
Understanding World or Predicting Future? A Comprehensive Survey of World Models

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Abstract

The concept of world models has garnered significant attention due to advancements in multimodal large language models such as GPT-4 and video generation models such as Sora, which are central to the pursuit of artificial general intelligence. This survey offers a comprehensive review of the literature on world models. Generally, world models are regarded as tools for either understanding the present state of the world or predicting its future dynamics. This review presents a systematic categorization of world models, emphasizing two primary functions: (1) constructing internal representations to understand the mechanisms of the world, and (2) predicting future states to simulate and guide decision-making. Initially, we examine the current progress in these two categories. We then explore the application of world models in key domains, including autonomous driving, robotics, and social simulacra, with a focus on how each domain utilizes these aspects. Finally, we outline key challenges and provide insights into potential future research directions.

1 Introduction

The scientific community has long aspired to develop a unified model that can replicate its fundamental dynamics of the world in pursuit of Artificial General Intelligence (AGI) [98]. In 2024, the emergence of multimodal large language models (LLMs) and Sora [130] have intensified discussions surrounding such **World Models**. While these models demonstrate an emerging capacity to capture aspects of world knowledge — such as Sora’s generated videos, which appear to perfectly adhere to physical laws — questions persist regarding whether they truly qualify as comprehensive world models. Therefore, a systematic review of recent advancements, applications, and future directions in world model research is both timely and essential as we look toward new breakthroughs in the era of artificial intelligence.

The definition of a world model remains a subject of ongoing debate, generally divided into two primary perspectives: *understanding the world* and *predicting the future*. As depicted in Figure 1, early work by Ha and Schmidhuber [59] focused on abstracting the external world to gain a deep understanding of its underlying mechanisms. In contrast, LeCun [98] argued that a world model should not only perceive and model the real world but also possess the capacity to envision possible future states to inform decision-making. Video generation models such as Sora represent an approach that concentrates on simulating future world evolution and thus align more closely with the predictive aspect of world models. This raises the question of whether a world model should prioritize understanding the present or forecasting future states. In this paper, we provide a comprehensive review of the literature from both perspectives, highlighting key approaches and challenges.

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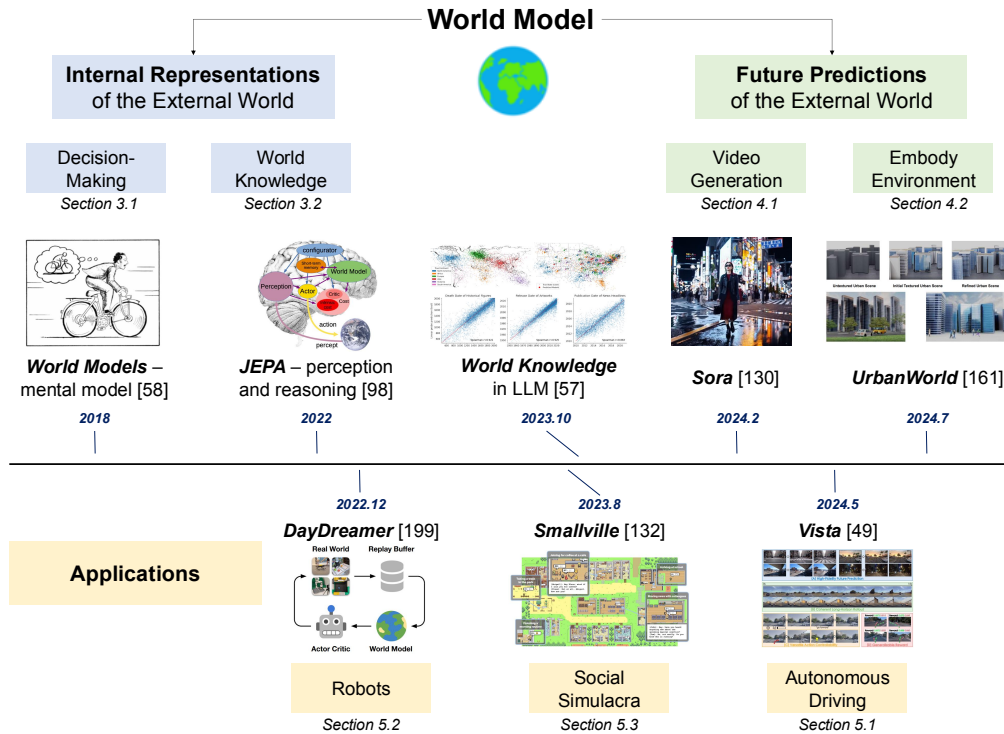


Figure 1: The overall framework of this survey. We systematically define the essential purpose of a world model as understanding the dynamics of the external world and predicting future scenarios. The timeline illustrates the development of key definitions and applications.

The potential applications of world models span a wide array of fields, each with distinct requirements for understanding and predictive capabilities. In autonomous driving, for example, world models need to perceive road conditions in real-time [195, 177] and accurately predict their evolution [127, 167, 241], with a particular focus on immediate environmental awareness and forecasting of complex trends. For robotics, world models are essential for tasks such as navigation [160], object detection [183], and task planning [62], requiring a precise understanding of external dynamics [47] and the ability to generate interactive and embodied environments [132]. In the realm of simulation of virtual social systems, world models must capture and predict more abstract behavioral dynamics, such as social interactions and human decision-making processes. Thus, a comprehensive review of advancements in these capabilities, alongside an exploration of future research directions and trends, is both timely and essential.

Existing surveys on world models can generally be classified into two categories, as shown in Table 1. The first category primarily focuses on describing the application of world models in specific fields such as video processing and generation [23, 242], autonomous driving [54, 100, 209], and agent-based applications [242]. The second category [116] concentrates on the technological transitions from multi-modal models, which are capable of processing data across various modalities, to world models. However, these papers often lack a systematic examination of what precisely constitutes a world model and what different real-world applications require from these models. In this article, we aim to formally define and categorize world models, review recent technical progress, and explore their extensive applications.

The main contributions of this survey can be summarized as follows: (1) We present a novel categorization system for world models structured around two primary functions: *constructing implicit representations to understand the mechanism of the external world* and *predicting future states of the external world*. The first category focuses on the development of models that learn and internalize world knowledge to support subsequent decision-making, while the latter emphasizes enhancing predictive and simulative capabilities in the physical world from visual perceptions. (2) Based on

Table 1: Comparison with existing surveys. This paper focuses on a comprehensive overview of the systematic definition and the capabilities of world models.

Survey	Venue and Year	Main Focus	Deficiency
[242]	Arxiv, 2024	General world model	Limited to discussion on applications
[116]	Arxiv, 2024	Efficient multimodal models	Limited to discussion on techniques
[23]	Arxiv, 2024	Text-to-video generation	Limited scope
[54]	IEEE T-IV, 2024	Autonomous driving	Limited scope
[100]	Arxiv, 2024	Autonomous driving	Limited scope
[209]	Arxiv, 2024	Autonomous driving	Limited scope

this categorization, we classify how various key application areas, including autonomous driving, robots, and social simulacra, emphasize different aspects of world models. (3) We highlight future research directions and trends of world models that can adapt to a broader spectrum of practical applications.

The remainder of this paper is organized as follows. In Section 2, we introduce the background of the world model and propose our categorization system. Section 3 and Section 4 elaborate on the details of current research progress on two categories of world models, respectively. Section 5 covers applications of the world model in three key research fields. Section 6 outlines open problems and future directions of world models.

2 Background and Categorization

In this section, we explore the evolving concepts of world models in the literature and categorize efforts to construct world models into two distinct branches: internal representation and future prediction.

The concept of a world model was first systematically introduced to the artificial intelligence community by Ha *et al.* [58, 59] in 2018. This article traces the origins of the world model concept back to the psychological principles of the "mental model" established in 1971 [43], which proposes that humans abstract the external world into simple elements and their interrelations to perceive it. This principle suggests that our descriptions of the world, when viewed from a deep, internal perspective, typically involve constructing an abstract representation that suffices without requiring detailed depiction. Building upon this conceptual framework, the authors introduce an agent model inspired by the human cognitive system, as illustrated in Figure 1. In this pioneering model, the agent receives feedback from the real-world environment, which is then transformed into a series of inputs that train the model. This model is adept at simulating potential outcomes following specific actions within the external environment. Essentially, it creates a mental simulation of potential future world evolutions, with decisions made based on the predicted outcomes of these states. This methodology closely mirrors the Model-based Reinforcement Learning (MBRL) method, where both strategies involve the model generating internal representations of the external world. These representations facilitate navigation through and resolution of various decision-making tasks in the real world.

In the visionary article on the development of autonomous machine intelligence in 2022 [98], Yann LeCun introduced the Joint Embedding Predictive Architecture (JEPA), a framework mirroring the human brain’s structure. As illustrated in Figure 1, JEPA comprises a perception module that processes sensory data, followed by a cognitive module that evaluates this information, effectively embodying the world model. This model allows the brain to assess actions and determine the most suitable responses for real-world applications. LeCun’s framework is intriguing due to its incorporation of the dual-system concept, mirroring "fast" and "slow" thinking. System 1 involves intuitive, instinctive reactions: quick decisions made without a world model, such as instinctively dodging an oncoming person. In contrast, System 2 employs deliberate, calculated reasoning that considers the future state of the world. It extends beyond immediate sensory input, simulating potential future scenarios, like predicting events in a room over the next ten minutes and adjusting actions accordingly. This level of foresight requires constructing a world model to effectively guide decisions based on the anticipated dynamics and evolution of the environment. In this framework, the world model is essential for understanding and representing the external world. It models the state of the

world using latent variables, which capture key information while filtering out redundancies. This approach allows for a highly efficient, minimalistic representation of the world, facilitating optimal decision-making and planning for future scenarios.

The ability of models to capture world knowledge is critical for their effective performance in a wide range of real-world tasks. In the recent wave of works on large language models starting from 2023, several have demonstrated the presence of latent world knowledge. In other words, these models capture intuitive knowledge, including spatial and temporal understanding, which enables them to make predictions about real-world scenarios [57, 119]. Furthermore, LLMs are capable of modeling the external world through cognitive maps, as indicated by recent research revealing the brain-like structures embedded within them [104]. These models can even learn to predict future events based on prior experiences, thereby enhancing their utility and applicability in real-world contexts.

The above world models primarily represent an implicit understanding of the external world. However, in February 2024, OpenAI introduced Sora model [130], a video generation model that is largely recognized as a world simulator. Sora inputs real-world visual data and outputs video frames predicting future world evolutions. Notably, it demonstrates exceptional modeling capabilities, such as maintaining consistency in 3D video simulations during camera movements and rotations. It can also produce physically plausible outcomes, like leaving a bite mark on a hamburger, and simulate digital environments, exemplified by rendering first-person views in a Minecraft game. These capabilities suggest that Sora not only mimics the appearance of but also models the real-world dynamics within simulation scenarios, focusing on realistically modeling dynamic world changes rather than merely representing static world states.

Whether focusing on learning internal representations of the external world or simulating its operational principles, these concepts coalesce into a shared consensus: the essential purpose of a world model is to understand the dynamics of the world and predict future scenarios. From this perspective, we conduct a thorough examination of recent advancements in world models, analyzing them through following lenses, as depicted in Figure 1.

- **Implicit representation of the external world** (Section 3): This research category constructs a model of environmental change to enable more informed decision-making, ultimately aiming to predict the evolution of future states. It fosters an implicit comprehension by transforming external realities into a model that represents these elements as latent variables. Furthermore, with the advent of large language models (LLMs), efforts previously concentrated on traditional decision-making tasks have been significantly enhanced by the detailed descriptive power of these models regarding world knowledge. We further focus on the integration of world knowledge into existing models.
- **Future predictions of the external world** (Section 4): We initially explore generative models that simulate the external world, primarily using visual video data. These works emphasize the realness of generated videos that mirror future states of the physical world. As recent advancements shift focus toward developing a truly interactive physical world, we further investigate the transition from visual to spatial representations and from video to embodiment. This includes comprehensive coverage of studies related to the generation of embodied environments that mirror the external world.
- **Applications of world models** (Section 5): World models have a wide range of applications across various fields, including autonomous driving, robotics, and social simulacra. We explore how the integration of world models in these domains advances both theoretical research and practical implementations, emphasizing their transformative potential in real-world applications.

3 Implicit Representation of the External World

3.1 World Model in Decision-Making

In decision-making tasks, understanding the environment is the major task in setting a foundation for optimized policy generation. As such, the world model in decision-making should include a comprehensive understanding of the environment. It enables us to take hypothetical actions without affecting the real environment, facilitating a low trial-and-error cost. In literature, research on how to learn and utilize the world model was initially proposed in the field of model-based RL.

Furthermore, recent progress on LLM and MLLM also provide comprehensive backbones for world model construction. With language serving as a more general representation, language-based world models can be adapted to more generalized tasks. The two schemes of leveraging world models in decision-making tasks are shown in Figure 2.

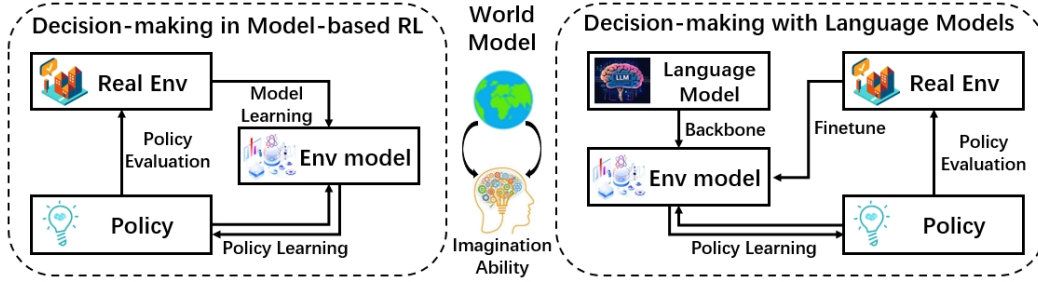


Figure 2: Two schemes of utilizing world model in decision-making.

3.1.1 World model in model-based RL

In decision-making, the concept of the world model largely refers to the environment model in model-based RL (MBRL). A decision-making problem is typically formulated as a Markov Decision Process (MDP), denoted with a tuple (S, A, M, R, γ) , where S, A, γ denotes the state space, action space and the discount factor each. The world model here consists of M , the state transition dynamics and R , the reward function. Since the reward function is defined in most cases, the key task of MBRL is to learn and utilize the transition dynamics, which can further support policy optimization.

World Model Learning To learn an accurate world model, the most straightforward approach is to leverage the mean squared prediction error on each one-step transitions [97, 115, 80, 145, 81],

$$\min_{\theta} \mathbb{E}_{s' \sim M^*(\cdot|s,a)} [\|s' - M_{\theta}(s, a)\|_2^2], \quad (1)$$

where M^* is the real transition dynamics used to collect trajectory data and M_{θ} is the parameterized transition to learn. Apart from directly utilizing the deterministic transition model, Chua et al.[25] further model the aleatoric uncertainty with the probabilistic transition model. The objective is to minimize the KL divergence between the transition models,

$$\min_{\theta} \mathbb{E}_{s' \sim M^*(\cdot|s,a)} [\log(\frac{M^*(s'|s, a)}{M_{\theta}(s'|s, a)})]. \quad (2)$$

In both settings, the phase of the world model learning task can be transformed into a supervised learning task. The learning labels are the trajectories derived from real interaction environments, also called the simulation data [114].

For more complex environments where high-dimensional state space exists, representation learning is widely adopted to improve the effectiveness of world model learning in MBRL. Ha and Schmidhuber[58] adopt an autoencoder structure to reconstruct images via latent states. Hafner et al.[61, 63] propose to learn visual encoder and latent dynamics for visual control tasks, whereas Samsami et al.[153] propose a Recall-to-Imaging framework to further improve memory ability while model learning. Another recent trend is to conduct unified model learning across different tasks [158], which is done by representing the MDP with a next-token-prediction paradigm [81] using transformer architectures. Such a scheme exhibits the potential of obtaining one generalist model for decision models on several tasks with other data modalities.

Policy Generation with World Model With an ideally optimized world model, one most straightforward way to generate a corresponding policy is model predictive control (MPC)[92]. MPC plans an optimized sequence of actions given the model as follows:

$$\max_{a_{t:t+\tau}} \mathbb{E}_{s_{t'+1} \sim p(s_{t'+1}|s_{t'}, a_{t'})} [\sum_{t'=t}^{t+\tau} r(s_{t'}, a_{t'})], \quad (3)$$

where τ denotes the planning horizon. Nagabandi et al.[125] adopts a simple Monte Carlo method to sample action sequences. Rather than sampling actions uniformly, Chua et al.[25] propose a new probabilistic algorithm that ensembles with trajectory sampling. Further literature also improves the optimization efficiency leveraging the world model usage [61, 224, 70, 187].

Another popular approach to generating world model policies is the Monte Carlo Tree Search (MCTS). By maintaining a search tree where each node refers to a state evaluated by a predefined value function, actions will be chosen such that the agent can be processed to a state with a higher value. AlphaGo and AlphaGo Zero are two significant applications using MCTS in discrete action space [169, 170]. Moerland et al. [123] extended MCTS to solve decision problems in continuous action space. Oh et al. [128] proposed a value prediction network that applies MCTS to the learned model to search for actions based on value and reward predictions.

3.1.2 World model with language backbone

The rapid growth of language models, especially LLM and MLLM, benefits development in many related applications. With language serving as a universal representation backbone, language-based world models have shown their potential in many decision-making tasks.

Direct Action Generation via LLM World Models LLM has shown its significant reasoning ability and is capable of directly generating actions in decision-making tasks based on corresponding constructed world models. For example, in the navigation scenarios, Yang et al. [212] transfer pre-trained text-to-video models to domain-specific tasks for robot control, successfully annotating robot manipulation with text instructions as LLM outputs. Zhou et al. [240] further learn a compositional world model by factorizing the video generation process. Such a method enables a strong few-shot transfer ability to unseen tasks.

Besides training or fine-tuning specialized language-based world models, LLMs and MLLMs can be directly deployed to understand the world environment in decision-making tasks. For example, Long et al. [112] propose a multi-expert scheme to handle visual language navigation tasks. They construct a standardized discussion process where eight LLM-based experts participate to generate the final movement decision. An abstract world model is constructed from the discussion and further imagination (of future states) of the experts to support action generation. Zhao et al. [232] further combine LLMs and open-vocabulary detection to construct the relationship between multi-modal signals and key information in navigation. They propose an omni-graph to capture the structure of the local space as the world model for the navigation task. Meanwhile, Yang et al. [217] utilize an LLM-based imaginative assistant to infer the global semantic graph as the world model based on the environment perception, and another reflective planner to directly generate actions.

Modular Usage of LLM World Models Although taking LLM outputs as actions directly is straightforward in application and deployment, the decision quality in such a scheme heavily relies on the reasoning ability of the LLM itself. It can be further improved by integrating LLM-based world models as modules with other effective planning algorithms.

Xiang et al.[203] deploys an embodied agent in a world model, the simulator of VirtualHome [139], where the corresponding embodied knowledge is injected into LLMs. To better plan and complete specific goals, they propose a goal-conditioned planning schema where Monte Carlo Tree Search (MCTS) is utilized to search for the true embodied task goal. Lin et al.[106] introduce an agent, Dynalang, which learns a multimodal world model to predict future text and image representations, and which learns to act from imagined model rollouts. The policy learning stage utilizes an actor-critic algorithm purely based on the previously generated multimodal representations. Liu et al. [111] further cast reasoning in LLMs as learning and planning in Bayesian adaptive Markov decision processes (MDPs). LLMs, like the world model, perform in an in-context manner within the actor-critic updates of MDPs. The proposed RAFA framework shows significantly increased performance in multiple complex reasoning tasks and environments, such as ALFWorld [168].

3.2 World Knowledge Learned by Models

After pretraining on large-scale web text and books [180, 129], large language models attain extensive knowledge about the real world and common sense relevant to daily life. This embedded knowledge is considered crucial for their remarkable ability to generalize and perform effectively in real-world tasks. For instance, researchers leverage the common sense of large language models for

Table 2: Overview of recent works in world knowledge learned by models.

Category	Methods/Model	Year&Venue	Modality	Content
Common Sense & General Knowledge	KoLA [221]	2024 ICLR	Language	Benchmark
	EWOK [77]	2024 arxiv	Language	Benchmark
	Geometry of Concepts [104]	2024 arxiv	Language	Analysis
Knowledge of Global Physical World	Space&Time [57]	2024 ICLR	Language	Analysis
	GeoLLM [119]	2024 ICLR	Language	Learning
	GeoLLM-Bias [118]	2024 ICML	Language	Learning
	GPT4GEO [150]	2023 NeurIPS(FMDM)	Language	Benchmark
	CityGPT [38]	2024 arxiv	Language	Learning
Knowledge of Local Physical World	CityBench [39]	2024 arxiv	Language&Vision	Benchmark
	Predictive [52]	2024 NMI	Vision	Learning
	Emergent [84]	2024 ICML	Language	Learning
	E2WM [203]	2023 NeurIPS	Language	Learning
Knowledge of Human Society	Dynalang [106]	2024 ICML	Language&Vision	Learning
	Testing ToM [174]	2024 NHB	Language	Benchmark
	High-order ToM [175]	2024 arxiv	Language	Benchmark
	COKE [198]	2024 ACL	Language	Learning
	MuMA-ToM [166]	2024 ACL	Language&Vision	Benchmark
SimToM [194]	2024 ACL	Language	Learning	

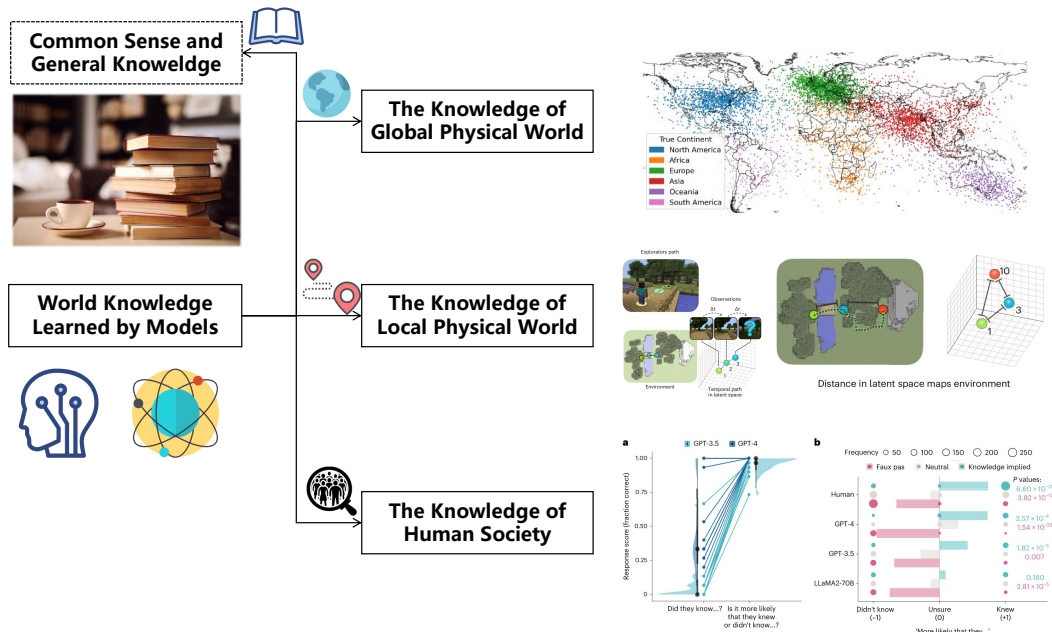


Figure 3: World knowledge in large language models for world model.

task planning [234], robot control [73], and image understanding [110]. Furthermore, Li et al.[104] discover brain-like structures of world knowledge embedded in the high-dimensional vectors that represent the universe of concepts in large language models.

Unlike common sense and general knowledge, we focus on world knowledge within large language models from the perspective of a world model. As shown in Figure 3, based on objects and spatial scope, the world knowledge in the large language models can be categorized into three parts: 1) knowledge of the global physical world; 2) knowledge of the local physical world; and 3) knowledge of human society.

3.2.1 Knowledge of the Global Physical World

We first introduce research focused on analyzing and understanding the knowledge of the global physical world. Gurnee et al. [57] present the first evidence that large language models genuinely acquire spatial and temporal knowledge of the world, rather than merely collecting superficial statistics. They identify distinct "spatial neurons" and "temporal neurons" in LLaMA2 [180], suggesting that the model learns linear representations of space and time across multiple scales. Distinct

from previous observations focused on embedding space, Manvi et al. [119, 118] develop effective prompts about textual address to extract intuitive real-world knowledge about the geospatial space and successfully improve the performance of the model in various downstream geospatial prediction tasks.

While large language models do acquire some implicit knowledge of the real world [57, 104], the quality of this knowledge remains questionable [150, 38]. For example, Feng et al. [38] find that the urban knowledge embedded in large language models is often coarse and inaccurate. To address this, they propose an effective framework to improve the acquisition of urban knowledge of specific cities in large language models. From these works, we can see that although large language models have demonstrated the ability to capture certain aspects of real-world knowledge [57, 104, 150], it is clear that further efforts are needed to enhance this knowledge to enable broader and more reliable real-world applications.

3.2.2 Knowledge of the Local Physical World

Unlike the knowledge of the global physical world, the local physical world represents the primary environment for human daily life and most real-world tasks. Therefore, understanding and modeling the local physical world is a more critical topic for building a comprehensive world model. We first introduce the concept of the cognitive map [179], which illustrates how the human brain models the external world. Although initially developed to explain human learning processes, researchers have discovered similar structures in large language models [104] and have leveraged these insights to enhance the efficiency and performance of artificial models in learning and understanding the physical world.

Recent studies explore actively encouraging models to learn abstract knowledge through cognitive map-like processes across various environments. For example, Cornet et al. [52] demonstrate the effectiveness of learning through spatial cognitive map construction using visual predictive coding in a simplified Minecraft world. After learning, the model can successfully predict the future by knowing the distance. Lin et al. [106] investigate teaching models to understand the game environments through a world model learning procedure, specifically by predicting the subsequent frame of the environment. In this way, the model can generate better actions in dynamic environments. Moreover, Jin et al. [84] find that language models can learn the emergent representations of program semantics by predicting the next token.

3.2.3 Knowledge of the Human Society

Beyond the physical world, understanding human society is another crucial aspect of world models. One such related theory is the Theory of Mind [138], which explains how individuals infer the mental states of others around them. Recent research has extensively explored how large language models develop and demonstrate this social world model. One line of investigation [174, 175] focuses on evaluating the performance of large language models across various Theory of Mind tasks to determine whether their human-like behaviors reflect genuine comprehension of social rule and implicit knowledge. For example, Strachan et al. [174] conduct a comparative analysis between human and LLM performance on diverse Theory of Mind abilities, such as understanding false beliefs and recognizing irony. While their findings demonstrate the potential of GPT-4 in these tasks, they also identify its limitations, particularly in detecting faux pas.

To address these limitations, researchers propose innovative methods to enhance the abilities of large language models in Theory of Mind for complex real-world applications. Wu et al. [198] introduce COKE, which constructs a knowledge graph to help large language models explicitly using theory in mind through cognitive chains. Additionally, Alex et al. [194] develop SimToM, a two-stage prompting framework, to enhance the performance of large language models in theory of mind tasks.

4 Future Prediction of the Physical World

4.1 World Model as Video Generation

The integration of video generation into world models marks a significant leap forward in the field of environment modeling [130]. Traditional world models primarily focused on predicting discrete or

static future states [59, 98]. However, by generating video-like simulations that capture continuous spatial and temporal dynamics, world models [130, 211] have evolved to address more complex, dynamic environments. This breakthrough in video generation has pushed the capabilities of world models to a new level.

4.1.1 Towards Video World Models

A video world model is a computational framework designed to simulate and predict the future state of the world by processing past observations and potential actions within a visual context [130]. This concept builds on the broader idea of world models, which strive to capture the dynamics of an environment and enable machines to predict how the world will evolve over time. In the case of a video world model, the focus is on generating sequences of visual frames that represent these evolving states.

Sora as a World Model. Sora [130], a large-scale video generation model, is a prominent example of a video world model. It is designed to generate high-quality, temporally consistent video sequences, up to one minute long, based on various input modalities such as text, images, and videos. Sora leverages a combination of powerful neural network architectures, including encoder-decoder frameworks and transformers, to process multimodal inputs and generate visually coherent simulations. Sora’s core capabilities lie in its ability to generate videos that align with real-world physical principles, such as the reflection of light on surfaces or the melting of candles. These properties suggest that Sora has the potential to act as a world simulator, predicting future states of the world based on its understanding of the initial conditions and simulation parameters.

Sora’s Limitations. However, despite its impressive video generation abilities, Sora has several limitations that prevent it from being considered a fully functional world model. One key limitation concerns causal reasoning [242, 23], wherein the model is limited in simulating dynamic interactions within the environment. Thus, Sora can only passively generate video sequences based on an observed initial state, but cannot actively intervene or predict how changes in actions might alter the course of events. Another limitation is that it still fails to reproduce correct physical laws consistently [86]. While Sora can generate visually realistic scenes, it struggles with accurately simulating real-world physics, such as the behavior of objects under different forces, fluid dynamics, or the accurate depiction of light and shadow interactions.

Other Video World Models. Sora has undoubtedly catalyzed a significant wave of research into video world models, inspiring a surge of advancements in this field. Following Sora’s success in generating high-quality video sequences, numerous subsequent models have been developed, each aiming to push the boundaries of what video world models can achieve. For example, some approaches have extended video lengths to enable long-form video simulation [220, 108, 68]. In addition to conventional language-guided video generation, more modalities are being integrated, such as images and actions [235, 202]. Researchers are also shifting their focus from basic video generation, which lacks user control, to interactive simulations that aim to replicate the decision space of the real world and facilitate decision-making [213, 215, 197, 227, 78, 202]. Several studies have worked to enhance the smoothness of action transitions, improve the accuracy of physical laws, and maintain temporal consistency [211, 16, 148, 207]. Meanwhile, the concept of world models has evolved beyond imagination and is being applied in various scenario-specific simulations, including natural environments, games, and autonomous driving [108, 190, 15, 120, 68, 188, 11, 238, 121]. Table 3 summarizes the categorization of improvements in video world models across different aspects.

4.1.2 Capabilities of Video World Models

Despite the ongoing debate about whether models like Sora can be considered full-fledged world models, there is no doubt that video world models hold tremendous potential for advancing environment simulation and prediction [242, 23, 86]. These models can offer a powerful approach to understanding and interacting with complex environments by generating realistic, dynamic video sequences. To achieve this level of sophistication, this section outlines the key capabilities that video world models must possess to set them apart from traditional video generation models.

Long-Term Predictive Ability. A robust video world model should be capable of making long-term predictions that adhere to the dynamic rules of the environment over an extended period. This capability allows the model to simulate how a scenario evolves, ensuring that the generated video

Table 3: Overview of recent models in video generation across various categories, which summarizes key models in long-term video generation, multi-modal learning, interactive video generation, temporal consistency, and diverse environment modeling.

Category	Model	Description	Technique
Long-term	NUWA-XL [220]	“Coarse-to-fine” Diffusion over Diffusion architecture for long video generation.	Diffusion
	LWM [108]	Training large transformers on long video and language sequences.	Transformer
	GAIA-1 [68]	Generative world model predicting driving scenarios for autonomous driving.	Transformer, Diffusion
Multimodal	3D-VLA [235]	Integrates 3D perception, reasoning, and action in a world model for embodied AI.	Diffusion
	Pandora [202]	World-state simulation and real-time control with free-text actions.	LLM
	Genie [15]	Generative model from text, images, and sketches.	Transformer
Interactive	UniSim [213]	Simulates real-world interactions for vision-language and RL training.	Diffusion, RL
	VideoDecision[215]	Extends video models to real-world tasks like planning and RL.	Transformer, Diffusion
	iVideoGPT [197]	Combines visual, action, and reward signals for interactive world modeling.	Transformer
	PhysDreamer [227]	Simulates 3D object dynamics to generate responses to novel interactions.	Diffusion
Consistency	PEEKABOO [78]	Enhances interactivity with spatiotemporal control without extra training.	Diffusion Transformer
	WorldGPT [211]	Improves temporal consistency and action smoothness with multimodal learning and refined key frame generation.	Diffusion
	DiffDreamer [16]	Long-range scene extrapolation with improved consistency.	Diffusion
Diverse environments	ConsistI2V [148]	Enhances visual consistency in image-to-video generation.	Diffusion
	WorldDreamer [190]	World model capturing dynamic elements across diverse scenarios.	Transformer
	Genie [15]	Unsupervised generative model for action-controllable virtual environments.	Transformer
Diverse environments	MUVO [11]	Multimodal world model using camera and lidar data.	Transformer
	UniWorld [121]	3D detection and motion prediction in autonomous driving.	Transformer

sequences remain consistent with the temporal progression of the real world. Although Sora has achieved the generation of minute-long video sequences with high-quality temporal coherence, it is still far from being able to simulate complex, long-term dynamics found in real-world environments. Recent efforts have explored extending video lengths to capture longer-term dependencies and improve temporal consistency [220, 108, 68].

Multi-Modal Integration. In addition to language-guided video generation, video world models are increasingly integrating other modalities, such as images and actions, to enhance realism and interactivity [235, 202]. The integration of multiple modalities allows for richer simulations that better capture the complexity of real-world environments, improving both the accuracy and diversity of generated scenarios.

Interactivity. Another critical capability of video world models is their potential for controllability and interactivity. An ideal model should not only generate realistic simulations but also allow for interaction with the environment. This interactivity involves simulating the consequences of different actions and providing feedback, enabling the model to be used in applications requiring dynamic

Table 4: Comparison of existing works on world models as embodied environments, including indoor, outdoor, and dynamic environments. In the ‘Modality’ column, ‘V’ refers to vision, ‘L’ refers to lidar, ‘T’ refers to text, and ‘A’ refers to audio. In the ‘Num of Scenes’ column, ‘-’ means no reported data, and ‘Arbitrary’ means the method can support generating any number of scenes.

Type	Environment	Year	Num of Scenes	Modality	Physics	3D Assets
Indoor	AI2-THOR [91]	2017	120	V	✓	✓
Indoor	Matterport 3D [17]	2018	90	V	✗	✗
Indoor	Virtual Home [139]	2018	50	V	✓	✓
Indoor	Habitat [155]	2019	-	V	✓	✓
Indoor	SAPIEN [201]	2020	46	V	✓	✓
Indoor	iGibson [164]	2021	15	V, L	✓	✓
Indoor	AVLEN [134]	2022	85	V, T, A	✓	✓
Indoor	ProcTHOR [28]	2022	Arbitrary	V	✓	✓
Indoor	Holodeck [216]	2024	Arbitrary	V	✓	✓
Indoor	AnyHome [44]	2024	Arbitrary	V	✓	✓
Indoor	LEGENT [20]	2024	Arbitrary	V, T	✓	✓
In & Outdoor	TDW [45]	2021	-	V, A	✓	✓
In & Outdoor	GRUtopia [184]	2024	100k	V, T	✓	✓
Outdoor	MineDOJO [37]	2022	-	V	✗	✗
Outdoor	MetaUrban [200]	2024	13800	V, L	✓	✓
Outdoor	UrbanWorld [161]	2024	Arbitrary	V	✓	✓
Dynamic	UniSim [214]	2023	Arbitrary	V, T	✗	✗
Dynamic	Streetscapes [29]	2024	Arbitrary	V, T	✗	✗
Dynamic	AVID [149]	2024	Arbitrary	V, T	✗	✗
Dynamic	EVA [22]	2024	Arbitrary	V, T	✗	✗
Dynamic	Pandora [202]	2024	Arbitrary	V, T	✗	✗

decision-making. Recent work is focusing on enhancing control over the simulations, allowing for more user-guided exploration of scenarios [215, 197].

Diverse Environments. Finally, video world models are being adapted to a variety of scenario-specific simulations, including natural environments, autonomous driving, and gaming. These models are evolving beyond basic video generation to replicate real-world dynamics and support a wide range of applications [108, 190, 15].

4.2 World Model as Embodied Environment

The development of world models for embodied environments is crucial for simulating and predicting how agents interact with and adapt to the external world. Initially, generative models focused on simulating visual aspects of the world, using video data to capture dynamic changes in the environment. More recently, the focus has shifted towards creating fully interactive and embodied simulations. These models not only represent the visual elements of the world but also incorporate spatial and physical interactions that more accurately reflect real-world dynamics. By integrating spatial representations and transitioning from video-based simulations to immersive, embodied environments, world models can now provide a more comprehensive platform for developing agents capable of interacting with complex real-world environments.

World models as embodied environments can be divided into three categories: indoor, outdoor, and dynamic environments, as shown in Figure 4, and the relevant works are summarized in Table 4. It can be summarized that most current works focus on developing static, existing indoor and outdoor embodied environments. An emerging trend is to predict the dynamic, future world through generative models producing first-person, dynamic video-based simulation environments. Such environments can offer flexible and realistic feedback for training embodied agents, enabling them to interact with ever-changing environments and improve their generalization ability.

4.2.1 Indoor Environments

Indoor environments offer controlled, structured scenarios where agents can perform detailed, task-specific actions such as object manipulation, navigation, and real-time interaction with users [48, 134, 91, 164, 17, 139, 155, 201]. Early works on establishing indoor environments like

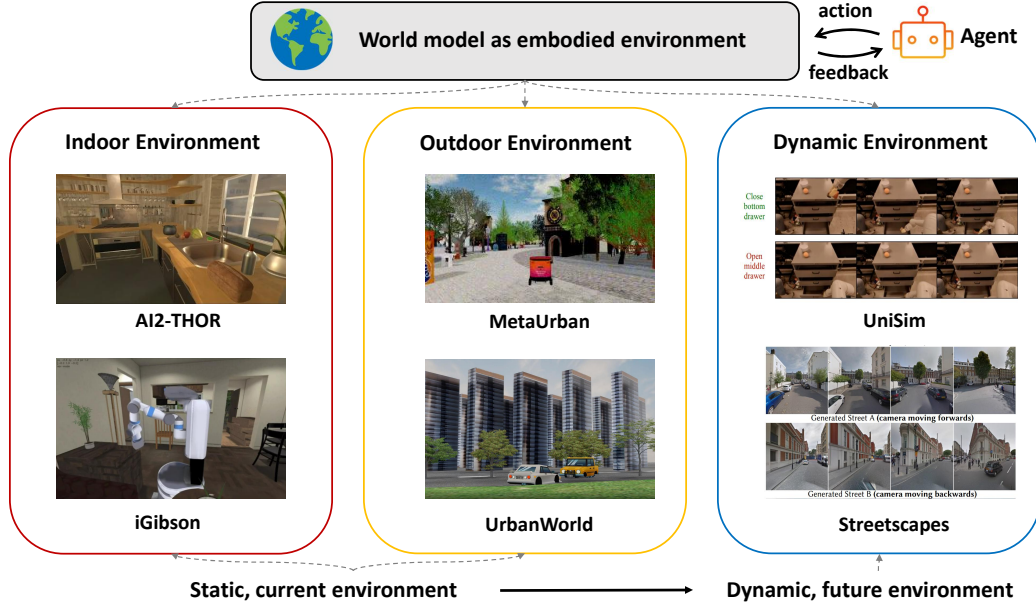


Figure 4: Classification of world models as interactive embodied environments, including indoor, outdoor and dynamic environments. The modeling of the outside world is evolving from constructing static, current environments to predicting dynamic, future environments.

AI2-THOR [91] and Matterport 3D [17] focus on providing only visual information. These works build indoor environments by providing photorealistic settings where agents can practice visual navigation and engage in interactive tasks that mimic real-life home activities. These environments emphasize the importance of using visual-based reinforcement learning techniques that allow agents to optimize their decision-making based on environmental cues. By simulating real-world tasks like cooking or cleaning, these platforms assess an agent’s capacity to generalize learned behaviors across different types of spaces and objects. A line of further works contributes toward expanding the data modalities of the provided environments. Among these, iGibson [164] introduces Lidar observation as additional signal feedback, contributing to more accurate environment perception of agents. AVLEN [134] further supplements audio signals allowing agents to execute tasks such as object manipulation and navigation in household-like settings. The challenge here lies in enabling agents to understand and act on multimodal input including vision, language, and sound within a constrained space. Adding a social dimension, environments like GRUtopia [184] introduce agents to spaces where they must navigate and interact with both objects and NPCs. Here, agents need to understand social dynamics, such as positioning and task sharing, which requires more advanced forms of interaction modeling. The inclusion of social interaction modules in these settings demonstrates how agents can be trained to balance human-like social behaviors with task performance. More recently, with the development of LLMs, some works [20, 216, 44] seek to provide a flexible environment generation pipeline, supporting the generation of arbitrary indoor environments with language instructions.

4.2.2 Outdoor Environments

In contrast to indoor environments, creating outdoor environments [184, 45, 200, 161, 37] faces greater challenges due to their larger scale and increased variability. Some existing works focus on urban environments, such as MetaUrban [200], where agents are deployed to navigate in large-scale urban environments, where they encounter challenges like dynamically changing traffic, varied building structures, and social interactions with other entities. These tasks often require the use of context-aware navigation algorithms that allow agents to adjust their trajectories and behaviors based on the layout and conditions of the environment. However, the environments in MetaUrban are created by retrieving and organizing 3D assets from existing libraries. Recently, utilizing advanced generative techniques, UrbanWorld [161] significantly enhances the scope of outdoor environments, using 3D generative models to create complex, customizable urban spaces that allow for more di-

verse urban scenarios. This shift from static asset-based environments to generative ones ensures that agents are exposed to a wider variety of tasks, from navigating unfamiliar street layouts to interacting with new types of objects or structures. In addition to the above real open-world generation works, there are also some virtual open-world platforms like MineDOJO [37] that extend these challenges even further by simulating procedurally generated, sandbox-like environments. These platforms, inspired by the open-ended world of Minecraft, push agents to engage in tasks like resource collection, construction, and survival, demanding continuous exploration and adaptive learning. In such environments, agents are motivated to seek out new information and adapt their behavior to finish given tasks. Training in such environments can help agents learn knowledge across a broad range of tasks and terrains, enabling them to operate effectively in various outdoor environments.

4.2.3 Dynamic Environments

Dynamic environments mark a significant evolution from traditional, static simulators by utilizing generative models to create flexible, real-time simulations. Unlike predefined environments that require manual adjustments, these models allow for the dynamic creation of a wide variety of scenarios, enabling agents to experience diverse, first-person perspectives. This shift provides agents with richer, more varied training experiences, improving their adaptability and generalization in complex, unpredictable real-world situations. A representative work is UniSim [214], which dynamically generates robot manipulation video sequences based on input conditions like spatial movements, textual commands, and camera parameters. Leveraging multimodal data from 3D simulations, real-world robot actions, and internet media, this system generates varied, realistic environments where agents can practice tasks like object manipulation and navigation. The key advantage of this approach is its flexibility, allowing agents to adapt to various scenarios without the limitations of static physical environments. Pandora [202] expands the dynamic environment generation from robot actions in Unisim to wider domains including human and robot actions in both indoor and outdoor scenes. Another subsequent work, AVID [149] builds on UniSim by conditioning on actions and modifying noise predictions from a pre-trained diffusion model to generate action-driven visual sequences for dynamic environment generation. Beyond the video diffusion-based framework of Unisim, EVA [22] introduces an additional vision-language model for embodied video anticipation, producing more consistent embodied video predictions. As for the generation of open-world dynamic environments, Streetscapes [29] employs autoregressive video diffusion models to simulate urban environments where agents must navigate dynamic challenges like changing weather and traffic. These environments offer consistently coherent, yet flexible, urban settings, exposing agents to real-world-like variability. The core trend in dynamic environments is the use of generative world models that provide scalable, adaptable simulations. This approach significantly reduces the manual effort required for environment setup, allowing agents to train across a diverse range of scenarios quickly. Moreover, the focus on first-person training closely mimics real-world decision-making, enhancing the agents' ability to adapt to evolving situations. These advances are key in developing embodied environments supporting agent learning in complex, dynamic scenarios.

Given the above developments, it is evident that world models as embodied environments have made significant advances in simulating and predicting how agents interact with dynamic, real-world scenarios. Current research predominantly focuses on developing indoor, static environments, with notable efforts expanding to large-scale outdoor environments and dynamic simulation environments. A promising direction is to construct dynamic environments, which can provide first-person, action-conditioned future world prediction, enabling agents to better adapt to unseen conditions. These methods are promising to offer flexible, scalable environments for training embodied agents, enhancing their generalization capabilities for real-world tasks.

5 Application

5.1 Autonomous Driving

In recent years, with the rapid development of vision-based generative models [66, 173, 13] and multimodal large language models [109, 1], world models, which serve as modules for understanding the state of the world and predicting its future trends, have garnered increasing attention in the field of autonomous driving. In this context, world models are defined as models that take multimodal data—such as language, images, and trajectories—as input, and continuously output future

world states in the form of vehicle perception data [55]. However, the concept of world models in autonomous driving existed long before the emergence of generation-based world simulators. The modern autonomous driving pipeline can be divided into four main components: *perception*, *prediction*, *planning*, and *control*. The entire process can be viewed as a decision-making pipeline. As we discussed in Section 3, the perception and prediction phases also represent the process of learning an implicit representation of the world for the vehicle. This can also be regarded as a form of world model. Therefore, in this section, we will elaborate on the application and development of world models in autonomous driving from two perspectives: modules that learn the implicit representation of the world and world simulators that output vehicle perception data.

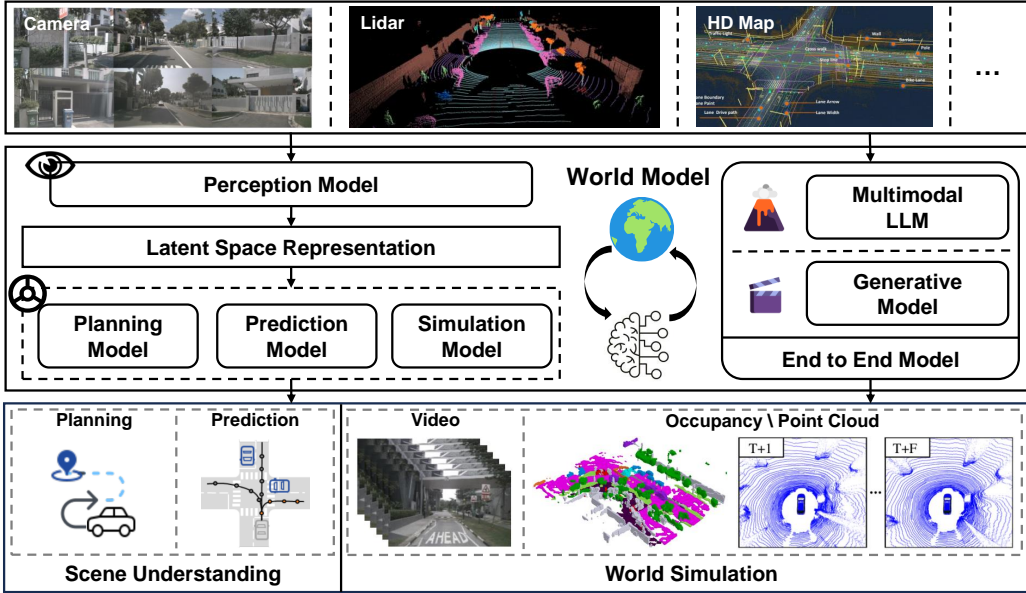


Figure 5: Application of world model in autonomous driving.

5.1.1 Learning Implicit Representations

Autonomous vehicles typically utilize cameras, radar, and lidar to perceive the real world, gathering information through images, video data, and point cloud data. In the initial decision-making paradigm [19, 156], models often take perceptual data as input and directly output motion planning results for the autonomous vehicle. Conversely, when humans operate vehicles, they typically observe and predict the current and future states of other traffic participants to determine their own driving strategies [74]. Thus, learning the implicit representation of the world through perceptual data and predicting the future states of the surrounding environment is a crucial step in enhancing the decision-making reliability of autonomous vehicles. We consider this process as it manifests in how autonomous vehicles learn a world model in latent space.

As shown in the left half of Figure 5, before the advent of multimodal large models and end-to-end autonomous driving technologies [71], the perception and prediction tasks of autonomous vehicles were typically assigned to distinct modules, each trained on their respective tasks and datasets. The perception module processed data from images, point clouds, and other sources to accomplish tasks such as object detection and map segmentation, projecting the perceived world into an abstract geometric space. Furthermore, the prediction module would typically operate within these geometric spaces to forecast the future states of the surrounding environment, including the trajectories and motions of traffic participants.

The processing of perceptual data is closely tied to the evolution of deep learning technologies, as shown in Table 5. Pointnet [141], introduced in 2017, was the first to employ deep learning methods for processing point cloud data. As convolutional neural networks advanced, perception techniques based on image data, exemplified by YOLOP [195] and MultiNet [177], emerged and excelled in driving scene understanding tasks [65, 182, 96, 239]. In recent years, the transformer architecture has gained prominence in natural language processing, and this technology has also been applied to

Table 5: Comparison of existing works in scene understanding and world simulation.

	Task	Work	Year	Data Modality	Technique
Driving Scene Understanding	Perception	Faster r-cnn [147]	2015	Camera	CNN
		Pointnet [141]	2017	Lidar	MLP
		MultiNet [177]	2018	Camera	CNN
		OmniDet [96]	2021	Camera	CNN & Attention
		YOLOP [195]	2022	Camera	CNN
		BEVFormer [105]	2022	Camera	Attention
	Planning & Prediction	Transfusion [7]	2022	Camera & Lidar	Transformer
		Wayformer [126]	2022	Geometric Space	Attention
		MTR [167]	2022	Geometric Space	Transformer
		QCNet [241]	2023	Geometric Space	Transformer
		HPTR [231]	2023	Geometric Space	Transformer
	End to End Scene Understanding	Jiang <i>et al.</i> [83]	2023	Geometric Space	Diffusion
		UniAD [71]	2023	Camera	Transformer
TOKEN [178]		2024	Camera	MLLM	
Driving World Simulation	Motion Simulation	OmniDrive [96]	2024	Camera	MLLM
		SUMO [113]	2000	Geometric Space	Rule-based
		Metadrive [103]	2022	Geometric Space	Data-driven
		Trafficbots [230]	2023	Geometric Space	Transformer
	End to End Sensor Simulation	Waymax [56]	2024	Geometric Space	Data-driven
		GAIA-1 [69]	2023	Camera	Transformer
		DriveDreamer [189]	2023	Camera	Diffusion
		Drive-WM [192]	2023	Camera	Diffusion
		OccWorld [237]	2023	Occupancy	Attention
		OccSora [185]	2024	Occupancy	Diffusion
Vista [49]	2024	Camera	Diffusion		
Copilot4D [226]	2024	Lidar	Diffusion		

image data understanding. BEVFormer [105] utilizes the attention mechanism to integrate images from multiple camera angles, constructing an abstract geometric space from a bird’s-eye view, and achieving state-of-the-art results in various tasks, including object detection. Additionally, Transfusion [7] enhances perceptual accuracy by fusing lidar and camera data through a cross-attention approach. Building on the perceptual results, a series of techniques such as RNNs [6, 243, 88], CNNs [136, 26, 24], and Transformers [75, 127, 167, 241] have been employed to encode historical scene information and predict the future behaviors of traffic participants.

With the emergence and rapid development of multimodal large language models in recent years, many efforts have sought to apply the general scene understanding capabilities of these models to the field of autonomous driving. TOKEN [178] tokenizes the whole traffic scene into object-level knowledge, using the reasoning ability of the language model to handle the long-tail prediction and planning problems, OmniDrive [96] sets up llm-based agents and covers multiple tasks including scene description, counterfactual reasoning and decision making through visual question-answering.

5.1.2 World Simulators

As shown in Table 5, before the emergence of multimodal large models and vision-based generative models, traffic scenario simulations are often conducted in geometric spaces. The scene data on which these simulations rely is typically collected by the perception modules of autonomous vehicles or constructed manually. These simulations represent future states of the scenario in the form of geometric trajectories [113, 103, 56, 230], which require further modeling and rendering to produce outputs suitable for vehicle perception. The cascading of multiple modules often results in information loss and increases the complexity of simulations, making scenario control more challenging. Furthermore, realistic scene rendering typically requires substantial computational resources, which limits the efficiency of virtual traffic scenario generation.

Using diffusion-based video generation models as a world model partially addresses the aforementioned issues. By training on large-scale traffic scenario datasets, diffusion models can directly

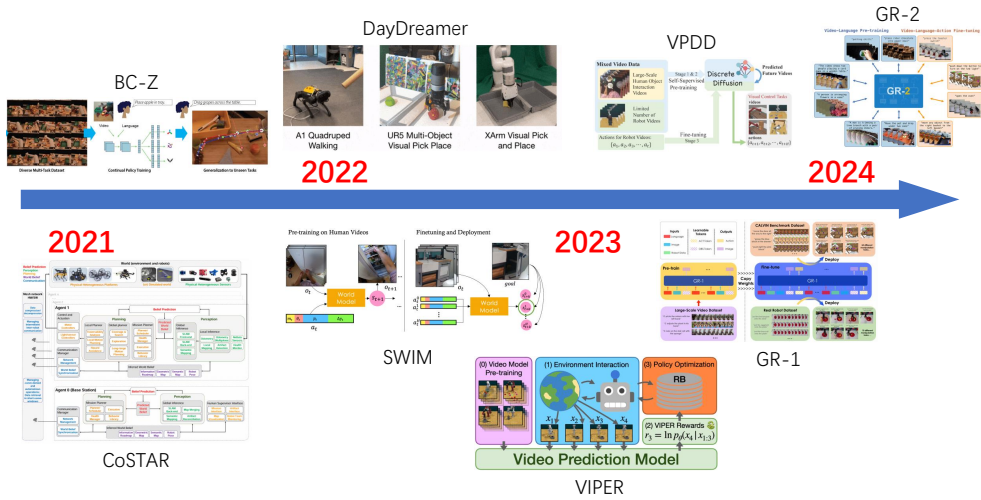


Figure 6: The development of robotic world model.

generate camera perception data that closely resembles reality. Additionally, the inherent controllability of diffusion models, combined with text-image alignment methods like CLIP [143], enables users to exert control over scenario generation in a straightforward manner. The GAIA-1 [69] and DriveDreamer series [189, 233] are among the first to employ this method for constructing world models. Building on this foundation, Drive-WM [192] introduces closed-loop control for planning tasks, while Vista [49] focuses on improving the resolution of generated results and extending prediction duration. In addition to methods that predict future states in video space, many other works have explored different forms of vehicle perception data. OccWorld [237] and OccSora [185] predict the future state of the world by forecasting 3D occupancy grids, whereas Copilot4D [226] constructs a world model by predicting changes in radar point cloud data. Compared to video data, these types of features better reflect the spatial characteristics of traffic scenarios.

5.2 Robots

World models have emerged as a transformative paradigm in robotics, enabling robots to perceive, predict, and perform effectively within complex environments. This revolution of robotics is partly made possible due to the advances in neural networks [181, 66] and machine learning algorithms [159, 144] that enable robots to build implicit representations that capture the critical components of the world. On the other hand, prediction models [41, 42] are capable of directly forecasting the future states of the world beyond abstract representations, allowing robots to anticipate possible environmental changes and react proactively. With the above powerful techniques, it is becoming practical for robots to directly interact with and learn from the real-world environment. As illustrated in Figure 6, LLMs [87, 218] and world models [18, 199, 64] are considered as one of the possible paths to artificial general intelligence (AGI) as they can be a starting point for machines to understand the underlying laws of the world. We summarize the development of the world model in robotics in Table 6.

5.2.1 Learning Implicit Representation

Traditional robotic tasks (e.g., object grasping) are typically performed in highly structured environments where the critical components are explicitly modeled [90, 34], eliminating the need for the robot to independently learn or adapt its understanding of the world. However, when the robot is deployed in unfamiliar environments, especially those in which key features or dynamics have not been explicitly modeled, tasks that were previously successful may fail as the robot struggles to generalize to these unknown features [122, 85]. Thus, enabling a robot to learn an implicit representation of its environment is a crucial first step toward achieving intelligence.

To help a robot understand the objects in the world, visual models such as convolutional neural networks (CNNs) [99, 93, 51] and vision transformers (ViT) [31, 183] integrate visual characteristics

of entities into representations, making it possible for robots to recognize critical objects for tasks. RoboCraft [165] transfers visual observation into particles and captures the structure of the underlying system through a graph neural network. Moreover, other attempts are made for the sensing of physical space. PointNet [140, 142] first encodes the unstructured 3D point clouds with asymmetrical functions, capturing the spatial characteristics of the environment. A recent work [52] assembles observations acquired along local exploratory paths into a global representation of the physical space within its latent space, enabling robots to tail and approach specific targets. With the advancement of language comprehension in LLMs [180, 14, 32], a novel paradigm for enabling robots to capture task intentions involves describing the task in textual form and then obtaining a textual representation through LLMs [124, 50, 72, 186]. BC-Z [79] utilizes language representations as task representations, enhancing the multi-task performance of robots. Text2Motion [107] splits the natural language instruction into task-level and motion-level plans with LLM to handle complex sequential manipulation tasks.

5.2.2 Predicting Future states of Environment

Robotic tasks are always sequential and long-term, and decisions made in the current moment could have a profound effect on future tasks' performance [171]. Therefore, by anticipating how their actions will affect future environmental states, robots can avoid potential mistakes and improve task performance over time. Classic robotics use closed-loop algorithms [9, 89] that use current observations to guide action selection, causing the robot to be short-sighted and potentially leading to irreversible mistakes, even if it eventually realizes that it has taken a wrong action. Even though some approaches claim to achieve groundbreaking performance in robotics, they rely on explicit dynamic functions based on expert knowledge, limiting the extent and robustness of prediction.

MORL [205] introduces a monotonic hyperbolic model to predict improvements in the updated policies. Meanwhile, Trajectron++ [152] predicts the environment by calculating the probability distribution over future trajectories via a conditional variational autoencoder. Recently, video generation models use diffusion [36, 21, 10, 64] and transformers [222, 208] as a backbone have become a popular choice for future state prediction. For example, UniPi [33] formulates action prediction as a video prediction problem and trains a constrained diffusion model with the initial state as an explicit conditioning context to enable an accurate imagining of the future. Similarly, VIPER [35] leverages a pretrained autoregressive transformer on expert video, guiding the robots to perform properly, whereas Genie [15], includes a dynamics model that predicts the next state of the environment with previous video frames and actions. Benefiting from the millions of unlabeled videos on the Internet, GR-2 [196, 18] is fine-tuned on robotics tasks, achieving accurate prediction of future images and action trajectory generation for robots.

5.2.3 From Simulation to Real World

Deep reinforcement learning shines in robot strategy learning, enabling robots to perform stable walking[172, 95], object grasping[223, 30], and even tying shoelaces[5] which is particularly complex autonomously. However, deep reinforcement learning is not as efficient as it should be in terms of sample efficiency. For example, it takes tens of thousands of years for a robot to learn to solve a Rubik's Cube in the real world[3], which greatly limits its real-world applications. Therefore, the majority of robotics work is carried out based on simulations, with various distributed training techniques [151, 60] improving the efficiency of sample collection. Despite the remarkable efficiency of simulation, a well-trained robot in simulated environments often fails in the real world. This incapability is because that simulation cannot fully recover the real-world, and the well-trained policies may fail in those out-of-distribution scenarios. On the other hand, accurately modeling real-world environments is challenging, as simulated environments often differ from the real world, and this difference accumulates in long-distance decision-making, resulting in policies that do not adapt to changes in the world.

World models have shown great promise for robots to handle universal tasks in the real world. NeBula [2] constructs a belief space where robots perform reasoning and decision-making, and can adapt to diverse robot structures and unknown environments, whereas DayDreamer [199] generalizes a world model from offline data, empowering robots to learn to walk directly in real-world environments within hours. Moreover, SWIM [120] learns from human videos and fine-tunes from robotics settings without any task supervision, which only requires less than 30 minutes of real-

Table 6: Comparison of robotic world models.

	Task	Model	Year	Input	Backbone
Learning Inner Representation	Visual Representation	CNN [99]	1998	Image	CNN
		ViT [31]	2024	Image	Transformer
	3D Representation	PointNet [140] predictive coder [52]	2017 2024	3D point clouds Image	MLP ResNet
Predicting Future Environment	Task Representation	BC-Z [79]	2022	Text& Video	LLM& ResNet
		Text2Motion [107]	2023	Text	LLM
		Gensim [186]	2023	Text	LLM
Real-world Planning	Trajectory Prediction	MORL [205] Trajectron++ [152]	2020 2020	Motion Image	Policy Gradient CVAE
	Video Prediction	UniPi [33] VIPER [35]	2024 2024	Video Video	Diffusion Transformer
	General Prediction	GR-2 [196] VIPER [35]	2023 2024	Video Video	Diffusion Autoregressive
Real-world Planning	Real-World Adaptation	DayDreamer [199]	2023	Video	RSSM
		SWIM [120] CoSTAR [2]	2023 2021	Video Multimodal	Transfer Learning Belief Space
	Evaluation	OpenEQA [117]	2024	Image& Text	LLM

Table 7: Representative works of social simulacra.

	Advance	What to simulate	Effects of world model
World Model as Social Simulacra	AI Town [132]	Machine Society	Stylized facts
	S3 [47]	Social network	Predictions
	Papachristou <i>et al.</i> [131]	Social network	Stylized facts & Predictions
	Xu <i>et al.</i> [206]	Games	Stylized facts
	EconAgent [101]	Macroeconomics	Stylized facts
	SRAP-Agent [82]	Resource Allocation	Stylized facts
World Model in Social Simulacra	Project Sid [4]	Collective rules (Tax)	Stylized facts
	Agent-Pro [228]	Games	Belief
	Zhang <i>et al.</i> [225]	Machine Society	Reflection & Debate
	GovSim [137]	Resource Sharing	Cognition
	AgentGroupChat [53]	Group Chat	Belief & Memory

world interaction data. OpenEQA [117] further presents a benchmark on the understanding of the robots on the environment and tasks, offering a general evaluation of real-world embodied agents.

5.3 Social Simulacra

The concept of ‘social simulacra’ was originally introduced as a prototyping technique in [133], aimed at helping designers create a virtual social computing system encompassing many diverse agents. The traditional methods of constructing agents based on expert-defined rules [157, 12] or reinforcement learning [236] face issues such as overly simplistic behaviors or a lack of interpretability. However, the emergence of LLMs provides a transformative tool for building more realistic social simulacra, achieving more convincing stylized facts [101] or accurate predictions. Social simulacra can be seen as a form of world model that mirrors real-world social computing systems. From another perspective, the agents within social simulacra also develop implicit representations of the external system; that is, they build an implicit world model that supports the generation of their social behaviors. The relationship between the world model and social simulacra is shown in Figure 7, and the summary of representative works is shown in Table 7.

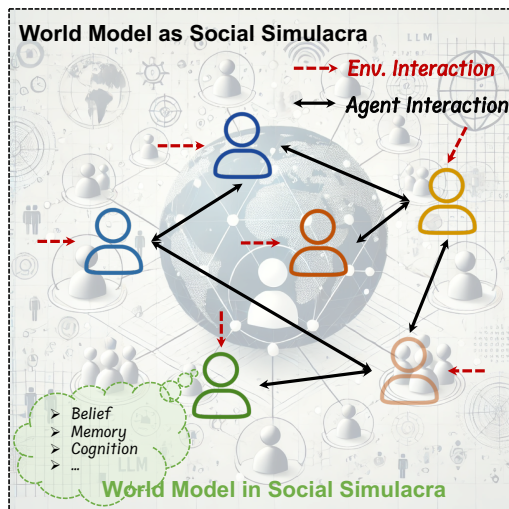


Figure 7: World model and social simulacra.

5.3.1 Building Social Simulacra Mirroring Real-world Society

In the era of the rapid rise of LLM agents, building realistic social simulation systems becomes more practical. One of the most famous examples of social simulacra is AI Town [132], a world model composed of 25 generative agents, essentially forming a sandbox social environment. In this virtual community, the agents exhibit believable individual behaviors, and at the group level, emergent social behaviors similar to those that might appear in the real world. Along these lines, more and more attempts are being made to replace humans in various social scenarios with LLM agents, in effect forming their own scenario-specific social simulacra. These works have used the simulacra paradigm in such scenarios as social networks and cooperative or competitive games, among others [46].

S3 [47] is a pioneering work that leverages LLM agents to simulate the dynamics of message propagation on social networks. By simulating human emotions, attitudes, and social behaviors such as message forwarding, S3 successfully reproduces the propagation dynamics of several real-world public events in the constructed virtual social network, with results that are qualitatively indistinguishable from reality. Similar studies [131] further explore the formation mechanisms of social networks led by LLM agents and compare them with real human social networks. Similarly, Xu *et al.* [206] use LLM agents to play the classic social interaction game, Werewolf. During the simulation, they observe the emergence of strategic behaviors, such as deception and confrontation, revealing the potential of LLMs in incomplete information games. Another popular area of research in social simulacra is the simulation of economic systems. EconAgent [101] constructs a macroeconomic system where individual economic behaviors are simulated based on LLM agents, incorporating key components of the economy such as the labor market, consumption market, and financial markets. The simulation results replicate stylized facts, including fluctuated macroeconomic indicators and macroeconomic regularities consistent with real-world evidence. EconAgent demonstrates the significant potential of using LLM agents in simulating economic decision-making and constructing economic systems. Other simulations of social simulacra in the economic field include the allocation of scarce resources [82] and the formation of tax systems [4], among others.

5.3.2 Agent’s Understanding of External World in Social Simulacra

LLM agents build their memory by storing observations obtained through interactions with the external environment [229], thereby forming implicit representations and basic cognition of the external world, especially in the context of simulating social scenarios. This cognition is stored in a memory bank in textual form for LLM agents to retrieve and use, enabling them to access useful information and fully leverage experiential knowledge from past interactions with the environment when making decisions.

Agent-Pro [228] transforms the memory of its interactions with the external environment (specifically with other agents in interactive tasks) into what are called ‘beliefs’. Based on these beliefs, it makes the next decision and updates its behavior strategy. These beliefs represent the agent’s social understanding of the environment and other agents within it, relating to Theory of Mind mentioned in Section 3.2. Other works on LLM agents have also adopted similar designs. For example, Zhang *et al.* [225] introduces mechanisms of reflection and debate from a social psychology view for modeling multi-agent collaboration tasks. A more advanced study is GovSim [137], which explores whether cooperative behaviors aimed at sustainable resource development can emerge within a society composed of LLM agents. In this setup, each agent gathers information about the external world and other agents’ behavioral strategies through multi-agent conversations and subsequently forms its own high-level insights, essentially creating an implicit representation of the world model. Another similar application scenario is Interactive Group Chat [53], where human-like behaviors and strategies emerge across four narrative scenarios, including Inheritance Disputes, Law Court Debates, etc.

6 Open Problems and Future Directions

The recent advance of hyper-realistic generative AI has brought a lot of attention to development of the world model, with particular focus on the multi-modal big models like Sora [130]. Despite the rapid innovation, there are also a lot of important open problems that remain to be solved.

6.1 Physical Rules and Counterfactual Simulation

A key objective of world models is to learn the underlying causal relationships of the simulated world, such as the physical rules of the environments. They provide important capabilities for inferring unobserved outcomes of counterfactual scenarios [135], going beyond data-driven prediction methods that assume identical data distribution. Such capabilities are crucial to address data scarcity problems, which are particularly important for modeling rare events in mission-critical applications. For example, simulating the corner cases is essential to improve the robustness of autonomous driving AIs [40]. Moreover, having an accurate model of the physical rules can also improve the consistency of simulated environments, which is essential for addressing simulation-to-reality gaps in many applications. Moreover, world models with realistic physical rules are believed to be a necessary training environment for AI agents to develop a comprehensive understanding of the physical world.

The recent breakthroughs of big generative models are mainly driven by deep learning models like the transformer and diffusion models, which are essentially data-driven. It is a controversial question whether the ability of simulating physical rules can emerge from the scaling of training data. Sora has shown the impressive ability of generating highly realistic videos of the physical world [130], including objects in motion and with changeable shapes like pedestrians, dogs, and hamburgers with bite marks. However, it still struggles to accurately simulate physical rules such as gravity and fluid dynamics. Furthermore, researchers also find that LLMs cannot adequately predict the state transition of the physical world [191], such as boiling water. These observations show that large generative models, although they are empowered by massive datasets, still have inherent limitations in learning causal representations of the world. One promising future direction is to explore the integration of large generative models with a physical rules simulator. Such solutions might reduce the resolution and quality of generated content, but they should improve generalization to unseen, counterfactual scenarios. Additionally, having explicit physical rules could also improve the interpretability and transparency of world models.

6.2 Enriching the Social Dimension

Simulating the physical elements alone is not sufficient for an advanced world model, since human behavior and social interaction also play a crucial role in many important scenarios [46]. For example, the behavior of urban dwellers is particularly important for building world models of the urban environment [8, 204]. Previous work shows that the human-like commonsense reasoning capabilities of LLMs provide a unique opportunity to simulate realistic human behavior with generative agents [132]. However, designing autonomous agents that can simulate realistic and comprehensive human behavior and social interactions remains an open problem. Recent studies suggest that theo-

ries of human behavior patterns and cognitive processes can inform the design of agentic workflows, which in turn enhance the human behavior simulation capabilities of LLMs [163, 132], representing an important direction for future research. In addition, the evaluation of the realism of generated human behavior still largely relies on subjective human assessment, which is challenging to scale up to a large-scale world model. Developing a reliable and scalable evaluation scheme will be another future research direction that can enrich the social dimension of the world model.

6.3 Bridging Simulation and Reality with Embodied Intelligence

The world model has long been envisioned as a critical step towards developing embodied intelligence [155]. It can serve as a powerful simulator that creates comprehensive elements of the environment and models realistic relationships between them. Such an environment can facilitate embodied agents to learn through interaction with a simulated environment, reducing the need for supervision data. To achieve this goal, improving the multi-modal, multi-task, and 3D capacities of generative AI models has become an important research problem for developing general world models for embodied agents. Moreover, closing the simulation-to-reality gaps [67] has been a long-standing research problem for embodied environment simulators, and it is therefore important to transfer the trained embodied intelligence from the simulation environment to the physical world. Collecting more fine-grained sensory data is also a critical step toward this goal, which can be facilitated through the interface of embodied agents. Therefore, an interesting future research direction is to create self-reinforcing loops to harness the synergy power of generative world models and embodied agents.

6.4 Simulation Efficiency

Ensuring high simulation efficiency of world models is important for many applications. For example, number of frames per second is a key metric for high quality for learning sophisticated drone manipulating AIs. The popular transformer architecture of most big generative AIs poses a huge challenge for high-speed simulation because its autoregressive nature can only generate one token at a time. Several strategies are proposed to accelerate the inference of large generative models, such as incorporating big and small generative models [162] and distilling big models [163]. More holistic solutions include building a simulation platform that optimally schedule LLM requests [210]. High computation cost is also a problem for classic physics simulators when they are tasked to simulate large and complex systems. Previous research finds deep learning models like graph neural networks can be used to efficiently approximate physical systems [154]. Therefore, an important research direction will be to explore the synergy between smaller deep learning models and big generative AI models. Additionally, the overall improvement from underlying hardware to programming platform and AI models is also needed to achieve substantial speedup.

6.5 Ethical and Safety Concerns

Data Privacy. The recent trend of building world models with big generative AIs raises significant concerns of privacy risk, largely due to the massive and often opaque training data [219]. Extensive research effort is devoted to assessing the risk of inferring private information with big generative AIs like LLM [102], which could be especially sensitive in the context of video generation models. To be compliant with privacy regulations like GDPR [176], it is important to improve the transparency of the life cycle of generative AIs, helping the public understand how data is collected, stored, and used in these AI models.

Simulating Unsafe Scenario. The incredibly intelligent power of generative AIs makes safeguarding their access a paramount task. Previous studies on LLMs found they can be misled to generate unsafe content with adversarial prompting [94, 76]. The risk of unsafe use of world models can be even larger. Adversarial users might leverage such techniques to simulate harmful scenarios, reducing the cost of planning illegal and unethical activities. Therefore, an important future research direction is to safeguard the usage of world models.

Accountability. The ability to generate hyper-realistic text, images, and videos has caused severe social problems of spreading misinformation and disinformation. For example, the emergence of deepfake technology gives rise to large-scale misuses that have widespread negative effects on social, economic, and political systems [193]. Thus, detecting AI-generated content has been a key

research problem in addressing these risks [146]. However, this problem is becoming increasingly challenging due to the advance of generative AIs, and it will be even more difficult with the arrival of a world model that can generate consistent, multi-dimensional output. Technology like watermarking could help improve the accountability of world model usage [27]. More research attention, as well as legal solutions, are needed to improve the accountability of world model usage.

7 Conclusion

Understanding the world and predicting the future have been long-standing objectives for scientists developing artificial generative intelligence, underscoring the significance of constructing world models across various domains. This paper presents the first comprehensive survey of world models that systematically explores their two primary functionalities: *implicit representations* and *future predictions* of the external world. We provide an extensive summary of existing research on these core functions, with particular emphasis on world models in decision-making, world knowledge learned by models, world models as video generation, and world models as embodied environments. Additionally, we review progress in key applications of world models, including autonomous driving, robotics, and social simulation. Finally, recognizing the unresolved challenges in this rapidly evolving field, we highlight open problems and propose promising research directions with the hope of stimulating further investigation in this burgeoning area.

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