the world, simulate interactions, and physically embody their cognition are a long-standing goal of artificial intelligence (AI). Early AI focused on abstract reasoning in disembodied settings (e.g. solving puzzles or playing text-based games). However, to achieve robust artificial general intelligence (AGI), researchers increasingly emphasize embodied intelligence – agents that are situated in and interact with the physical world [1]. Such agents need to perceive complex environments, understand the consequences of actions, and adapt to new situations. This has led to growing interest in world models and simulations as enabling technologies.

A world model in AI refers to an internal model or representation that an agent uses to predict future states of the environment and evaluate outcomes of actions [2]. Classic work in robotics and cognitive science argued that intelligence emerges from the coupling of brain, body, and environment, without requiring explicit abstract representations [3]. Rodney Brooks famously advocated for "intelligence without representation" in mobile robots [3], emphasizing real-time interaction over internal world models. Nonetheless, as AI systems tackle more complex tasks, having a predictive model of the world (even if learned implicitly) has proven extremely powerful. Modern world models often take the form of learned neural networks that capture environment dynamics [4]. They enable model-based planning and imagination: agents can simulate possible futures "in their head" to make better decisions [4]. World models have become especially prominent in reinforcement learning (RL) and robotics, where interacting with the real world is costly or dangerous. By learning a model from data, agents can dream or simulate outcomes internally and thus reduce the need for physical trials [5].

Meanwhile, simulation has become a cornerstone for developing and testing embodied AI. In simulation, an agent interacts with a virtual environment that approximates the real world's physics and visuals. Simulation allows safe, fast, and parallel experiences, accelerating learning and enabling reproducible evaluation [6]. For instance, training a robot in a physics simulator avoids wear-and-tear on real hardware and can explore countless scenarios at accelerated speed. Simulations range from simple grid worlds to rich 3D worlds with photorealistic rendering and accurate physics. The fidelity of simulators has improved to the point that sim-to-real transfer—transferring knowledge or policies learned in simulation to the real world—has become feasible for tasks like robotic grasping and autonomous driving [7].

This paper provides a comprehensive survey of world modeling, simulation, and embodied intelligence. We examine seminal models and systems, discuss their design and evolution, and map out how they connect across research and industry. In particular:

- We review core concepts of embodied intelligence and why physical embodiment and interaction are crucial for general intelligence (Section II).
- We survey major simulation platforms (physics engines, virtual environments) used in robotics and AI research, from early open-source projects to modern high-fidelity simulators (Section III).
- We explore learned world models in deep learning, including generative models that simulate physics or video, and model-based RL agents that plan with learned dynamics (Section IV).
- We discuss how these components come together in cutting-edge embodied AI systems, including recent foundation models (large pretrained models) that interface with robotic control (Section V).
- We highlight connections to industry, such as how simulation and world models are employed in autonomous vehicles, robotics, and virtual reality.
- Finally, we outline future directions and speculate on upcoming developments, such as differentiable simulations, more general world simulators, and the integration of language, vision, and action in embodied agents (Section VI).

Throughout, we cite key literature (with hyperlinks when available) and provide pseudocode and diagrams to illustrate important architectures and pipelines. Our aim is that the reader gains a deep understanding of the state of the art in world modeling, simulation, and embodied intelligence, appreciating both the individual advances and the synergistic whole that is driving the field toward more general, capable AI.

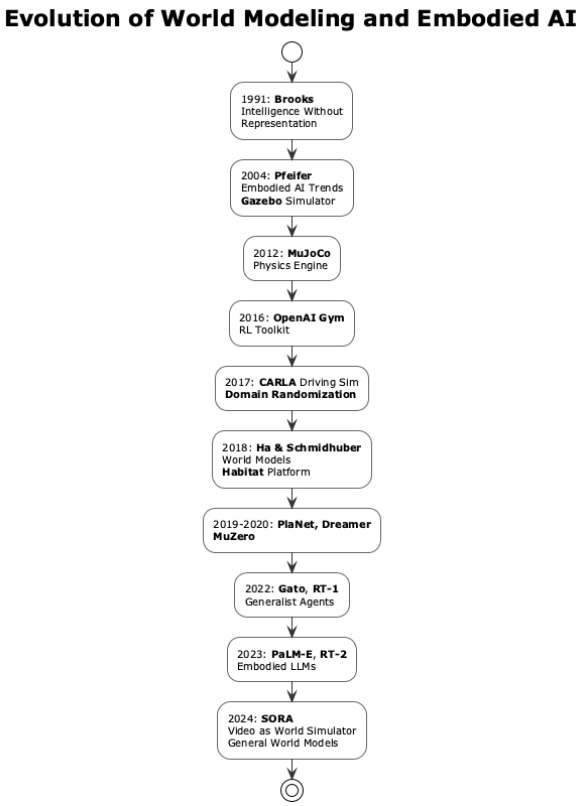

Fig. 1. *Timeline showing the evolution of world modeling, simulation, and embodied intelligence research from early behavior-based robotics to modern foundation models and video generation systems.*

II. Embodied Intelligence: Background and Concepts

What do we mean by embodied intelligence? In essence, it is the idea that intelligence arises in the context of a body interacting with an environment [1]. Unlike disembodied AI (e.g. a text-based chatbot living only in cyberspace), an embodied agent has a physical or virtual presence – it observes through sensors (cameras, microphones, touch, etc.) and acts through effectors (motors, limbs, etc.) in a world.

The concept has roots in cognitive science and robotics. Alan Turing himself proposed an "embodied Turing Test" in 1950, suggesting that true intelligence might be demonstrated by a machine that can interact with the physical world indistinguishably from a human. In the 1990s, roboticists like Rodney Brooks argued that classical AI (which relied on internal symbolic world models and planning) was too divorced from the reality of sensorimotor interaction. Brooks' subsumption architecture advocated reactive layers in robots that directly connect perception to action, eschewing explicit representation of the world [3]. This was summarized in his paper "Intelligence Without Representation" (1991)[3], which became a seminal work in behavior-based robotics.

Around the same time, researchers like Rolf Pfeifer championed embodied cognitive science, examining how an agent's body (morphology) and environment play integral roles in cognition. Pfeifer and Iida (2004)[8] outlined trends and challenges in embodied artificial intelligence, highlighting that intelligence cannot be fully understood without considering the physical instantiation and real-world constraints. Key ideas include situatedness (intelligence is situated in a specific environment), embodiment (the agent's body affects what it can sense and do), and structural coupling (continuous two-way interaction between agent and world leads to emergent behavior).

Today, embodied intelligence encompasses a broad array of research:

- **Robotics**: Autonomous robots, from mobile service robots to drones and manipulators, are prime examples of embodied AI. They perceive the real world and must deal with noise, uncertainty, and physical dynamics.
- **Embodied virtual agents**: These are agents in simulated environments (games, virtual reality) with an avatar or presence that can navigate and act. For example, an AI controlling a character in a 3D game like Minecraft or controlling an agent in a physics simulator is an embodied agent, albeit in a virtual world.
- **Interactive AI systems**: This includes agents that communicate with humans or manipulate digital/physical objects, requiring grounding of language in perception and

action (e.g. a household robot following natural language instructions).

An embodied agent faces unique challenges. It must handle continuous high-dimensional sensory inputs (e.g. pixel images, depth maps, joint angles) and produce continuous actions (motor torques, velocities). The agent typically operates under real-time constraints and partial observability (it never has complete information about the state of the world). It must deal with physics – the rigid-body dynamics, collisions, friction, etc., that govern how the world changes in response to actions. This is fundamentally harder than the self-contained abstract problems often tackled by early AI.

To succeed, embodied agents often rely on two critical tools:

1) **Simulation**: Before deploying in reality, agents can be trained and tested in simulated environments. As we discuss in the next section, simulation provides a safe and efficient approximation of the real world.
2) **World models**: Rather than act blindly or reactively, advanced agents build predictive models of their environment's dynamics. This allows them to plan and reason about the future outcomes of actions, which is especially important for long-horizon decision making [4].

Recent research in embodied AI has seen a convergence with developments in machine learning:

Deep reinforcement learning (Deep RL) has been a game-changer for training policies in complex environments, beginning with breakthroughs in game domains like Atari and Go. Deep RL methods have since been applied to robotics and embodied tasks, with simulation as a training ground. However, pure model-free deep RL (which learns by trial-and-error without an explicit world model) can be extremely data-inefficient in complex environments. Thus, model-based approaches that learn a world model (either explicitly or implicitly) are gaining traction to improve sample efficiency and generalization [4].

Another convergence is with large models from AI fields like computer vision and natural language processing. Large-scale pretraining has produced powerful visual encoders and language models. These foundation models are now being integrated into embodied agents to equip them with rich perceptual understanding and high-level reasoning [1]. For example, a large vision-language model can help a robot interpret a verbal command and plan a sequence of steps to execute it [1]. Google's RT-2 (Robotics Transformer 2) is an example where a vision-language model was trained to output robot actions, allowing web-scale knowledge to directly transfer to robot control [9]. Similarly, PaLM-E (Section V) extends a large language model with embodied sensor inputs [10].

In summary, embodied intelligence provides the context in which world modeling and simulation become vital:

- Without simulation, learning by interacting with the real world is often impractical (due to time, cost, risk).
- Without world models, planning and understanding in complex worlds would require prohibitively many trial-and-error interactions.

We now turn to simulation platforms, before diving into the details of world models and how they are learned.

III. Simulation for Embodied AI

Simulation has a rich history in robotics and AI. A simulator is a software environment that emulates aspects of the real world – from physics to visuals to semantics – in which an agent can be placed. Simulators allow researchers to create controlled, repeatable conditions and generate massive amounts of training data for AI models without real-world consequences [6]. This section surveys major types of simulation platforms and their evolution.

A. Physics Engines and Robotics Simulators

In robotics, early simulators were often simplistic, but they set the stage for more advanced platforms. One influential early open-source simulator is Gazebo, introduced by Koenig and Howard (2004) [11]. Gazebo provided 3D rigid-body dynamics simulation with plug-in support for sensors and robots, and it became a standard tool integrated with the Robot Operating System (ROS). Its design emphasized multi-robot scenarios and a high degree of modularity [11]. Gazebo allowed researchers to simulate wheeled robots, legged robots, flying drones, and more in outdoor or indoor environments, and to test algorithms for SLAM, navigation, etc., before real-world trials.

Another seminal physics engine is MuJoCo (Multi-Joint dynamics with Contact), developed by Todorov et al. and presented in 2012 [12]. MuJoCo was designed for model-based control and optimization, providing accurate simulation of contact dynamics and soft constraints at high performance. It became widely used in the reinforcement learning community for continuous control benchmarks. Many popular RL tasks (HalfCheetah, Hopper, Ant, Humanoid, etc.) are simulated in MuJoCo, and OpenAI Gym's benchmark environments heavily rely on MuJoCo. MuJoCo's key feature was a smooth contact model that is amenable to optimization and even differentiable computation, which made it appealing for control research.

In parallel, commercial game physics engines like Havok and Bullet emerged to power video game and visual effects physics. Bullet, by Erwin Coumans, was released open-source and became popular in both graphics and robotics. Coumans (2015) documented the design of Bullet for broad use [13]. Bullet provides rigid body dynamics, collision detection, and even soft body and fluid simulation. It has been integrated into many robotics simulators and toolkits (including PyBullet for Python).

Over time, robotics simulations have grown more realistic. NVIDIA's PhysX (also open-source now) offers GPU-accelerated physics. More recently, NVIDIA has emerged as a major player with its suite of simulation tools specifically designed for AI and robotics.

NVIDIA Isaac Platform: NVIDIA's Isaac ecosystem represents one of the most comprehensive commercial simulation

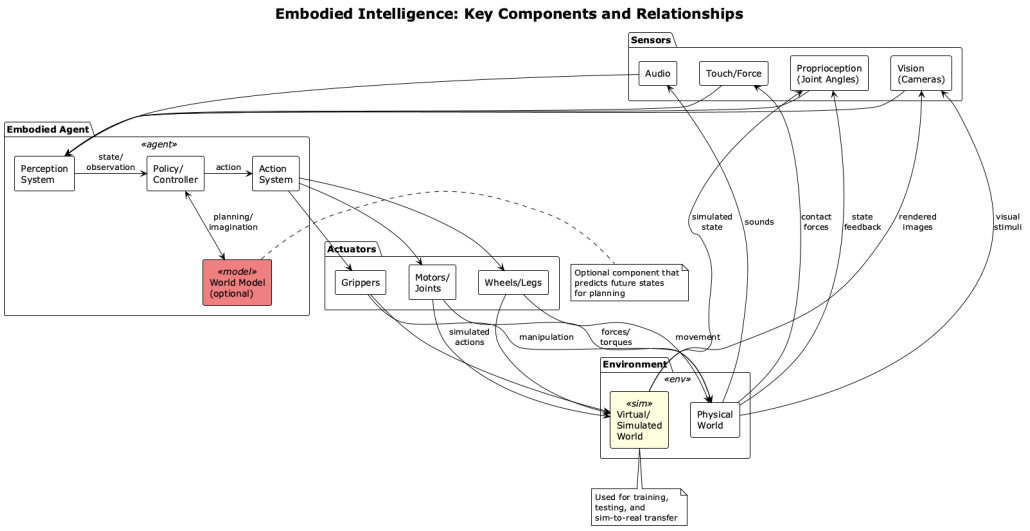

Fig. 2. *Core components of embodied intelligence systems showing the interaction between sensors, actuators, the environment, and the agent's internal processing including perception, world model, and control policy.*

platforms for robotics and embodied AI. Isaac Gym, introduced in 2021, revolutionized RL training by enabling thousands of parallel robot simulations on a single GPU, achieving 10-100x speedups compared to CPU-based simulators. This massive parallelization allows researchers to train complex locomotion and manipulation policies in hours rather than days. Isaac Gym has become particularly influential in legged robotics, with numerous research labs using it to develop controllers for quadrupeds and humanoid robots.

Isaac Sim [14], built on NVIDIA's Omniverse platform [15], provides photorealistic rendering and accurate physics simulation, bridging the gap between synthetic and real-world data. It supports ROS integration, making it accessible to the existing robotics community, and includes pre-built robot models, sensors, and environments. The platform's ability to generate synthetic data with perfect ground truth labels has proven invaluable for training perception systems.

NVIDIA Omniverse extends beyond robotics to provide a collaborative platform for 3D simulation and digital twins across industries including manufacturing, logistics, and autonomous vehicles [15]. Companies use Omniverse to simulate entire warehouses or production lines, optimizing robot coordination and workflow before deployment. This represents a clear example of how simulation technology developed for AI research has been commercialized for industrial applications.

Key features modern physics simulators offer include:

- Rigid body dynamics with contacts, friction (for simulating robots, objects).
- Articulated body simulation (robot joints, linkages, kinematics).
- Soft body dynamics (cloth, deformables) if needed.
- Sensor simulation: cameras (rendering scenes to images), LIDAR, depth sensors, etc.
- Domain randomization capabilities (ability to randomize environment properties for sim-to-real, see Section III-C).

B. High-Fidelity Virtual Environments

Beyond raw physics, embodied AI often requires realistic environments – for example, houses, streets, or natural terrains – to develop agents that will work in those contexts. A number of simulators and platforms have been created in the last decade to provide such environments:

- **Habitat (Facebook/Meta AI)**: Habitat is a simulation platform introduced by Savva et al. (2019) [6] to train embodied agents in indoor environments. It consists of Habitat-Sim, a fast 3D renderer and physics simulator, and Habitat-API, a high-level API for defining tasks (like navigation, object search, question answering) [6]. Habitat emphasized efficiency: it can render thousands of frames per second by leveraging graphics APIs, enabling learning at scale [6]. It works with 3D scene datasets (Matterport3D, Gibson, etc.) to provide photorealistic houses. As a result, researchers could train, say, a point-goal navigation agent in Habitat and evaluate generalization to new houses [6].
- **Gibson (Stanford)**: The Gibson Environment [16] provided a large dataset of real-world indoor scenes (scans of buildings) and a simulator for navigation and interaction in those scenes. The focus was on real-world perception – using real imagery to make simulation more true-to-life for vision-and-navigation tasks [16].
- **DeepMind Lab**: DeepMind Lab [17] is a 3D game-like environment for AI research, focusing on first-person navigation and puzzle-solving in synthetic worlds. It's built on a game engine and was used for research on navigation and memory in agents.
- **CARLA**: CARLA [18] is an open-source urban driving simulator. It provides realistic urban layouts, vehicles, pedestrians, and sensors (cameras, lidar) for autonomous driving research. CARLA has been influential in devel-

Fig. 3. *The robotics and AI simulator ecosystem showing relationships between physics engines (MuJoCo, Bullet, PhysX), high-fidelity environments (Habitat, CARLA, AirSim), and integration frameworks (ROS, OpenAI Gym, Unity ML-Agents).*

oping and evaluating self-driving car algorithms under different weather, lighting, and traffic conditions [18].

- **AirSim**: AirSim [19] is a high-fidelity simulator originally for drones and later extended to cars. It's built on Unreal Engine and emphasizes realistic rendering and physics for vehicles. AirSim supports hardware-in-loop and was designed from the ground up to be extensible to accommodate new types of vehicles, hardware platforms, and software protocols [19]. It includes a physics engine that can operate at a high frequency for real-time hardware-in-the-loop simulations.
- **Unity and Unreal Engine Environments**: Both Unity and Unreal are game engines that have been leveraged to create simulation environments. Unity, in particular, released an ML-Agents Toolkit to use Unity as a platform for AI agents [20]. Researchers and companies have built simulations ranging from robotic arm manipulation to multi-agent games using these engines, benefiting from the engines' advanced graphics and physics.
- **MuJoCo-based and Custom RL Suites**: OpenAI's Gym [21] provided a standard API to many simulation environments (including classical control and MuJoCo tasks). DeepMind's Control Suite (2018) similarly offered a set of continuous control tasks with a consistent interface,

often using MuJoCo. These are not full "worlds" but standardized simulated tasks to drive algorithm development.
- **Others**: There are numerous others like Webots, CoppeliaSim (V-REP), Microsoft's Project Malmo (for Minecraft), AI2-THOR and ThreeDWorld (interactive home environments), VizDoom (first-person environment based on Doom), ProcGen (procedurally generated RL environments), and more. Each targets different niches (e.g., interactive home environments, generated game levels, etc.).

An important trend in simulators is the push toward photo-realism and physical accuracy. Early simulators often had cartoonish graphics and imperfect physics. But modern ones like Habitat, CARLA, and AirSim strive for realism to reduce the "reality gap" – the difference between simulated and real sensor data. Some simulators incorporate real sensor noise models (e.g., camera noise, motion blur) to further mimic reality.

Simulators have also become essential for dataset generation. For example, in computer vision, synthetic data from simulators (with perfect ground truth annotations) can train models that are later fine-tuned on smaller real datasets. In robotics, simulation can generate large datasets of robot experience (images, poses, etc.) to train visual navigation or manipulation models.

C. Sim-to-Real Transfer and Domain Randomization

A perennial challenge is that policies or models learned in simulation often fail on real robots or environments due to the reality gap. Differences in dynamics, sensor noise, and visual appearance can cause an agent to generalize poorly. Over the last few years, researchers have developed techniques to improve sim-to-real transfer:

Domain Randomization: Introduced by Tobin et al. (2017) [7], the idea is to randomize non-essential aspects of the simulation during training (e.g., textures, lighting, object shapes, physical parameters like friction) so that the agent experiences a wide range of variations. The policy thus learns to focus on robust cues that generalize to the real world. Tobin's work famously showed that a robotic vision model trained on images with random textures and lighting could successfully detect objects in real images [7]. OpenAI applied domain randomization in training a robot hand to solve a Rubik's cube, randomizing factors like object appearance and physics to enable the policy to transfer to the physical robot.

Increasing Fidelity: The closer the simulator to reality, the easier the transfer. This includes accurate physics modeling (e.g., using system identification to tune simulator parameters to match real world) and photo-realistic rendering (even using techniques like ray tracing or neural renderers).

Training with Real Data in the Loop: Approaches like sim-to-real fine-tuning involve first learning in sim, then updating the policy or model with a smaller amount of real-world data to adapt. Also, domain adaptation techniques from computer vision can translate simulated images to look like real images (using GANs, etc.), or vice-versa, to bridge the visual gap.

Direct sim-to-real learning: End-to-end approaches train a policy in simulation but with some constraints that ensure reality transfer. For example, learning dynamics-invariant state representations, or using sensor modalities less affected by gap (e.g., using depth sensing which may be easier to simulate realistically than raw RGB).

One example of sim-to-real success is in autonomous driving: models trained extensively in CARLA (simulated urban driving) can be used as a starting point for real car driving systems, especially by synthesizing varied scenarios that may be rare in real data (like rare dangerous situations). In robotics manipulation, simulated data is used for training vision-based grasping, and the real robot then only needs a bit of practice to adapt.

It's worth noting that simulation is not only a training tool but also a testing tool for safety-critical systems. For instance, before deploying a self-driving car update, companies run it through millions of simulated miles to catch regressions or failures in rare scenarios. In such cases, simulation acts as a virtual proving ground complementing real-world testing.

The interplay of simulation and reality has also prompted research into digital twins – high-fidelity models of specific real-world systems that run in parallel to the real system. For example, a factory robot might have a digital twin in simulation that is continuously updated with real sensor data, allowing testing of "what-if" scenarios and predictive maintenance.

In summary, simulation is an indispensable part of modern embodied AI:

- It provides the playground where agents can be trained and evaluated efficiently.
- When combined with strategies like domain randomization, it can produce agents that are remarkably robust in the real world (sometimes even surpassing human-engineered controllers).
- Simulation development is increasingly a cross-disciplinary effort, drawing from computer graphics, physics, and AI, to create ever more realistic and useful virtual worlds.

Next, we delve into the concept of world models – how agents learn and use internal models of their environment dynamics – and how these learned models are advancing the capabilities of AI.

IV. World Models and Predictive Simulation

In artificial intelligence, a world model generally refers to a model that an agent uses to predict aspects of the environment's future state. It can be as simple as a physics equation or as complex as a deep neural network that generates hypothetical next sensor inputs. Building good world models is at the heart of making AI agents that can plan and reason. Here we discuss the evolution from explicit, human-designed models to modern learned world models, and survey key approaches.

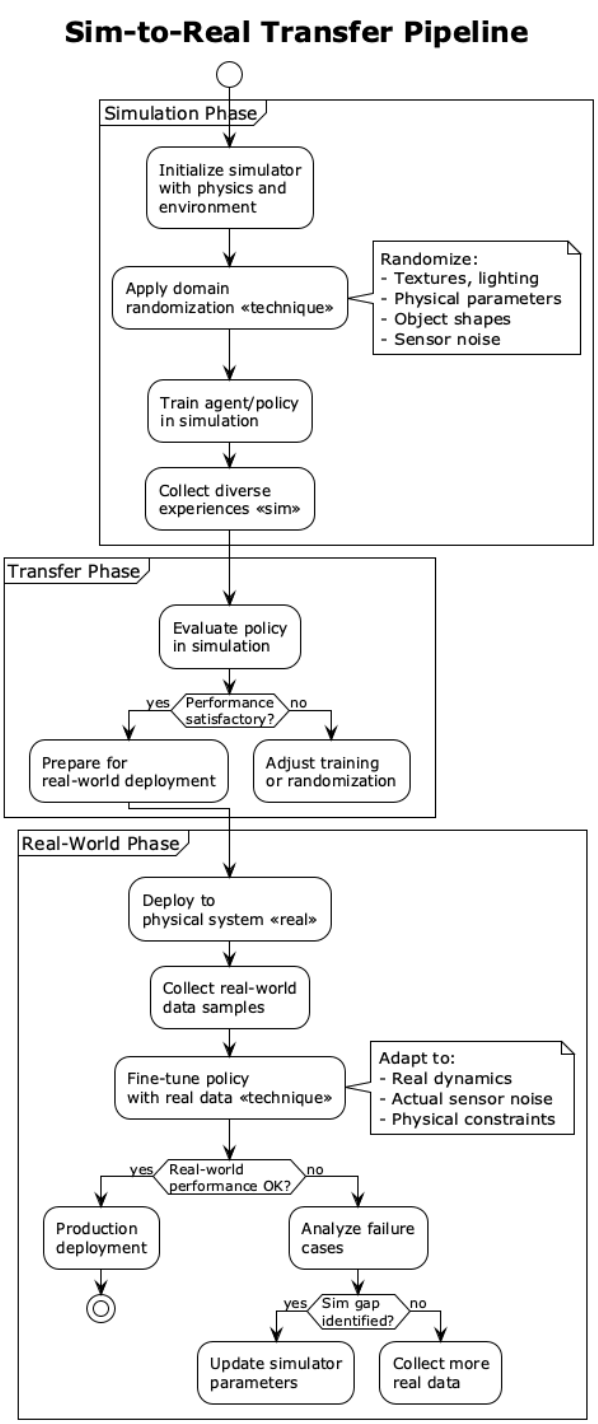

Fig. 4. *The sim-to-real transfer pipeline showing how policies trained in simulation with domain randomization, physics calibration, and photorealistic rendering are validated and deployed to real-world robotic systems.*

Model-Based vs. Model-Free Approaches: In reinforcement learning and control, approaches are often categorized as *model-based* or *model-free*. In model-based methods, the agent learns or uses a predictive model of the environment's dynamics to simulate potential outcomes and plan actions—essentially asking "what will happen if I do x?" before choosing the best action [22]. In contrast, model-free methods bypass the modeling step entirely, learning a control policy or value function directly from experience without an intermediate predictive model. Model-based approaches are generally more sample-efficient, making them particularly valuable for robotics where real-world data collection is costly and time-consuming.

A. Explicit Models vs. Learned Models

Traditional control theory and robotics have long used explicit models. For example, if you know the kinematic equations of a robot arm and the physics of its motors, you have an explicit model to predict how the arm will move given a torque input. Such models are often manually derived and require system identification to calibrate to the real robot.

However, not everything can be modeled analytically, especially in complex or unknown environments. Learned models come into play where we use data to approximate the environment's dynamics:

Early examples: In the 1980s-90s, neural networks were used to learn forward models of robot dynamics or inverse models for control. But limited data and compute made these less reliable than analytic models at the time.

In reinforcement learning, learned models were used in algorithms like Dyna (Sutton, 1990) – the agent learns a model and uses it to simulate experience (planning) in between real interactions. Yet, for a long while, learned models struggled in high-dimensional spaces (like images).

The resurgence of learned world models is tied to deep learning. A milestone was the paper "World Models" by Ha and Schmidhuber (2018) [5]. They demonstrated that a compact, learned model of a simple video game (CarRacing and VizDoom) could enable a policy to be trained entirely inside the model's "dream" and then successfully control the real game [5]. Their approach had three components:

- A Vision Model (V): a variational autoencoder (VAE) that compresses high-dimensional images (game frames) into a latent code.
- A Memory / Dynamics Model (M): a recurrent neural network (LSTM) that predicts the next latent state given the current state and an action (essentially learning the state transition dynamics in the compressed space).
- A Controller (C): a policy (in their case, a simple linear or evolutionary strategy) that outputs actions based on the latent state.

They showed that once V and M were learned from random rollouts, the controller could be optimized within the latent model (by evolutionary strategies in their case) to drive a car in the racing game. This work illustrated the power of representation learning for building world models, and how planning or policy search can happen in a learned latent space.

Another key development came from DeepMind with MuZero [23]. MuZero learned a model to master board games and Atari games without being given the game rules. It uses a neural network to represent:

- The dynamics: how the hidden state changes with actions,

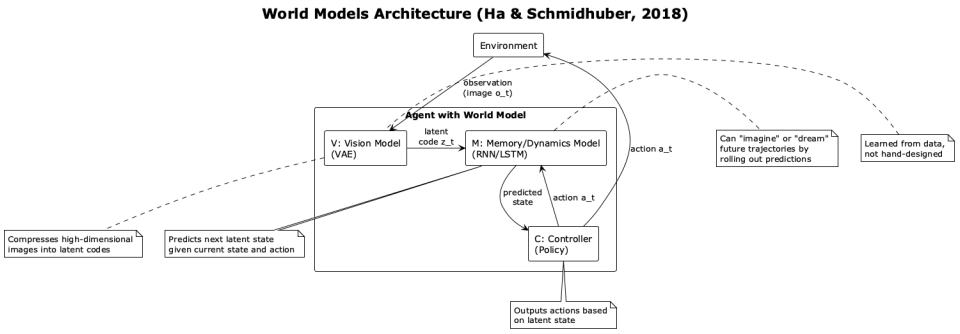

Fig. 5. *World Models architecture (Ha & Schmidhuber, 2018) showing the Vision model (VAE) compressing observations into latent codes, the Memory/Dynamics model (RNN/LSTM) predicting future latent states, and the Controller outputting actions based on predicted states.*

- The reward: what immediate reward is received,
- The policy & value: what actions are plausible and how good a state is.

MuZero then performs a tree search planning in its learned model (combining MCTS with learned predictions)[23]. Remarkably, MuZero matched the performance of AlphaZero (which knew the exact rules) in Chess, Shogi, and Go, and set a new state-of-art on Atari, demonstrating the efficacy of learning a world model even for very complex domains [23]. MuZero's model is not interpretable as a physics or game rule model – it's a kind of implicit world simulator optimized for planning relevant quantities (like future value) – yet it serves the role of a world model in enabling lookahead.

B. Learning World Models from Pixels

The hardest case of world modeling is when the agent only gets high-dimensional sensory inputs like pixels. Here, the world model must both learn perception (making sense of pixels) and dynamics (how the state evolves). Approaches typically involve learning some compressed state representation, as in Ha & Schmidhuber's VAE.

After the 2018 World Models paper, there was rapid progress:

PlaNet [24] was an algorithm for planning in latent spaces. It learned a variational recurrent state-space model and used it for planning actions via a gradient-based optimization.

Dreamer [4] and its successor DreamerV2 improved the learning of world models (with a model called RSSM – Recurrent State-Space Model) and showed that an agent could solve continuous control tasks purely from pixel inputs using far fewer samples than model-free methods. Dreamer uses latent imagination: it rolls out trajectories in the latent state space of the world model and trains a policy and value on those imagined trajectories, by backpropagating through the model (i.e., using analytic gradients through the model network rather than sampling)[4]. This significantly improved efficiency on tasks like controlling a hopper or a cheetah from pixel observations.

Models for Atari: The challenge of Atari games (high-dimensional pixel input, long-term dependencies) led to methods like SimPLe (2019) and DreamerV2 (2021) which combined world models with model-free components. DreamerV2 was able to reach human-level performance on Atari with a single GPU, a testament to how far latent world models had come.

These world models often borrow architecture ideas from sequence modeling (recurrent networks, transformers) and from generative modeling:

- The variational autoencoder (VAE) or its discrete cousin VQ-VAE (Vector Quantized Variational Autoencoder) is common for encoding images into latent codes that still retain important factors.
- Recurrent networks (like LSTMs or GRUs—Gated Recurrent Units) or newer architectures like transformers keep track of state across time.
- Some models explicitly include stochasticity to handle uncertainty, using stochastic latent variables at each time step (e.g., as in Stochastic Latent Actor-Critic, SLAC 2019, or in PlaNet).
- Hybrid models: A notable example is combining world models with Monte Carlo Tree Search, like the Predictron [25] which learned a state transition model and rolled it out multiple "imagined" steps internally for planning, or MuZero as discussed.

A concrete example pseudocode for training a typical world-model-based RL agent (like Dreamer) is given in Algorithm 1.

This kind of loop alternates between collecting real data, improving the world model, and then improving the policy by using the world model as a simulator (imagining many trajectories cheaply). In practice, systems like Dreamer perform these updates continually, and they include additional nuances like reusing a replay buffer of past data, regularizing the latent space, etc.

C. Video Generation as World Models

Interestingly, another strand of research on world models comes from unsupervised video prediction/generation. A model that can generate plausible future frames of a video given past frames is, in a sense, a world model – it simulates what might happen next visually.

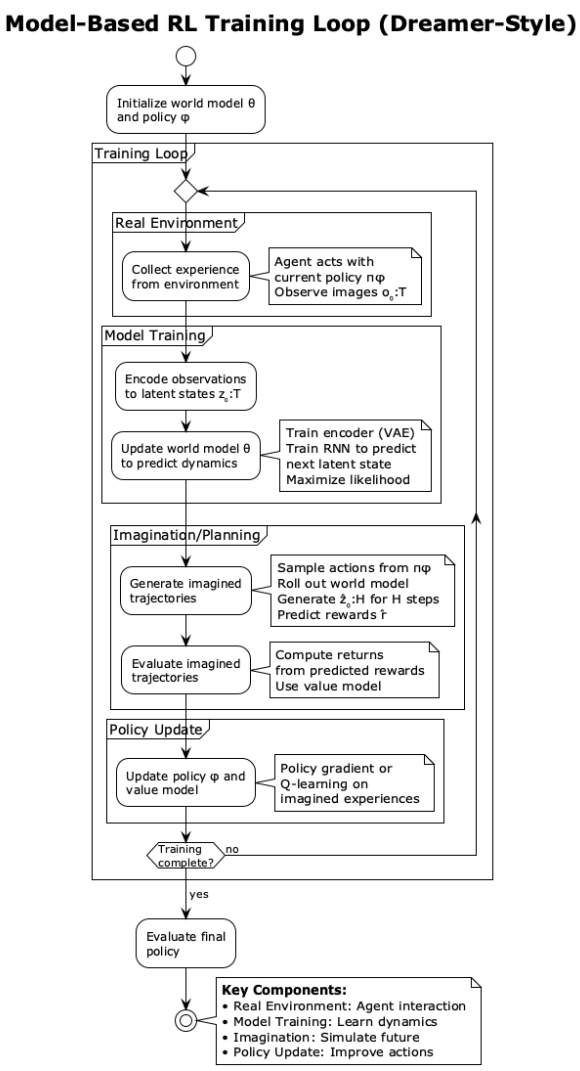

Fig. 6. *Model-based reinforcement learning loop showing how real environment interactions are used to train a world model, which then generates imagined trajectories for policy optimization, enabling sample-efficient learning.*

Recently, extremely large generative models have been trained on video data:

In 2024, OpenAI's SORA model [26] was unveiled as a diffusion model trained on a massive dataset of videos, capable of generating up to a minute-long videos with coherent temporal dynamics. The technical report titled "Video Generation Models as World Simulators" [26] positions such models as stepping stones to general world models. SORA compresses video into latents and uses a transformer-based diffusion in latent space, conditioned on text, to generate video. The fact that SORA can generate a video where, say, a painter's brushstrokes accumulate on a canvas or a person takes a bite of a burger and the burger has a missing piece, indicates it has learned some physical and temporal consistency (examples given in the technical report) – essentially understanding and predicting the results of actions. These are simple examples

Algorithm 1 Simplified model-based RL with a learned world model (e.g., Dreamer-style)

Initialize parameters for world model f_θ and policy π_ϕ
for episode = 1 **to** N **do**
  Collect experience from the environment: observe sequence of images $o_{0:T}$ by acting with current policy π_ϕ
  Encode observations o into latent states (e.g. via encoder E); let $z_{0:T}$ be those encodings.
  Update world model θ by maximizing likelihood of the observed sequence $z_{0:T}$ and rewards $r_{0:T}$ (if applicable).
  # (e.g., train VAE on images, train RNN dynamics to predict z_{t+1}, etc.)
  # World model can generate predictions $\hat{z}, \hat{r}$ for hypothetical action sequences.
  Imagine trajectories in latent space using f_θ: for each of several rollouts, sample actions from current policy and generate latent sequence $\hat{z}_{0:H}$ forward H steps.
  Evaluate returns of imagined trajectories (using predicted rewards $\hat{r}$ or a learned value model).
  Update policy π_ϕ (and value model if used) using imagined trajectory data to improve expected return.
  # (e.g., policy gradient or Q-learning on imagined experiences)
end for

of "understanding the result of an action," which align with the goals of world modeling.

Academic research surveys [2] have begun calling these large video models "general world models", as they encompass knowledge of physics and causality in videos. They highlight that scaling up video models (with transformers and huge training sets) yields emergent abilities like basic physical common sense [2]. If you prompt such a model with "a ball is dropped, what happens next?", it can visually show the ball falling and bouncing – effectively simulating a physical outcome.

These video models differ from the RL-focused world models in that they are not necessarily agent-centric (often they predict dynamics passively for whatever is in the video) and they might not have an explicit notion of actions. However, they can often be conditioned on actions or controlled to simulate different outcomes. For example, research on conditional video prediction allows inputting an action (like a driving command) and the model predicts the video of what would happen if that action is taken.

There's also intersection with robotics: models like Gato [27] and PaLM-E [10] incorporate visual perception and language with some form of world understanding. Gato is a "generalist agent" trained on image, text, and robotic data, which can output either language or control signals. While not exactly a world model by itself, Gato's single neural network can play Atari games (requiring learning game dynamics), caption images, and control a real robot arm, showing that

a large model can implicitly learn to model many worlds (simulated and real) in a unified way.

The evolution of world models is moving toward more general and scalable systems:

- Early world models were task-specific and small-scale (like modeling one video game).
- Current research is on general world models that capture broad aspects of the physical world (as seen in video datasets) [2].
- Incorporating multi-modal inputs (vision, language, proprioception) into world models is an active area. For instance, an embodied world model might take in not only images but also text instructions and output predicted future sensor readings [1].

Another frontier is differentiable simulators that blend learned components with known physics. For example, one could have a neural network for the parts of the world that are hard to model (like complex fluid dynamics or contact properties) while using analytical equations for parts that are known. Some works use Graph Neural Networks to learn physical interactions (e.g. how objects collide or joints articulate), effectively learning a physics engine from data.

D. Reality Capture: Grounding World Models in Real Environments

A critical but often overlooked component in the world modeling pipeline is reality capture—the process of digitizing real-world environments into 3D representations that can inform and validate world models. While learned models can simulate dynamics from training data, grounding these models in accurate geometric and visual representations of actual spaces is essential for robotics, autonomous vehicles, and spatial AI applications.

Neural Radiance Fields (NeRF): In 2020, Mildenhall et al. introduced Neural Radiance Fields (NeRF), revolutionizing 3D scene reconstruction [28]. NeRF represents scenes as continuous volumetric radiance fields encoded by multilayer perceptrons (MLPs). Given a set of posed 2D images, NeRF learns to synthesize novel views by predicting color and density at any 3D coordinate. This implicit representation enables photorealistic view synthesis and has been adopted widely for digitizing real environments. However, NeRF's rendering is computationally expensive, requiring numerous network evaluations per pixel, limiting real-time applications.

3D Gaussian Splatting: At SIGGRAPH 2023, Kerbl et al. presented 3D Gaussian Splatting, achieving a breakthrough in real-time neural rendering [29]. Unlike NeRF's implicit representation, Gaussian Splatting uses an explicit representation of 3D scenes as collections of anisotropic 3D Gaussians. The method achieves real-time rendering at $\geq$100 fps at 1080p resolution while maintaining high visual quality. The approach performs interleaved optimization and density control of Gaussian properties (position, covariance, opacity, color) and uses a fast, differentiable rasterization pipeline for rendering. This dramatic speedup—orders of magnitude faster than NeRF—has made Gaussian Splatting the dominant technique for novel view synthesis as of 2024-2025, with adoption in gaming, VR/AR, and robotics applications.

Segment Anything 2 (SAM 2): Meta AI's Segment Anything Model 2, released in July 2024, provides foundational capabilities for object segmentation and tracking across images and videos [30]. SAM 2 extends the promptable segmentation paradigm to video, maintaining temporal consistency through a memory mechanism that tracks objects across frames, even when temporarily occluded. The model achieves 44 fps real-time performance and is 6x faster than its predecessor while improving accuracy. SAM 2 was trained on the SA-V dataset (51,000 videos, 600,000+ masklets), making it the largest video segmentation dataset to date. For world modeling, SAM 2 enables semantic understanding of dynamic scenes—identifying, tracking, and segmenting objects as they move and interact, providing the object-centric representations that many world models require. Rumors of SAM 3 suggest continued evolution toward even more capable zero-shot scene understanding.

Reality Capture for Embodied AI: These technologies converge to enable comprehensive scene understanding for embodied systems. Google Maps uses NeRF-based techniques to transform street imagery into immersive 3D views. Bentley Systems' iTwin Capture employs neural reconstruction for engineering and infrastructure analysis. For robotics, reality capture provides ground truth environments where learned world models can be validated—does the model's predicted geometry match the captured scene? Can the robot navigate using both its learned dynamics and the reconstructed spatial map? Companies like NVIDIA have integrated reality capture into Isaac Sim, allowing real scanned environments to serve as training grounds for robot policies. As reality capture becomes faster (via Gaussian Splatting), more semantic (via SAM 2), and more accessible (smartphone-based capture), the gap between simulated training environments and real deployment narrows, enabling world models grounded in actual physical spaces rather than purely synthetic or imagined ones.

Overall, world models, whether learned as neural nets or engineered as simulators, aim to provide an agent with the ability to predict "if I do X, then Y will happen." This is crucial for planning and safe decision-making. We have seen that at small scales (simple tasks), learned world models coupled with planning can already surpass human performance (e.g., MuZero in Atari). At large scales, generative models are beginning to capture common sense about the physical world, while reality capture techniques ground these models in real environments. The gap between these approaches is closing – one can imagine future AI agents whose world model is a massive generative model, fine-tuned with interactive experience and grounded in captured real-world geometry, that can simulate rich outcomes for arbitrary tasks.

In the next section, we discuss how these world models and simulations are put to use in building advanced embodied AI systems, and how the research ideas transition to real-world applications in industry.

V. Integrating World Models, Simulation, and Embodied Agents

Thus far, we discussed simulation environments and world modeling largely in isolation. Modern embodied AI systems often integrate both: they train in simulation, learn world models from data, and then deploy in real-world or complex scenarios. We now illustrate these integrations with examples and highlight interfaces to industry and practical deployments.

A. Robotics: Learning to Act in the Real World

Consider a robot that must perform tasks in a home (e.g., fetch objects, clean up, interact with appliances). Building such a robot touches on all our topics:

- It can benefit from simulation during development (to practice navigation or manipulation in virtual homes without risking damage).
- It may employ a learned world model for planning (to predict, for instance, how objects move when pushed or what it will see if it turns around).
- It is an embodied system requiring the combination of vision, language (if following human instructions), and physical action.

Google's Robotics Transformer Series: Google's Everyday Robots project (later integrated into Google DeepMind) represents one of the most ambitious efforts to bridge foundation models with physical robot control. The project deployed a fleet of over 100 mobile manipulator robots in Google's offices, collecting real-world interaction data at unprecedented scale.

RT-1 (Robotics Transformer, Brohan et al., 2022) marked a breakthrough by training a single vision-language-action model on 130,000 robot demonstrations across 700+ tasks [31]. Unlike traditional task-specific policies, RT-1 showed emergent generalization: a robot trained on various pick-and-place tasks could handle novel objects and instructions it had never seen. The model architecture treats robot actions as tokens, similar to how language models treat words, enabling the use of Transformer networks—the same architecture powering GPT and other large language models.

RT-2 [9] took this further by co-fine-tuning a vision-language model (PaLI-X, trained on web data) to also output robot actions. This approach transfers internet-scale knowledge directly to robot control. For instance, RT-2 could successfully respond to commands like "move the extinct animal" (correctly identifying toy dinosaurs) without explicit training on that task, leveraging its understanding from web data. The model achieved 3x better generalization on novel scenarios compared to RT-1, demonstrating how pre-training on diverse internet data provides robots with common-sense reasoning abilities.

The evolution continued with RT-X, a project aggregating robotics data from 22 institutions, creating the Open X-Embodiment dataset with data from 34 different robot types. This represents a paradigm shift toward treating robotics like other foundation model domains: large, diverse datasets enabling models that work across different robot morphologies and tasks.

PaLM-E and Multimodal Integration: PaLM-E [10] represents Google's effort to create truly multimodal embodied agents. By extending the 540B-parameter PaLM language model with continuous sensor observations (images, robot state, sensor readings), PaLM-E can reason about both language tasks and physical manipulation. The model can process commands like "bring me the rice from the drawer in the kitchen," decompose them into sub-goals, and generate low-level robot actions—all while maintaining conversational ability.

Critically, PaLM-E demonstrated that scaling helps: the 562B parameter version significantly outperformed smaller variants, suggesting that emergent capabilities in language models transfer to embodied reasoning. The model could handle long-horizon tasks requiring dozens of steps, maintaining context and adapting to unexpected situations (like objects being moved mid-task).

Google's Simulation Strategy: Google's robotics work heavily leverages simulation, but with a data-centric approach. Rather than training policies entirely in simulation, Google uses simulators primarily for: (1) generating synthetic demonstration data to augment real robot experience, (2) testing policies in diverse scenarios before real-world deployment, and (3) discovering edge cases through adversarial simulation. Their use of domain randomization in simulation, combined with massive real-world data collection, exemplifies the commercial-academic synthesis: techniques developed in academia (domain randomization, Transformer architectures) deployed at industrial scale with proprietary data and computing resources.

Still, classical approaches haven't disappeared. For instance, in autonomous driving, companies use a combination of analytical world models (like motion models for vehicles, maps of road geometry) and learned components (like neural networks for perception and planning refinements). The industry uses simulation (e.g. Waymo's Carcraft, Tesla's simulation, CARLA in academia) heavily to test driving agents, but also builds explicit predictive models (like predicting trajectories of other cars, which can be done via learned models).

B. Mixed Reality and Digital Twins

Industry applications sometimes involve digital twin simulations, where a live model of a physical system is maintained. For example, in manufacturing, an entire factory might be simulated in software (NVIDIA Omniverse is used in some cases for this). The simulation can run faster-than-real-time to predict bottlenecks or detect anomalies. The line between simulation and world modeling blurs here: the digital twin is an explicit world model (mostly manual/engineering-based) of a specific real environment.

Robotics companies use simulation for training, but also increasingly for continuous integration: any time they tweak their robot's software, they run a battery of simulated tests overnight to ensure nothing breaks (like "unit tests" for robot

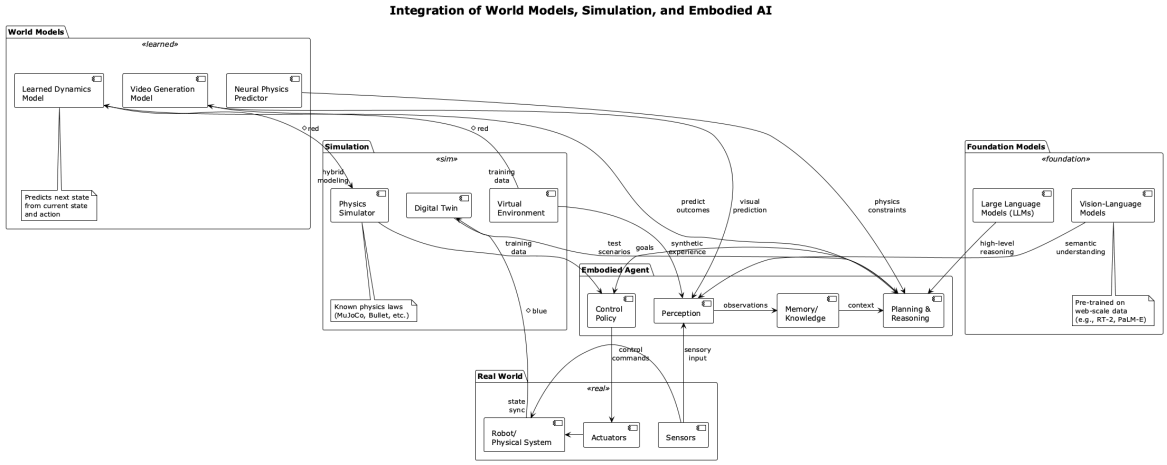

Fig. 7. *Integration of world models, simulation, and embodied AI systems showing how components work together: simulated training environments, learned world models for planning, vision-language models for reasoning, and deployment to real-world robots.*

behaviors). This is akin to how self-driving car firms test new code on thousands of simulated scenarios for regression testing.

In AR/VR (augmented/virtual reality) and gaming, simulated worlds are the product itself. AI is used inside these worlds (for NPC behavior, for example), and techniques like world modeling can allow NPCs to plan ahead or adapt (imagine an NPC with an internal model of the game world, planning several moves ahead like MuZero). Game companies are exploring such ideas to create more realistic and challenging opponents.

C. Multi-Agent and Social Simulation

Another facet is simulation of not just physics but social or multi-agent environments. For example, "learning in games" often uses multi-agent simulations (like AlphaStar in StarCraft II) – essentially these are world models with multiple embodied agents interacting. AlphaStar's training involved having agents play against each other millions of times in the StarCraft simulator, as well as using neural networks that predict the game state and opponent behavior; this was an instance where a commercial game simulator (StarCraft II) was repurposed as a training ground for reinforcement learning, and the resulting AI achieved grandmaster level play[32].

There's also research in agent-based simulations of social behavior, where many agents with learned policies interact (e.g., to model pedestrian movement, traffic, economics). These use world models implicitly as each agent might predict others' moves. It's not our focus here, but it shows how simulation and modeling are key even outside robotics – from games to urban planning.

D. Interfaces: From Research to Industry

Open-source projects have played a large role in transferring simulation and world model tech to industry:

- OpenAI Gym [21] standardized how environments are defined and interacted with. This made it easy for anyone (including industrial teams) to benchmark algorithms or to create custom environments. Many industry teams still use Gym or its variants (like the newer Gymnasium) to structure their simulation tasks.
- ROS + Gazebo: In robotics, ROS is widely used in industry (from robotics startups to large companies) and Gazebo, being the default ROS simulator, often provided companies a readily available testing environment for their robots.
- PyBullet (Bullet's Python wrapper) is popular for quick prototyping of robotics algorithms in industry because it's free and easy to use.
- CARLA has been used beyond academia; some autonomous vehicle startups use it to test certain modules or as a source of synthetic data.
- Unity and Unreal: These engines are industry tools for game development but have seen cross-over. For instance, Microsoft's AirSim is built on Unreal and targeted both researchers and industry. Unity's ML-Agents toolkit made it simple for game developers to experiment with AI and for researchers to use Unity's rich assets.

Industry also pushes research: for example, Tesla built a custom simulation (and also uses techniques like Neural Radiance Fields (NeRFs) to reconstruct environments from video). NeRF is an interesting emerging method: it learns a neural 3D representation of a scene from images, which can then be used as a kind of world model for rendering new views or simulating sensors. This kind of learned simulator may become part of the toolkit for creating virtual worlds from real data.

We also see specialized simulators in areas like warehouse automation (where you simulate hundreds of robots moving in a warehouse to optimize coordination, c.f. Wurman et al. 2008[33] for an early example from Amazon Robotics). That work by Kiva Systems effectively used discrete-event

simulation to design algorithms for coordinating robots, an early example of industry using simulation to revolutionize logistics.

E. Emerging Trends in Systems

Several new system paradigms are arising:

- **Embodied agents with memory and internet access**: Agents like say a virtual home assistant might have a simulation of the household (a learned or programmed model of where things are and how they behave) to help plan long-term. They might constantly update this model as they observe changes (like a mental model of the house).
- **World-model-as-a-service**: One can imagine APIs where an AI agent queries a world model for outcomes. For example, an LLM might call on a physics simulator plugin when asked a question about "what if I do X". This kind of modular integration is being explored (tools for LLMs that use simulations).
- **Neurosymbolic combinations**: A world model could be partly neural (for raw perception predictions) and partly symbolic (for high-level reasoning, constraints). For instance, an agent could use a neural net to imagine visual outcomes but a symbolic planner to choose optimal sequences.

Large companies are unifying simulation and reality with cloud services. Microsoft's Project Bonsai, for instance, integrates simulations to train industrial control agents. Amazon's RoboMaker provided simulation as a cloud service for robotics testing. These indicate the commercial importance of simulation in deploying AI solutions.

F. 2025: Breakthrough Year for Embodied AI

The field experienced remarkable acceleration in 2025, with multiple organizations announcing systems that bring together world modeling, foundation models, and physical embodiment at unprecedented scale.

Google DeepMind's Gemini Robotics: In early 2025, Google DeepMind unveiled Gemini Robotics, a vision-language-action (VLA) model built on Gemini 2.0 that directly controls robots, alongside Gemini Robotics-ER (embodied reasoning) focused on spatial understanding [34]. Gemini Robotics 1.5 represents their most capable VLA model to date, featuring transparent reasoning that allows robots to "think before acting" and show their decision process. This transparency addresses a long-standing challenge in deploying AI in physical systems where understanding failure modes is critical for safety.

DeepMind announced partnerships with leading humanoid robotics companies including Apptronik, Agile Robotics, Agility Robotics, Boston Dynamics, and Enchanted Tools. Most notably, their collaboration with Apptronik aims to integrate Gemini as the core intelligence for next-generation humanoid robots, suggesting that foundation models are transitioning from research demonstrations to commercial deployment.

Perhaps most significantly, Google DeepMind formed a new team led by Tim Brooks (formerly co-lead of OpenAI's Sora) dedicated to building "massive generative models that simulate the world." This team is developing real-time interactive generation tools and studying integration with existing multimodal models like Gemini, marking a major industrial commitment to general world simulators.

OpenAI Sora 2 and Video World Models: OpenAI released Sora 2 in 2025, which the team characterized as reaching "a GPT-3.5 moment for video" [35]. Sora 2 demonstrates substantially improved physics understanding compared to its predecessor—when generating a basketball player shooting, if the shot is off, the system respects physics and shows the ball rebounding off the backboard rather than artificially guiding it into the net. This emergent property of respecting physical laws was not explicitly programmed but arose from scaling.

Technical improvements in Sora 2 stem from its diffusion transformer (DiT) architecture, which processes the entire spacetime continuum simultaneously rather than generating frames sequentially. This approach inherently maintains consistency and coherence, enabling properties like object permanence and nascent physics understanding without explicit 3D or object inductive biases. However, research suggests that while scaling improves performance, these models may still exhibit "case-based" generalization—mimicking closest training examples—rather than learning fundamental physical laws from first principles.

NVIDIA Isaac GR00T and Newton: NVIDIA made several major announcements in 2025 for robotics simulation and humanoid robot development [36]. Isaac GR00T N1, followed by the enhanced N1.5, represents "the world's first open, fully customizable foundation model for generalized humanoid reasoning and skills." The N1.5 version significantly improves adaptability and instruction-following for material handling and manufacturing tasks.

Supporting these models, NVIDIA introduced the Newton Physics Engine, an open-source GPU-accelerated simulator co-developed with Google DeepMind and Disney Research specifically designed for humanoid robot simulation. The collaboration extends to MuJoCo-Warp, which accelerates robotics machine learning workloads by more than 70x. Using the Isaac GR00T Blueprint, NVIDIA demonstrated generating 780,000 synthetic trajectories—equivalent to 6,500 hours of human demonstrations—in just 11 hours. Combining synthetic data with real data improved GR00T N1's performance by 40%, validating simulation-based training at industrial scale.

Tesla Optimus Reality Check: Tesla announced ambitious production targets for 2025: producing 5,000 to 12,000 Optimus robots for internal factory use, with plans to scale to 50,000 units in 2026 and ultimately 1 million units per year by late 2026. The Optimus Gen 2 prototype showed impressive improvements: 30% faster walking, 10kg weight reduction, and new hands with 11 degrees of freedom plus tactile sensing.

However, independent reporting suggests production remains in the hundreds rather than thousands, with robots operating reliably only in structured, controlled environments.

The June 2025 leadership change—Milan Kovac departing and being replaced by Ashok Elluswamy from the Autopilot team—hints at challenges in scaling. Additionally, China's export restrictions on rare earth metals threaten production of Optimus units, which rely on rare earth magnets for movement and manipulation. This highlights a reality of 2025: while technical capabilities are advancing rapidly, industrial-scale deployment faces significant non-technical barriers.

Physical Intelligence and Open Collaboration: In November 2024 (continuing into 2025), OpenAI invested in Physical Intelligence, a startup focused on bringing general-purpose AI to the physical world through large-scale models and algorithms for robots [37]. Physical Intelligence released the Pi0 model as open source, contributing to a growing ecosystem of accessible foundation models for robotics.

The Open X-Embodiment dataset expanded significantly, now aggregating data from 22 institutions across 34 different robot types. This collaborative approach demonstrates 50% performance improvements when training on diverse robot data versus single-embodiment approaches, suggesting the field is approaching a "ChatGPT moment" where broad commercial viability emerges from open collaboration and data sharing.

VERSES AI Genius: Active Inference World Modeling: While most 2025 advances rely on transformer-based architectures, VERSES AI introduced a fundamentally different approach with Genius, their agentic enterprise intelligence platform commercially launched in April 2025 [38]. Genius is built on active inference and causal modeling—principles derived from neuroscience and the free energy principle—rather than statistical pattern matching.

VERSES earned recognition from Gartner's 2025 Emerging Tech Impact Radar for Spatial AI, specifically named as a sample vendor in World Models. Their AXIOM architecture learns by recognizing real-world objects and causal relationships rather than memorizing pixel patterns, using modular components that mirror distinct cognitive functions: vision, memory, prediction, reasoning, and planning.

Real-world deployments demonstrate Genius's capabilities: a smart cities mobility pilot achieved a 32% increase in completed rides, and the platform developed active inference causal models for financial portfolio optimization in partnership with a major global investment firm. This alternative approach suggests multiple pathways may lead to effective world modeling—statistical learning from massive data versus principled causal reasoning from first principles.

NVIDIA Cosmos and World Foundation Models: At CES 2025, NVIDIA CEO Jensen Huang announced Cosmos, a platform for world foundation models that produces virtual-world-like videos. Combined with World Labs (founded by AI pioneer Fei-Fei Li, which achieved unicorn status within four months) [39], the industry is converging on the vision of general world simulators that can create interactive media and run realistic training environments for robots.

The 2025 developments mark a transition point: world modeling and embodied AI are moving from research demonstrations to industrial deployment, with diverse technical approaches competing. Transformer-based models (Google, OpenAI, NVIDIA) scale through massive compute and data, while active inference approaches (VERSES) emphasize principled causal reasoning. Significant challenges in reliability, safety, scaling, and supply chains remain to be solved across all paradigms.

We now turn to the future: what can we expect in the coming years as these technologies evolve and converge?

VI. Future Directions and Speculations

The rapid progress in world modeling, simulation, and embodied AI suggests several trends that are likely to shape the future.

1. Differentiable and Learned Simulation: We already see steps toward making simulators differentiable (e.g., Brax by Google is a physics engine that is end-to-end differentiable and runs on accelerators). This means one can directly optimize parameters through simulation outcomes, or even embed the simulator inside a learning loop. Differentiable simulations combined with neural networks could allow learning parts of physics that are hard to model (like fluid dynamics, contact friction) by fitting them to real data, essentially blending first-principles and learned models. Moreover, differentiable simulators can aid in system identification (learning exact environment parameters) and even in planning (by backpropagating through possible action sequences, as with trajectory optimization methods).

2. Scale and Generality of World Models: On the world model front, one speculation is that models like OpenAI's SORA represent the beginning of general world simulators. Imagine training a single model on diverse videos, robot interaction data, and text describing physics – it might become a general predictive model that can answer "what if" for a wide range of domains. Early surveys [2] suggest that leveraging video generation advances and multimodal training is a promising path. Future world models might incorporate not just vision but also audio (predicting sound), and maybe even tactile or other sensor modalities, providing a holistic prediction of the future state.

3. Long Horizon and Memory: A challenge for current world models is limited memory – RNNs and transformers have finite context windows. Truly embodied AI will need to maintain an understanding of the world over long periods (hours, days) and learn from lifetime experience. We might see world models augmented with external memory (databases of facts or maps that are updated). For example, a home robot should build a persistent map (a classic SLAM outcome) – integrating such mapping with learned world models is fertile ground. Perhaps the world model provides the predictions, while a symbolic memory stores stable facts (like layout of the environment, locations of objects).

4. Safety and Causal Reasoning: As agents rely more on learned world models, ensuring they adhere to physical laws and safety constraints is vital. There is interest in causal world models – models that understand cause and effect, not

just correlations. This could make them more robust when encountering novel situations (extrapolating better by knowing underlying physics, not just patterns). Also, verifiable or unit-tested simulations might be required in high-stakes scenarios (like verifying that an autonomous car's learned model respects the invariant that two solid objects cannot occupy the same space, etc.). Combining neural and symbolic approaches might yield models that are both expressive and rule-abiding.

5. Human-in-the-loop Simulation: Future simulation platforms may integrate humans as part of the environment (for example, simulating realistic human-robot interaction). This includes better models of human behavior. Gaming and VR tech may provide photo-real avatars and behavior models to simulate crowds, customers in a store, or a person working alongside a robot. Embodied AI that needs to collaborate with humans (e.g., assistive robots) could be trained in such mixed simulations to anticipate human actions and learn social norms.

6. Industry Uptake and Standardization: We expect industry will further embrace these technologies:

- Standard simulator scenarios might be part of regulation (e.g., self-driving cars might need to pass defined simulation suites akin to crash tests).
- Simulated data will likely be used even more to pre-train models. We already see synthetic images used for training vision models; similarly, simulated tactile or auditory data might pre-train those modalities.
- Open standards for environments (like the emerging OpenXR for AR/VR) might extend to embodied simulations, making it easier to move an agent from one sim platform to another or to incorporate multiple simulators in a loop (for different scales or aspects of the environment).

7. Toward Embodied AGI: A speculative but exciting direction is the combination of large language models (LLMs) with embodied experience. A recent NeurIPS 2024 paper by Xiang et al. suggests that giving language models embodied experiences (training them in simulators) can enhance their understanding and reasoning [40]. This hints that an AI which both learns from text and by interacting in the world could gain more human-like intelligence. The gap between conversational AI and robotics may shrink: a future household assistant might use an LLM for dialogue and knowledge, but also maintain a world model to plan physical actions, with both components working together seamlessly.

8. Planetary-Scale Simulations and Digital Worlds: On a grander scale, projects like virtual replicas of entire cities (for autonomous driving or urban planning) and even the Earth's climate system (for climate science) are essentially enormous simulations. AI will both help build these (e.g., learning to fill in details or speed up calculations) and use them (agents learning to manage traffic lights city-wide, or to optimize energy usage). There's a cross-pollination between these fields and embodied AI – a self-driving car agent in simulation is participating in a city traffic simulation, overlapping with operations research and networked system control.

In conclusion, the trajectory is pointing toward AI agents that have:

- Embodied presence: either in reality or high-fidelity virtual worlds,
- Simulation support: being able to safely explore hypotheticals,
- Internal world models: to predict and plan with imagination,
- Integration with knowledge: using abstract knowledge (from language or code) together with sensory experience.

Realizing this vision will likely require overcoming current limitations in generalization, scaling, and safety. But the progress of the past decade, from robots that barely navigate a room to ones that can use vision-language models to reason about tasks [1], fueled by simulation and learned models, gives cause for optimism.

VII. Conclusion

We have explored the landscape of world modeling, simulation, and embodied intelligence, covering the key developments and how they feed into one another. From physics engines like MuJoCo and Bullet that simulate bodies and contacts, to platforms like Habitat and CARLA that provide rich virtual environments, simulation technology has enabled AI systems to train and be evaluated more rigorously than ever before. In parallel, learned world models – powered by deep learning – have given agents the ability to predict and imagine outcomes far beyond their immediate sensory horizon, improving their decision-making and data efficiency.

Embodied intelligence serves as the unifying context: the pursuit of AI that can understand and operate in the real world. The systems we discussed show multiple ways of tackling this – some rely more on scaling up learning (large models absorbing internet-scale data), others on carefully constructing simulations and models to inject prior knowledge. The most successful approaches tend to merge these extremes: for instance, using a simulation (with known physics) but learning any aspects that are unknown or too complex to model; or using a pretrained foundation model (with lots of prior knowledge) and fine-tuning it for the embodied task at hand.

For practitioners, the modular book-style structure of this paper hopefully provides a reference:

- If you need to pick a simulator for a project, Section III gives an overview of options and considerations.
- If you are wondering how to incorporate learning into your robotics pipeline, Section IV shows what learning a world model can do and how to approach it.
- If you aim to build a complex system (like a home assistant robot or an autonomous vehicle), Section V indicates how industry and research are marrying the pieces together.

The references cited serve as a gateway to the seminal work in each area, and we took care to ensure they are valid and

accessible (with URLs where possible). They include classic foundational papers [3], important surveys [1][2], and cutting-edge results [26][9], reflecting the depth and evolution of the field.

As AI moves forward, the boundary between "virtual" and "real" is likely to blur. Robots act in the real world using policies trained in virtual ones; AI agents in virtual worlds are starting to exhibit behaviors (and misbehaviors) we once only saw in reality. World models inside these agents make the virtual more real by injecting understanding of physics and causality; conversely, simulations make the real more accessible by translating it into a sandbox where AI can practice. The interplay of these elements is accelerating progress towards more competent, safer, and more general AI.

The journey is far from over, but with the synergy of simulation and world modeling, embodied intelligence is inching ever closer to science fiction visions – machines that truly understand the worlds they inhabit, because they can model them, explore them in simulation, and live in them for real.

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