

Video Generation Models in Robotics: Applications, Research Challenges, Future Directions

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Video generation models have emerged as high-fidelity models of the physical world, capable of synthesizing high-quality videos capturing fine-grained interactions between agents and their environments conditioned on multi-modal user inputs. Their impressive capabilities address many of the long-standing challenges faced by physics-based simulators, driving broad adoption in many problem domains, e.g., robotics. For example, video models enable photorealistic, physically consistent deformable-body simulation without making prohibitive simplifying assumptions, which is a major bottleneck in physics-based simulation. Moreover, video models can serve as foundation world models that capture the dynamics of the world in a fine-grained and expressive way. They thus overcome the limited expressiveness of language-only abstractions in describing intricate physical interactions. In this survey, we provide a review of video models and their applications as embodied world models in robotics, encompassing cost-effective data generation and action prediction in imitation learning, dynamics and rewards modeling in reinforcement learning, visual planning, and policy evaluation. Further, we highlight important challenges hindering the trustworthy integration of video models in robotics, which include poor instruction following, hallucinations such as violations of physics, and unsafe content generation, in addition to fundamental limitations such as significant data curation, training, and inference costs. We present potential future directions to address these open research challenges to motivate research and ultimately facilitate broader applications, especially in safety-critical settings.

Keywords: Video Generation Models, World Modeling, Visual Planning, Policy Learning and Evaluation

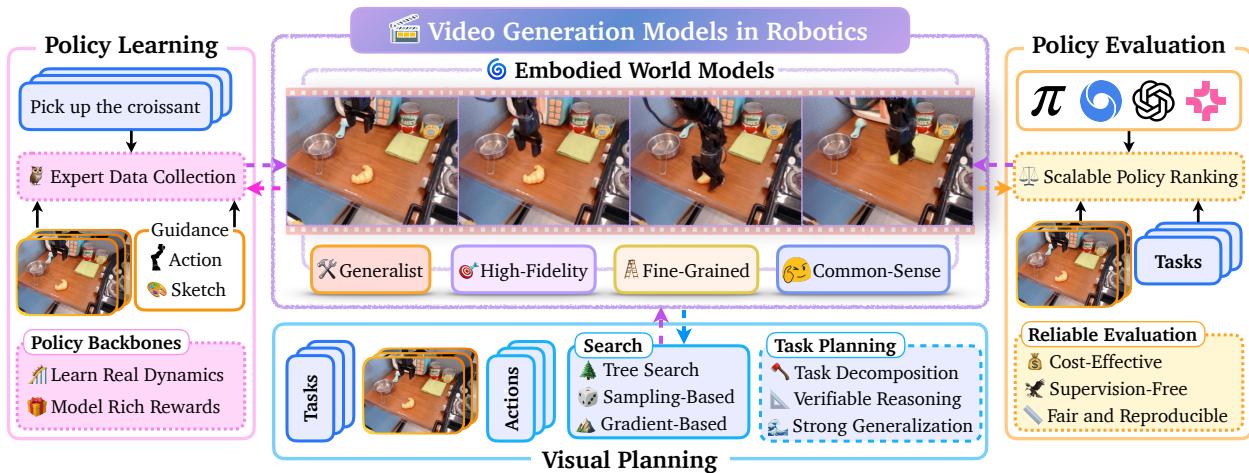


Figure 1 Overview. As embodied world models, video models generate high-fidelity predictions of the spatiotemporal evolution of real-world environments, capturing fine-grained robot-environment interactions that have been traditionally challenging for classical physics-based simulators. Their remarkable capabilities enable generalist robot policy learning, policy evaluation, and visual planning that is well-aligned with commonsense knowledge.

1 Introduction

Recent breakthroughs in generative modeling, such as diffusion and flow-matching [1, 2], have enabled high-fidelity controllable video synthesis conditioned on user inputs such as text prompts, robot actions, and video frames. By training on internet-scale data, state-of-the-art (SOTA) video models learn to create rich videos that capture aesthetic and dynamic (motion) effects (e.g., with cinematic lighting, camera motion, and physical interaction between agents), driving widespread applications in video editing and content creation [3–11]. As a result, these models have been increasingly integrated into robotics, e.g., in robot data generation, visual planning, policy learning, and policy evaluation [12–17], drawing upon their impressive zero-shot generalization capabilities [18]. In this survey, we provide a review of video models, highlighting their capabilities, applications in robotics, and limitations.

The advent of large vision-language models (VLMs/LLMs) [19–21] has significantly transformed the state of the art in many problem domains (e.g., natural language processing, computer vision, robotics, etc.) due to their remarkable language generation and commonsense reasoning capabilities. Through pretraining on internet-scale data, LLMs learn broad foundational knowledge required to solve a wide range of tasks, which has resulted in their emergence as impressive zero-shot AI models. For example, VLMs function as the backbones of SOTA vision-language-action robot policies [22–24], which enable robots to perform diverse tasks with a single (unified) policy in place of multiple task-specific policies. Despite these impressive capabilities, language models face some important limitations. First, language-only abstractions lack the expressiveness required to efficiently capture the intricate interaction processes inherent in the physical world. For example, consider the task of creating a concise fine-grained description of the contact interactions between a robot’s gripper and a target deformable object, e.g., a cloth. Such a task is immensely challenging due to the high density of information and the limited capacity of language. Second, language-centric modeling fails to accurately model the spatial and temporal dependencies between real-world phenomena (events) that are crucial to comprehensively understanding the physical world. Although physics-based simulators offer visual world modeling capabilities, their practical effectiveness is limited by a number of fundamental challenges. Particularly, physics-based simulation generally requires restrictive simplifying assumptions that hinder the visual and physical fidelity of their predictions. For example, physics engines require expensive asset curation procedures to minimize the sim-to-real gap and struggle to accurately simulate deformable bodies with complex morphology and dynamics. Video generation models address these aforementioned limitations by providing a photorealistic, physically consistent spatiotemporal model of the world. These capabilities have driven growing applications of video models in robotics.

In robotics, video models have been increasingly adopted as embodied world models [25–28]. High-fidelity world modeling establishes a trustworthy foundation for efficient evaluation of robot policies [16, 17, 29, 30]. *Policy evaluation* has traditionally necessitated setting up real-world robot stations for online policy roll-outs, which is notably expensive given the pertinent hardware and labor cost. Video models circumvent this bottleneck without compromising the reliability of evaluation results. As high-fidelity world models, video models also provide accurate dynamics and rewards predictions, which is essential in training robot policies using reinforcement learning [31–34]. Additionally, video models enable *cost-effective robot data generation*, which is particularly important in imitation learning. While data scaling has proven to be a critical recipe for advancing the performance of SOTA robot policies [23, 35], collecting expert demonstration data is incredibly expensive, posing a significant limitation. Video models facilitate scalable data generation without relying on human supervision, addressing this pressing challenge. The expert demonstrations from video models can also be directly applied to a robot through motion retargeting [36–38]. Beyond generating successful task demonstrations, video models can also synthesize failure video trajectories that endow robot policies with corrective behaviors for more robustness. Furthermore, the generated data can be optimized through *visual planning* to compute more optimal robot trajectories [14, 15, 39–42].

Although video models provide valuable capabilities, their integration into robotics faces notable limitations. Like LLMs, video models tend to hallucinate, generating videos that are physically unrealistic, e.g., with objects appearing/disappearing or deforming in ways that violate physics [43–46]. Video models also struggle to follow user instructions [47, 48], especially in long-duration video generation tasks [49–51]. Further, significant data curation, training, and inference costs and the lack of adequate content safeguards in video generation remain critical challenges [52, 53], hindering broader adoption in robotics.

This survey provides an extensive overview of video models, identifying prevailing model architectures, key applications in robotics, and major challenges. We highlight four prominent applications of video models as embodied world models in robotics, including: (i) robot data generation and action prediction in imitation learning, (ii) dynamics and rewards modeling in reinforcement learning, (iii) policy evaluation, and (iv) visual planning, as illustrated in [Figure 1](#). Furthermore, we outline important open research challenges impeding trustworthy applications of video models in robotics and present important directions for future research to address these problems.

Comparison to Existing Surveys. Prior survey papers have covered video generation models broadly, particularly video diffusion models, identifying the prevailing model architectures [54, 55], techniques for controllable video generation [56], core applications in video generation, video editing, and video understanding [57]. Other surveys [58–61] provide a broad discussion of world models, presenting a valuable review of research across a wide range of model architectures, such as recurrent neural networks, transformers, language models, and scene reconstruction models, e.g., Gaussian Splatting. Prior work also highlights the unified framework for information representation and task formulation provided by video models [62] and discuss the progression in the capabilities of video models, through a primarily historical lens, along with potential future capabilities [63]. Although relevant for broader understanding, these existing surveys lack a comprehensive review of generative video models as world models in robotics [58–61] or an extensive discussion of specific applications, associated challenges, and future directions of generative video models in robotics [54–57, 63]. In contrast, our survey provides an exhaustive discussion of video generation models in robotics, especially in robot manipulation, which has not been considered by existing surveys unlike areas such as autonomous driving [64–67].

Organization. We discuss the organization of this survey, as summarized in [Figure 2](#). In [Section 2](#), we provide an overview of important concepts that are crucial to understanding generative video modeling. We begin with a discussion of learned world models, highlighting the evolution of these models from (latent) state-based representations to high-fidelity video-based representations. Further, we review diffusion/flow-matching-based modeling highlighting the core principles behind their success. In [Section 3](#), we present major applications of video models in robotics, encompassing robot data generation and action prediction in imitation learning, dynamics and rewards modeling in reinforcement learning, policy evaluation, and visual planning. In [Section 4](#), we highlight useful metrics and benchmarks for evaluating video models. Subsequently, we identify open research challenges in [Section 5](#) and suggest directions for future research. We conclude the survey in [Section 6](#).

2 Background

In this section, we provide relevant background concepts that are essential to understanding the material presented in this survey. We begin with a brief introduction of world models, followed by an overview of video models. Specifically, we categorize video models broadly into non-diffusion-based video models and diffusion/flow-matching-based video models. State-of-the-art video models generally utilize diffusion or flow-matching for high-fidelity video synthesis. As a result, we provide a more comprehensive discussion of these models.

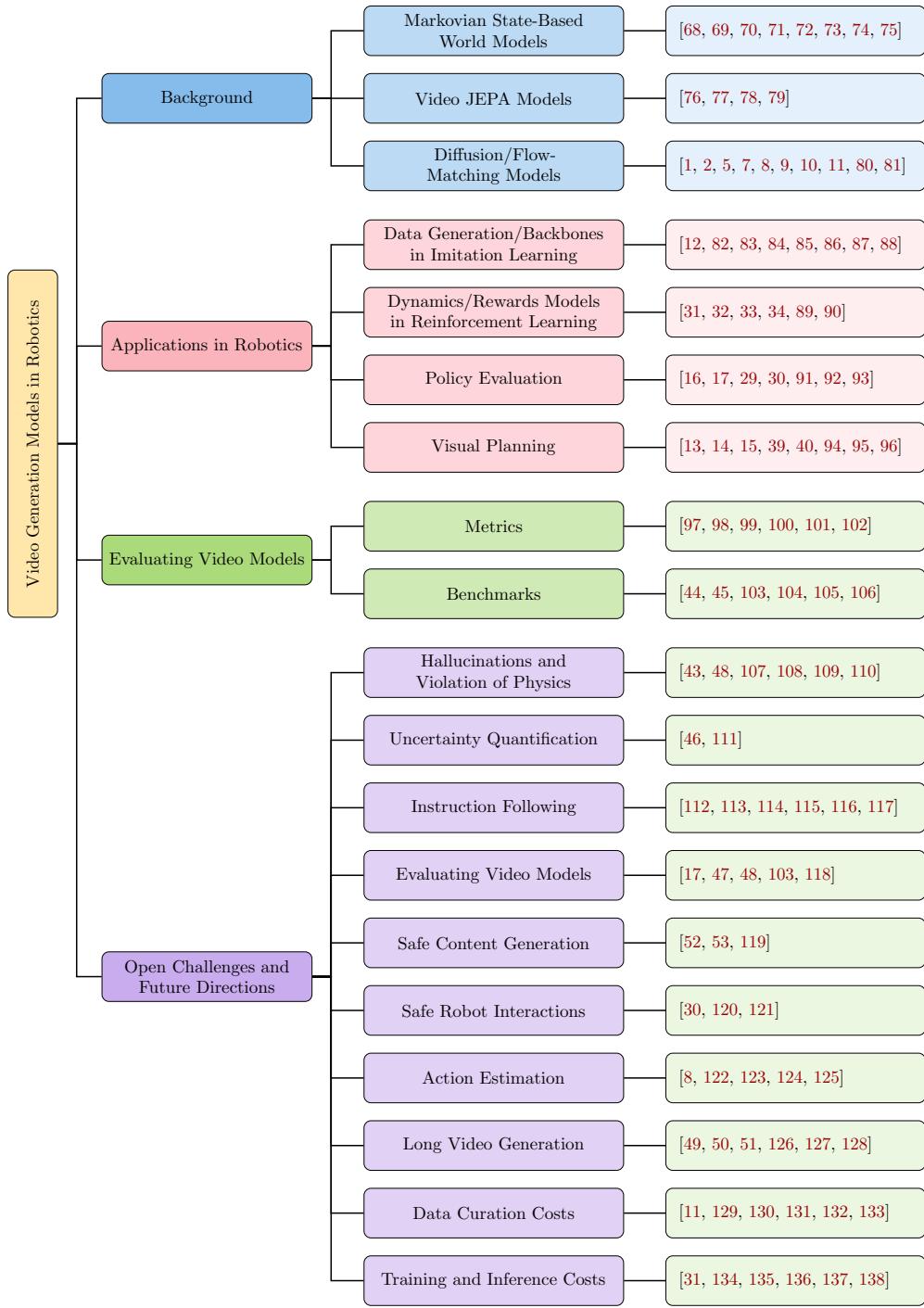


Figure 2 Organization. The organization of this survey, including background material, taxonomy of robotics applications, evaluation metrics and benchmarks, and open challenges and directions for future research.

2.1 Learned World Models

Many robotics algorithms require a model of the robot’s environment to efficiently learn policies that are effective in the real-world, especially when real-world interactions are prohibitively costly or unsafe. For example, reinforcement learning (RL) methods [139, 140] generally require a large number of interactions between an agent and its environment to learn useful behaviors, which is typically expensive in the real-world. World models enable scalable data collection for training these policies with little to no real-world interaction.

At their core, world models predict the evolution of the environment of an agent due to interactions. Traditionally, physics-based simulators [141, 142] have been utilized as world models for predicting the dynamical effects of a robot’s actions. However, physics-based simulators typically utilize simplified physics engines that approximate physical laws for computational feasibility, introducing inductive biases that limit their realism, e.g., in simulating non-rigid objects. Importantly, these approximations often contribute to the sim-to-real gap in robotics, impeding successful transfer of simulation-trained robot policies to the real-world. Moreover, robot manipulation tasks have become increasingly complex, exacerbating these challenges.

Learned world models [143, 144] have emerged as an effective solution to these challenges. We can broadly classify learned world models into two categories: *Markovian state-based* world models and *video* world models.

Markovian State-Based World Models. A state refers to a description of the environment of an agent at a given time step, which could include its RGB observations, proprioception, or latent embeddings of these observations at past and current time steps. Markovian state-based world models assume that the future evolution of the agent’s environment only depends on the agent’s state s_t at the current time step t and its action a_t , which represents either a physical action or a latent action. Markovian state-based world models are trained to predict the future state s_{t+1} , given the current state s_t and action a_t :

$$s_{t+1} \sim p_\eta(s_{t+1}|s_t, a_t), \quad (1)$$

where p_η represents the dynamics predictor with parameters η . These world models generally operate in latent space and are composed of an encoder for embedding observations into a latent space, dynamics predictor, and rewards predictor, given by:

$$\text{Encoder: } s_t \sim \mathcal{E}_\gamma(s_t|o_t), \quad (2)$$

$$\text{Dynamics Predictor: } \hat{s}_{t+1} \sim p_\eta(\hat{s}_{t+1}|s_t, a_t), \quad (3)$$

$$\text{Rewards Predictor: } \hat{r}_{t+1} \sim p_\zeta(\hat{r}_{t+1}|\hat{s}_{t+1}), \quad (4)$$

with parameters γ and ζ for the encoder and rewards predictor, respectively.

Prior work [68, 69, 145–148] has largely parameterized the dynamics predictor p_η using recurrent neural networks (RNNs) or recurrent state-space models (RSSMs). However, more recent works employ transformers [70] and diffusion in pixel space [149–151] or latent space [152, 153] for more expressive dynamics prediction. In general, world models [70, 74, 75, 88, 154–156] are trained to minimize the error between the predicted and ground-truth next state, either in latent space or reconstructed pixel space using the mean-squared error (MSE) loss function [70, 149] or the Kullback-Leibler (KL) divergence loss [68]. We refer interested readers to [58] for a detailed review of Markovian state-based world models.

Video World Models. To model the world, video models learn spatiotemporal mappings that capture the evolution of an environment over space and time, without explicitly modeling a Markovian state, in contrast to Markovian state-based world models. In general, video models apply non-linear transformations to the patches or pixels of a video frame to propagate the environment dynamics. Early research in video prediction applied spatial transformations to pixels to generate future frames [157, 158]. However, these transformations capture only local perturbations of the frames, limiting their expressiveness in more complex video generation tasks, e.g., with dynamic backgrounds. Other methods [71, 159] extend generative adversarial networks (GANs) [160] to the video prediction setting, demonstrating higher-fidelity video generation. However, the susceptibility of GANs to mode collapse limits their ability to model diverse potential video evolution paths.

Subsequent work [72, 73, 161–163] uses variational inference via variational autoencoders [164] to learn a latent distribution over pixels, explicitly encoding the stochasticity in video prediction within the latent distribution. Some of these methods [72] utilize a convolutional decoder to map back to the RGB space, while others [161, 163] apply GANs and long-short term memory networks [165] for decoding the sampled latent variables. Given the success of transformers in language modeling, the work in [166] introduces the video transformer, achieving higher-quality video generation through autoregressive predictions. However, powerful autoregressive decoders introduce the challenge of latent collapse, where the learned model fails to efficiently use the latent space. Vector-quantized variational autoencoders (VQ-VAEs) [167] address this issue by quantizing the latent representations into discrete codes in a codebook. VQ-VAEs are typically pre-trained on large-scale image

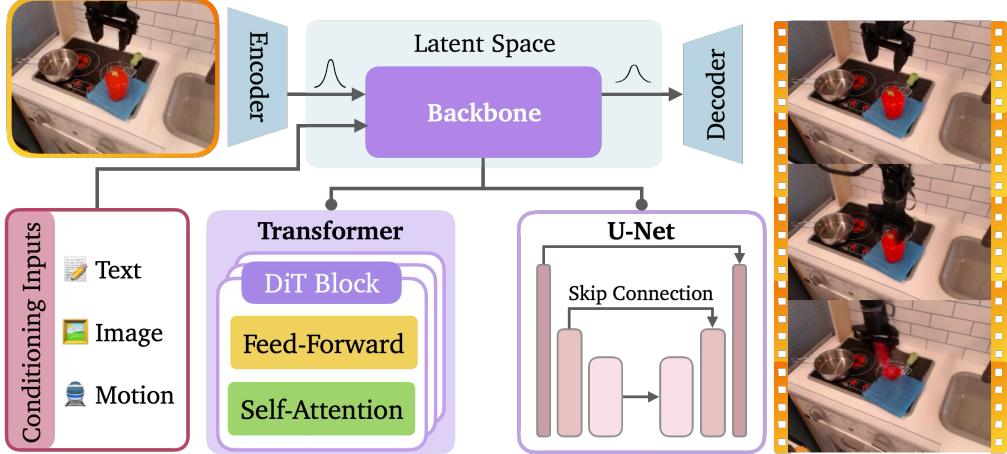


Figure 3 Diffusion Video Model Architectures. Diffusion/Flow-matching has emerged as the dominant model architecture for training photorealistic controllable video models that can be steered using text, image, and other conditioning inputs. These models broadly utilize diffusion transformers (DiTs) or U-Nets to learn important interdependencies across space and time within a compact latent space.

and video datasets with a reconstruction objective and typically utilize spatial and temporal compression for compact latent embeddings across frames. To enforce temporal causality, VQ-VAEs replace GroupNorm operations with RMSNorm operations for temporal feature caching [10, 11]. Building on these advances, later research efforts use VQ-VAEs to learn the latent distribution with autoregressive convolutional decoders [162] or autoregressive transformers [73, 168] for higher-fidelity video generation. Further, Genie [28] trains a controllable video model using a VQ-VAE and a latent action model for frame-by-frame control.

Despite the resulting performance gains, these video models lack the ability to capture complex interactions within an environment, limiting their applications. These limitations have been addressed by diffusion and flow-based matching, enabling video models to learn highly expressive representations of the physical world. We provide a detailed discussion of these video models in the subsequent subsections, along with a brief overview of joint-embedding predictive architectures, which seek to learn world models from video data without predicting pixel-level visual details.

2.2 Diffusion/Flow-Matching Video Models

The emergence of diffusion modeling [1] and flow-matching [2] has transformed the SOTA in image and video generation [169, 170], achieving high-fidelity video generation that capture fine-grained realistic and cinematic effects. Given the similarity between diffusion modeling and flow-matching, we limit our discussion to diffusion models for simplicity. We refer readers to [2] for a more detailed presentation of flow-matching.

Diffusion models [1] have gained prominence as a powerful formulation for generative models that synthesize data by modeling an iterative denoising process. We review the mathematical formulation of diffusion models, common architectural designs, and their supported input/output modalities, which is summarized in Figure 3.

2.2.1 Mathematical Formulation

Diffusion models [1, 171] learn a generative process by reversing a gradual noising process that transforms data into pure noise. Instead of directly modeling the likelihood function, diffusion models learn the gradient of the log-probability density, enabling them to effectively guide any sample \mathbf{x} to the desired data manifold, without explicitly parameterizing the data distribution. Formally, given data $\mathbf{x}_0 \sim q(\mathbf{x}_0)$, the *forward process* (also called the diffusion process) progressively corrupts clean data \mathbf{x}_0 with Gaussian noise over T time steps under some noise schedule $\{\beta_t\}_{t=1}^T$, given by:

$$q(\mathbf{x}_t | \mathbf{x}_{t-1}) = \mathcal{N} \left(\mathbf{x}_t; \sqrt{1 - \beta_t} \mathbf{x}_{t-1}, \beta_t \mathbf{I} \right). \quad (5)$$

The forward diffusion process can be expressed in closed form as the marginal distribution over noisy samples at any time step t [172]:

$$q(\mathbf{x}_t | \mathbf{x}_0) = \mathcal{N}(\mathbf{x}_t; \sqrt{\bar{\alpha}_t} \mathbf{x}_0, (1 - \bar{\alpha}_t) \mathbf{I}), \quad (6)$$

where $\alpha_t = 1 - \beta_t$ and $\bar{\alpha}_t = \prod_{i=0}^t \alpha_i$. In contrast, the *reverse process* iteratively removes the noise added to the images in the forward process. More specifically, each denoising step is parameterized by a Gaussian transition $p_\theta(\mathbf{x}_{t-1} | \mathbf{x}_t)$ with learnable weights θ that approximates the true posterior $q(\mathbf{x}_{t-1} | \mathbf{x}_t, \mathbf{x}_0)$:

$$p_\theta(\mathbf{x}_{t-1} | \mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \mu_\theta(\mathbf{x}_t, t), \Sigma_\theta(\mathbf{x}_t, t)). \quad (7)$$

Diffusion models are trained to minimize the divergence between the distribution of the forward and backward transitions by predicting the ground-truth noise ϵ with the (simplified) loss function [1]:

$$L_\epsilon = \mathbb{E}_{\mathbf{x}_0, t, \epsilon} \left[\|\epsilon - \epsilon_\theta(\mathbf{x}_t, t)\|^2 \right]. \quad (8)$$

Alternatively, the loss function can be expressed using a velocity-based parameterization [173] for better numerical stability and faster convergence, where the model is trained to predict the velocity $\mathbf{v} = \sqrt{\bar{\alpha}_t} \epsilon - \sqrt{1 - \bar{\alpha}_t} \mathbf{x}_0$, with the loss function:

$$L_v = \mathbb{E}_{\mathbf{x}_0, t, \mathbf{v}_t} \left[\|\mathbf{v}_t - \mathbf{v}_\theta(\mathbf{x}_t, t)\|^2 \right]. \quad (9)$$

To enable controllability of diffusion models, the loss function is modified for conditioning using input prompts or actions, which we discuss next.

2.2.2 Classifier-Based and Classifier-Free Guidance

Conditioning for diffusion models is used to steer the outputs of diffusion models towards desired attributes specified by an input prompt through classifier-based and classifier-free guidance. Classifier-based guidance [169] trains an external classifier that learns to predict an attribute (label) y from a noisy sample x_t , denoted as $p_\phi(y | x_t)$. At inference time, the model can be steered towards a desired attribute by biasing the sampled noise towards the direction that increases the likelihood of that attribute via:

$$\hat{\epsilon}_\theta(x_t, t, y) = \epsilon_\theta(x_t, t) - s \cdot \sigma_t \nabla_{x_t} \log p_\phi(y | x_t), \quad (10)$$

where $\hat{\epsilon}_\theta$ denotes the biased noise sample.

Classifier-based guidance is limited by high computation costs and training instability since it requires training a classifier on noisy data. Classifier-free guidance [174] addresses these challenges by training a joint conditional and unconditional model. At inference time, the strength of the conditioning can be modulated by adjusting the guidance scale w :

$$\tilde{\epsilon}_\theta(x_t, t, y) = (1 + w) \epsilon_\theta(x_t, t, y) - w \epsilon_\theta(x_t, t). \quad (11)$$

where $\tilde{\epsilon}_\theta$ denotes the biased noise sample. Classifier-free guidance has become the dominant conditioning strategy due to its simplicity, versatility, and robustness [175–178].

2.2.3 Model Architecture

Early diffusion models [80] operate directly in the pixel space, which is prohibitively expensive at high resolutions. To overcome this limitation, recent approaches adopt a latent diffusion paradigm, where observations are first compressed into a lower-dimensional latent space using a variational autoencoder (VAE) [10, 11, 81, 179, 180] prior to the diffusion process. Other alternative latent representations can also be used, e.g., DINO features [181]. Diffusion models are broadly parameterized using U-Nets [182, 183] or transformers [184, 185], which we discuss in the rest of this section.

U-Net Architectures. The U-Net architecture [182, 183] has become a foundational backbone for a wide range of vision tasks, including diffusion modeling. U-Nets consist of a downsampling path that progressively reduces the spatial resolution of an input image (video frame) with hierarchical convolution layers to capture high-level semantic features, followed by an upsampling path that recovers the original resolution of the input data. U-Nets rely on skip connections between corresponding layers in the encoder and decoder to preserve fine-grained spatial information and to stabilize training. Building on its success in image generation, early works

on video diffusion [80, 135, 186] extend 2D U-Nets to the spatiotemporal domain by lifting 2D convolutions to 3D or by introducing temporal attention modules to jointly model spatial and temporal dependencies. To create a unified strategy for training (U-Net) video diffusion models, Stable Video Diffusion [81] explored effective strategies for data curation, text-to-image pretraining, video pretraining, and video model finetuning, demonstrating the superior performance of the resulting video models. The resulting training recipe has been widely adopted by open-source video model implementations.

Transformers. Recent work has utilized transformers in video diffusion modeling, given their effectiveness in language and computer vision tasks, e.g., language generation and object segmentation. Transformer-based diffusion models [184, 185] replace the traditional U-Net backbone with a diffusion transformers (DiT), leveraging the expressivity of self-attention mechanisms. In DiTs, visual inputs are first partitioned into patches and then embedded as tokens with positional encodings to preserve spatial relationships. Unlike U-Nets, which rely on an encoder-decoder hierarchy with skip connections to fuse multi-scale features, DiTs employ a uniform transformer architecture that jointly processes all tokens. This design trades the U-Net’s inductive biases toward locality and translation equivariance for a more flexible capacity to model long-range dependencies and higher-order semantic relationships. For video generation tasks, these key characteristics enable DiTs to better capture temporal coherence and overall scene consistency, making them particularly effective for large-scale video diffusion models. Consequently, SOTA video models [5, 7, 9, 10, 185] utilize DiT-based architectures. Many methods employ specialized video encoders to perform temporal compression, substantially reducing token counts and thereby improving overall generation efficiency.

2.2.4 Conditioning Modalities

Modern video diffusion models support a wide range of generation modalities for different levels of granularity in controllable video generation. Before discussing specific conditioning modalities in video diffusion models, we first clarify the primary mechanisms by which conditioning signals are applied to the diffusion process. Video diffusion models generally introduce conditioning inputs into the video generation process through channel concatenation, cross-attention, or adaptive normalization. Channel concatenation augments the inputs or latent representations along the channel dimension, which is most effective when the conditioning signal is spatially aligned with the target output, such as in image-to-video generation, depth guidance, or pose conditioning. This approach enforces a strong, pixel-wise correspondence and imposes a hard structural constraint on the generation process. In contrast, cross-attention captures interactions between intermediate video features (queries) and the conditioning signal (keys and values) [187], making it the dominant approach for semantic, non-spatial conditions like text prompts. Finally, adaptive normalization methods such as AdaLN or FiLM [188, 189] modulate the scale and shift parameters of normalization layers using a global conditioning vector and are typically employed in (scalar) global attribute control, such as target frame rate or motion intensity, that affect overall generation statistics rather than localized structure. The primary conditioning modalities supported by video diffusion models include text prompts, input images, and motion or trajectory primitives, described in the subsequent discussion.

Text-to-Video (T2V) Generation. Text-to-Video (T2V) generation requires translating high-level semantic descriptions into temporally coherent visual sequences. To achieve this, conditioning is most commonly injected through cross-attention layers, enabling the model to selectively attend to individual words or phrases while synthesizing specific spatial regions and temporal segments of the video [190, 191]. This mechanism allows linguistic concepts to exert fine-grained, context-dependent influence, while preserving temporal consistency across frames.

Image-to-Video (I2V) Generation. Image-to-Video (I2V) generation pipelines synthesize a video from a reference image (usually the first frame) and optionally a text prompt. The initial frame provides contextual information that seeds the generation process [81, 175]. Existing approaches generally incorporate image conditioning through either frame-level input concatenation or cross-layer attention. For low-level, frame-aligned conditioning, the conditioning frames are concatenated with the video input along the temporal or channel dimension. For higher-level semantic guidance, the image features (extracted using pretrained encoders such as CLIP [100]) are incorporated via cross-attention layers, either independently or jointly with text tokens.

Motion/Trajectory-Guided Generation.. Prior work [192] encodes motion trajectories as coordinate maps, optical flow fields, keypoint heatmaps, or applied forces, which are injected via channel concatenation, dense cross-attention, or specialized conditioning adapters such as ControlNet [193]. More recent efforts focus on embodiment-specific video models tailored to robots, directly conditioning on low-level robot states or actions (e.g., joint positions or torques) [11, 16, 17, 30, 194]. The fine-grained conditioning inputs enable impressive controllability and physical grounding of the generated videos.

2.3 Video Joint-Embedding Predictive Architecture Models

Here, we discuss methods based on joint-embedding predictive architectures (JEPAs) [76, 77, 79] that learn world models from internet-scale videos for future prediction, video understanding, and planning in latent space. In contrast to diffusion/flow-matching video models, which prioritize photorealistic video generation, video JEPA models [77, 79] seek to learn effective latent representations through self-supervised training on video data. These latent representations form a foundational component for robust video understanding in downstream tasks, such as video question answering, motion understanding, and action recognition, using task-specific models trained on latent features extracted by JEPA models. Importantly, JEPA models [79] can be directly applied to robot planning by conditioning the JEPA backbone on robot actions during the training process. JEPAs build on contrastive learning approaches for effective self-supervised learning. Next, we review contrastive methods before discussing JEPA methods.

Contrastive learning. Contrastive-based methods learn latent space representations that identify salient characteristic features of (image) inputs to distinguish between similar and dissimilar (image) pairs. Under the assumption of separability of the inputs, contrastive models map inputs to a latent space such that similar data are encoded close together in the latent space while differing inputs are further apart. Contrastive learning [195] typically applies random transformations, such as cropping, resizing, color distortions, or noise injection, to generate augmentations of an input data point. Subsequently, the augmented inputs are mapped to latent embeddings using a learned model, which is trained using the InfoNCE loss function:

$$\mathcal{L}_{i,j} = -\log \frac{\exp(\text{sim}(z_i, z_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{k \neq i} \exp(\text{sim}(z_i, z_k)/\tau)}, \quad (12)$$

where $\text{sim}(\cdot)$ corresponds to the normalized dot product of the two vectors, given a positive image pair (x_i, x_j) from a dataset of N image pairs.

Contrastive learning suffers from two core issues. First, since positive pairs come from different augmentations of the same image, other similar images are treated as negative examples, forcing the model to push apart representations that should be close. Second, these methods are prone to representation collapse, where the encoder learns to produce a trivial solution for all inputs. To address these challenges, Bootstrap Your Own Latent (BYOL) [196] introduces a slow-moving teacher network that guides a student network. During training, the teacher network’s weights are updated as an exponential moving average of the student’s weights. In place of a contrastive loss, BYOL minimizes a normalized mean squared error between the student’s and teacher’s predictions, stabilizing training and enabling effective representation learning using only positive pairs. DINO encoders [197–199] build upon BYOL by recasting the teacher-student framework as a knowledge distillation process, where the student learns to match the teacher network’s probability distribution over K classes by minimizing the cross-entropy loss between the predicted probabilities.

Joint-Embedding Predictive Architecture. Joint-embedding predictive architectures [76] extend self-supervised learning (e.g., BYOL) to the predictive domain through the introduction of a predictor and a conditioning variable to steer the outputs. To avoid representation collapse, JEPAs utilize an asymmetric architecture for embedding input images, composed of a student encoder, target encoder, and predictor. Video joint-embedding predictive architecture (V-JEPA) models [77, 79] build upon this foundation for video generation, predicting spatially and temporally masked features within the latent space. By making predictions within the latent space as opposed to pixel space, the model is encouraged to predict higher-level representations rather than pixel-level information [78]. This abstract understanding allows the model to build an internal world model, enabling it to also make predictions about future states and plan without task-specific training or reward.

Implicit World Models



Figure 4 Video Models for Embodied World Modeling. Video models provide high-quality representations of the physical world, which could be implicit (e.g., latent and video representations) or explicit (e.g., point clouds and Gaussian Splatting models).

To train a V-JEPA video model, masked video frames are passed to an encoder E_θ , while the unmasked frames are fed into an exponential moving average of E_θ , denoted by $E_{\bar{\theta}}$. Given these embeddings, a predictor network P_ϕ computes the latent representations of the masked frames conditioned on a learnable mask token Δ_y . The model is trained with the loss function:

$$\min_{\theta, \phi, \Delta_y} \|P_\phi(\Delta_y, E_\theta(x)) - \text{sg}(E_{\bar{\theta}}(y))\|_1,$$

where $\text{sg}(\cdot)$ stands for the stop-gradient operator. After E_θ has been trained, it can be frozen and used to train a transition model with additional action-labeled trajectory data [79]. JEPA models are still prone to representation collapse [200], although they are more robust compared to prior approaches. Regularizers [201, 202] have been shown to help prevent posterior collapse, but are difficult to tune and interpret [200].

3 Applications of Video Models in Robotics

In this section, we explore applications of video models as high-fidelity world models in robotics. World models capture the evolution of an environment under the effects of actions applied by an agent. However, modeling physical interactions is extremely challenging, given the stochastic nature of dynamical interactions, which is often not fully described by simplified physical laws. Although early world models [69, 154] effectively learn high-level scene dynamics, they struggle with modeling intricate dynamical changes, especially with high-fidelity. Notably, in fine-grained interaction tasks in robotics, such as dexterous manipulation, these models often fail to predict the effect of subtle changes in robot actions that have significant impacts on the success of such tasks. For high-fidelity world modeling, these models generally require lots of training data centered around such dynamical events for effective supervision, which is often difficult to collect in many practical applications. More traditional physics-based simulators function as world models; however, their capabilities are often limited by restrictive assumptions built on simplified object models and dynamics models. For example, physics-based simulators typically struggle with deformable-body simulations, which require higher-fidelity dynamics model. Importantly, these assumptions contribute to the sim-to-real gap faced by physics-based simulators, e.g., through the use of primitive object shapes, appearance and visual conditions. Recent work in robotics seeks to address these limitations by leveraging video models as *embodied world models*.

Video models can generate high-quality predictions of the future state of the physical world without a prohibitive demand for large-scale action-labeled datasets. In general, recent approaches [8, 25, 26, 203, 204]

fine-tune pre-trained video models to synthesize high-accuracy 4D scene representations autoregressively, repeatedly generating future frames conditioned on the previously generated video frames. Video world models can be classified into two categories, based on the maintained scene representation, namely: *implicit* and *explicit* video world models, as illustrated in Figure 4.

Implicit video world models. In implicit video world models, the 3D scene representation is encoded exclusively within the video model, without any external representation. As such, visualization of the evolving scene can only be achieved by generating videos from the video model. While some methods [203] only support text-conditioned video generation, others [25, 26, 157, 205–207] fine-tune these models on robot datasets, e.g., Bridge [208], DROID [209], etc., for action-conditioned generation using robot actions. Pandora [203] enables finer control over longer-duration videos by fine-tuning the DynamicCrafter video model [210] for text-conditioned video generation with language instructions for any video frame. Similarly, FreeAction [194] modulates classifier-free guidance with the magnitude of the input actions to improve action-conditioned video generation. Likewise, Vid2World [25] extends the DynamicCrafter video model to autoregressive action-conditioned video generation using causal attention and diffusion forcing [126]. Other approaches fine-tune video models to predict a target object’s dynamics for object-centric video generation [211] and also explore wrist-camera video generation [205] given only scene-camera input images.

Explicit video world models. In contrast to implicit video world models, explicit video world models create a concrete 3D scene representation using video models, e.g., with multi-view videos or depth maps. For example, Enerverse [26] trains an autoregressive video generation model on multi-view video data conditioned on text and image inputs using simulation data since many open-source large-scale robot datasets lack multi-view inputs. The resulting multi-view video frames provide a sparse representation of the 3D world, which might not be detailed enough in fine robotics tasks. Consequently, Enerverse trains a 4D Gaussian Splatting scene representation [212] for high-fidelity novel-view synthesis. In contrast, Aether [204] fine-tunes a video model (CogVideoX [129]) to generate depth and camera raymap videos, from which a 3D scene representation is extracted via back-projection. Other methods [213] construct a voxel-grid scene representation of the world from generated videos, which also serves as a memory bank for the video model. Genie Envisioner [27] trains a video generation model alongside an action decoder to create a world model amenable to action prediction, policy evaluation, and data generation. With its action decoder, Genie Envisioner transforms latent video states to predicted actions given a language-conditioned robot task, and uses the video model for policy rollouts.

The high-fidelity world modeling capabilities of video models enable a broad range of downstream robotics applications, including: (i) efficient data generation and action prediction in imitation learning, (ii) expressive dynamics and rewards modeling in reinforcement learning, (iii) scalable policy evaluation, and (iv) visual planning.

3.1 Cost-Effective Data Generation and Action Prediction in Imitation Learning

In recent years, impressive research advances in robotics have been driven by imitation learning on large-scale expert demonstrations, circumventing the well-documented challenges associated with explicitly modeling dynamical interactions between robots and their environments. For example, SOTA vision-language-action (VLA) models [23, 24, 214, 215] have demonstrated remarkable capabilities in generalist language-conditioned robot manipulation, exhibiting strong task and environment generalization and robust recovery behaviors in the presence of disturbances. Scaling foundation models in terms of model and training data size has proven to be essential to realizing these significant leaps in performance, a fact that has been further underscored by the success of LLMs trained on internet-scale data. Although this path to advancing robot learning holds significant promise, the costs associated with collecting large-scale expert demonstrations, such as time and labor costs, pose notable challenges. To address this challenge, recent work [12, 83, 118, 216–218] employs video generation models as cost-effective data generators of expert demonstrations, eliminating the overhead associated with human-supervised data collection. Concurrently, recent research has explored the use of video models as policy backbones in imitation learning, seeking to harness the synergies between dynamics prediction and policy learning to ground proposed robot actions. We present these application areas in the subsequent discussion.

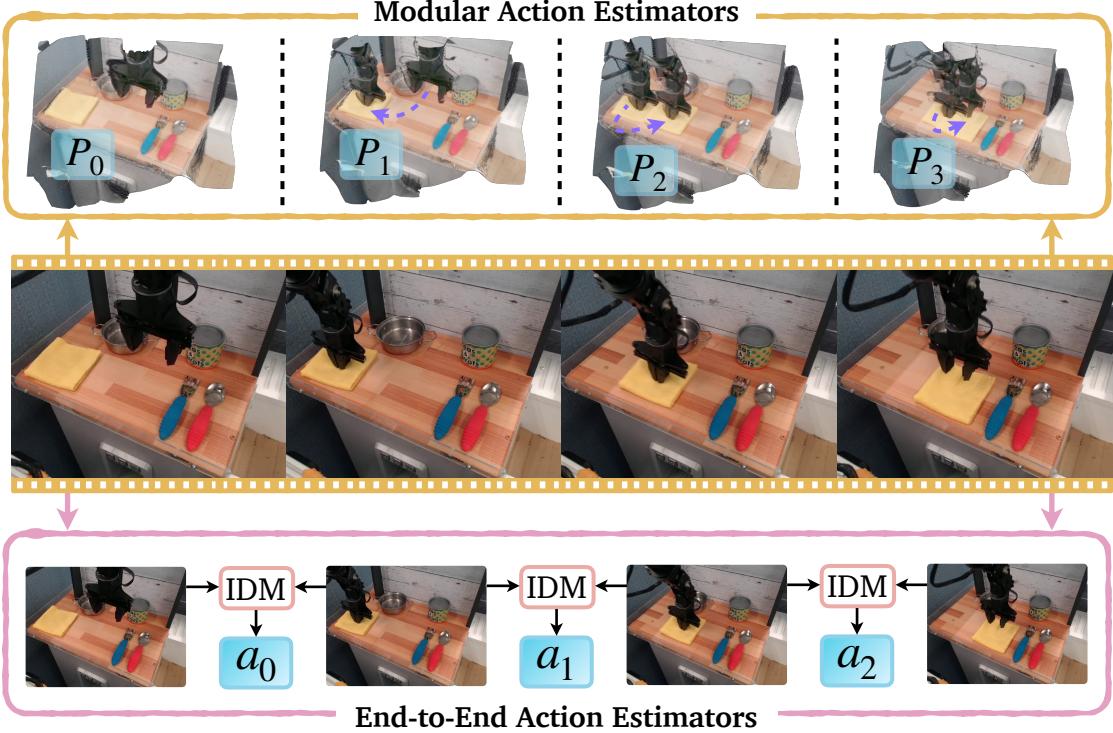


Figure 5 Video Models for Data Generation. Video models enable high-fidelity data generation for cost-effective policy learning. Robot actions can be extracted from videos through modular approaches using end-effector pose tracking or end-to-end approaches, such as inverse-dynamics methods.

Video Models as Data Generators. For scalable data generation, existing methods fine-tune pre-trained video models, such as Cosmos Predict [219] and Wan [10], on robot datasets for adaptation to robot embodiments and environments. However, the expressiveness of text-conditioned and image-conditioned video models is often too limited to capture the diversity of the training data required to train generalizable robot policies. Subsequent research on controllable video models [118, 220–222] seek to overcome this limitation through finer control of camera and object motion in generated videos, given an input text, image, keypoints, or trajectory vectors, describing spatial changes in the scene temporally. Some methods [218] further decompose the task into a set of subtasks for generating keyframes, which serve as conditioning inputs to generate video data for longer-horizon tasks. Other methods train video models for effective cross-embodiment transfer. For example, Human2Robot [216] trains a video model to generate robot videos given human videos, from which robot actions are estimated. The resulting action-annotated data is used for policy learning, e.g., with VLA models [12, 219], or directly applied to a robot [36, 37, 223]. In general, robot data generation methods recover robot actions from generated videos using an end-to-end approach or a modular approach, which is illustrated in Figure 5.

End-to-end methods typically utilize latent action models or inverse-dynamics models to estimate actions from videos. Latent action models [122, 123, 224] infer actions that explain the transition between a pair of video frames in latent space without the need for ground-truth actions, which often resides in a different action space. To learn latent actions without supervision, existing methods train an encoder-decoder model with a reconstruction-based loss function, generally implemented in latent space. The encoder takes in a pair of frames and outputs a latent action, which is passed into the decoder to recover the future frame. SOTA latent action models use VQ-VAEs as the model architecture for the encoder and decoder, given the superior tradeoff offered by VQ-VAEs in terms of expressiveness and training efficiency. Given the non-equivalence between the action space of the ground-truth and latent actions, latent action models often require a subsequent fine-tuning stage at deployment time to align the ground-truth and latent action spaces using a small set of action-labeled data. Unlike latent action models, inverse-dynamics models (IDMs) [124, 125, 225] learn to predict actions from videos in a supervised fashion from action-labeled video data. Recent methods

parameterize the video-to-action mapping using an encoder-decoder model trained with a diffusion objective. Although the need for ground-truth action labels poses a challenge to IDMs, IDMs do not require a fine-tuning stage, enabling zero-shot deployment. For example, DreamGen [12] trains an IDM using action-annotated robot datasets for action estimation. Likewise, Video Prediction Policy (VPP) [226] trains an IDM based on a diffusion model architecture to regress robot actions from latent features generated by a text-conditioned video model. ARDuP [227] and Vidar [217] employ a similar approach. Whereas Vidar supervises the IDM by predicting action-relevant regions of the videos, ARDuP directly feeds active region masks to the video model as conditioning inputs.

Broadly, modular approaches estimate the target object’s pose in each video frame. Some of these methods [82–84] utilize learned pose trackers [228, 229] and monocular depth estimators [230] for 3D object pose estimation from 2D image keypoints. Further, methods such as AVDC [38] and VideoAgent [85] use an off-the-shelf optical flow predictor to extract pixel movement, from which the motion of the target object is estimated. Other methods [86] estimate the target object’s pose using computer-aided design (CAD) models. The resulting object trajectory is subsequently retargeted (i.e., applied) to the robot, under the assumption that a fixed rigid transformation exists between the object’s reference point and the robot’s end-effector. By taking advantage of low-level control routines, these methods can be deployed zero-shot without the need for a separate fine-tuning stage for aligning the action spaces between training and deployment.

Video Models as Policy Backbones. Using video models as policy backbones, unified video-action methods train robot policies to jointly predict videos and actions conditioned on a language instruction and initial observation. While most unified video-action methods [87, 231–233] utilize a VLA architecture for these policies, more recent work [41, 234, 235] directly adapts pre-trained video models for joint video and action generation. GR1 [232, 236] trains an autoregressive transformer-based model to jointly predict future images and actions, given the language instruction, sequence of observation images, and a sequence of robot states. RPT [231] takes a masking-based training approach, by masking the model’s inputs, e.g. actions, images, or robot states, before action prediction. In contrast, UVA [87] trains an encoder to learn a joint latent representation over video frames and actions. The resulting latent embeddings are used in training an autoregressive transformer for action prediction, video generation, and inverse-dynamics modeling. Unlike UVA, PAD [237] and Video Policy [234] use a pre-trained Stable Diffusion encoder [179] with diffusion transformers or U-Nets for video and action generation, reducing training overhead. Like UVA, UWM [233] uses independent diffusion processes for action and video generation. Meanwhile, DreamVLA [88] further supervises the VLA with depth maps, dynamic regions, and semantic feature prediction to more strongly guide the model in learning useful features. Likewise, UniVLA [238] introduces stronger supervisory signals into the training process by predicting language tokens (e.g., text descriptions) in addition to video frames and actions.

3.2 Dynamics and Rewards Modeling in Reinforcement Learning

As discussed in the preceding subsection, SOTA robot policies are generally trained using imitation learning, which provides more efficient training compared to reinforcement learning (RL) but does not generalize well outside of the training data distribution. Although RL circumvents this challenge, RL requires the specification of dynamics and rewards models, which are often non-trivial in many practical problems. Further, RL suffers from low sample efficiency, requiring large amounts of training data to achieve the same level of performance as imitation-learned policies. Recent research seeks to address these limitations by using generative video models as expressive dynamics and rewards models in RL, shown in Figure 6.

Whereas earlier work utilized recurrent state-space models [239] or image diffusion models [240] for dynamics prediction, more recent work trains video diffusion models, which provide higher-fidelity predictions that are more physically consistent. Dreamer 4 [31] trains an action-conditioned video model from scratch by first training a text-conditioned video model and subsequently fine-tuning the model on action-labeled data. The resulting action-conditioned video model serves as a dynamics predictor to fine-tune imitation-learned policy and reward heads using RL, e.g., in Minecraft. In contrast, World-Env [32] uses a pre-trained action-conditioned video model [89] for video generation and a VLM (instance reflector) for dense reward signals to fine-tune a VLA using RL. Another subclass of methods directly use video models as reward models in RL. While VIPER [33] uses the video prediction likelihood as the reward signal, Diffusion Reward [34] uses the

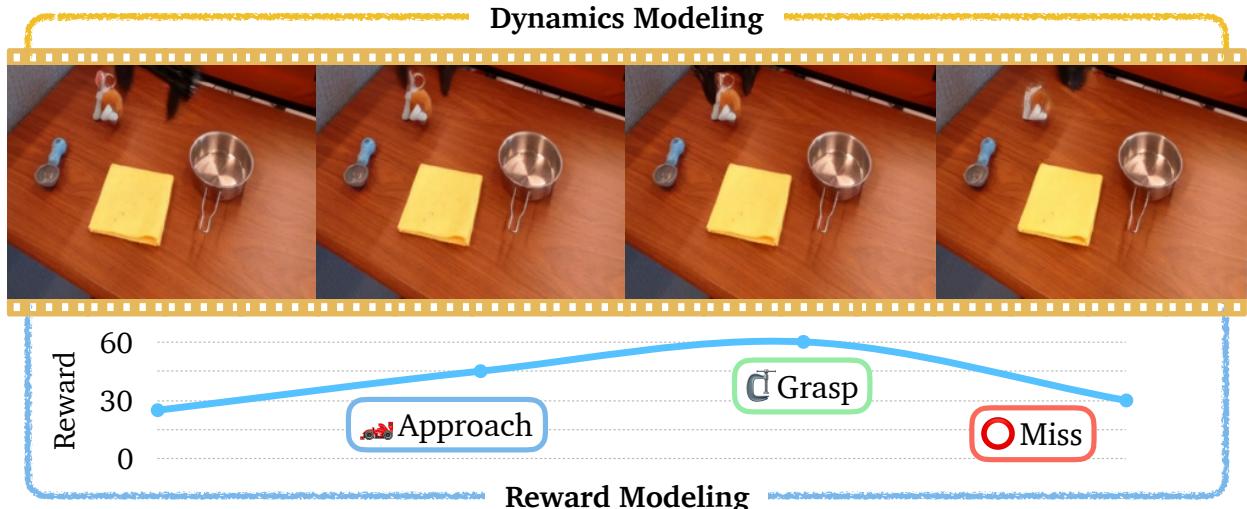


Figure 6 Dynamics and Rewards Modeling. Video models provide high-accuracy dynamics modeling and rich reward signals, which are essential in reinforcement learning, circumventing long-standing challenges in system identification and reward engineering.

conditional entropy of the video generation distribution as the reward signal, inspired by the idea that video trajectories closer to the expert trajectories seen in the training data have lower entropy. Further, the work in [90] uses a video model to generate videos that guide exploration during robot policy learning. The resulting experience is saved to a buffer for fine-tuning the policy. Although this work uses a goal-conditioned policy, where the video frames serve as image subgoals, the approach can be applied to RL.

3.3 Scalable Policy Evaluation

Beyond policy learning, video models enable reliable policy evaluation that is reproducible across different environments and task settings. Real-world evaluation of robot manipulation policies is notably challenging due to the significant inherent hardware and labor costs, especially for generalist robot policies, which typically require evaluation across a combinatorial number of operating environments. For example, each hardware trial requires human monitoring to reset the environment, observe the policy rollout, and record success scores, which is expensive. While hardware evaluation is the gold-standard, policy evaluation in simulation is the best available alternative, especially with recent improvements in visual fidelity, system identification, and careful tuning of material properties. However, physics-based simulation requires significant setup time, as each real environment needs to be manually recreated, including the careful tuning of several parameters such as lighting and material properties to minimize the sim-to-real gap. In contrast, video models [241–243] offer a higher-fidelity, more scalable framework for policy evaluation, modeling intricate robot-environment interactions that are challenging for physics-based simulators, e.g., in deformable-body simulation.

Here, we survey a growing body of research on the application of video models to policy evaluation, including policy comparison and estimation of real-world success rates [16, 17, 26, 29, 30, 91–93]. These studies demonstrate that video models can offer useful sanity checks prior to real-world policy deployment. Real-world success rates can be estimated by rolling out the policy in closed-loop with a video model on sampled initial observations (e.g., camera images) and task instructions. To improve the quality and consistency of video generation, some architectures [91] condition the video model on the latent action representation in the policy, instead of conditioning on the robot’s physical actions [16, 17]. As robot manipulation setups often involve multiple camera views, several architectures are adapted for consistent multi-view generation [17, 26, 30, 93], which has been empirically shown to reduce hallucinations [17]. To further mitigate prediction errors that accumulate over long rollouts, existing methods incorporate history during video generation, conditioning future video frames not only on the current observation but also on past observations. The history may consist of all frames within a fixed window length [16, 29, 92] or a sparsely sampled subset of past frames [17, 26]. Moreover, augmenting observations with corresponding robot joint poses has been shown to improve frame-level

action controllability [17].

Each rollout is scored according to a rubric to quantify success (e.g., Bernoulli score, partial credit) on task completion and instruction following, and the scores of individual rollouts are aggregated into empirical success rates. To assess the accuracy of video models in policy evaluation, existing approaches [17, 30, 93] use metrics such as the Pearson correlation coefficient and the Mean Maximum Rank Violation (MMRV). The Pearson correlation coefficient measures the strength of the linear relationship between predicted and real-world success rates — a high correlation is achieved when policies with high real-world success rates also exhibit high success rates in video model evaluations, and policies with low real success rates similarly have low video model success rates. In contrast, rank violation captures ranking inconsistencies between policy pairs, weighting each violation by the absolute difference in real-world success rates. The MMRV score is computed as the average across policies of their maximum rank violations. Although the predicted and real-world success rates do not always match, the evaluation results provide valuable insights for ranking the relative performance of policies, which is essential in improving robot policies in subsequent design and training stages.

Furthermore, video models can also be used to assess the robustness and safety of robot policies, particularly in out-of-distribution conditions [16, 30]. In the Veo World Simulator [30], such out-of-distribution scenarios can be rapidly constructed via image editing, e.g., to alter the background or add novel objects and distractors. This pipeline enables the use of video models to consistently predict performance degradation along different axes of generalization. Additionally, the pipeline can be readily interfaced with a VLM to generate safety-critical scenes and tasks for testing whether the policy executes semantically or physically unsafe behavior [30]. For accurate predictions across successful and failure scenarios, existing methods [29, 92, 93] incorporate failure data when training video models to avoid a bias towards always predicting success, which we discuss further in Section 5.9.

3.4 Visual Planning

Robot planning offers a compelling alternative to imitation learning, enabling impressive generalization beyond the distribution of the training dataset. However, the design of high-fidelity models that closely predict the scene dynamics often proves prohibitively challenging. To address these drawbacks, recent work has explored utilizing video models in *visual planning*, defined as the problem of synthesizing a sequence of images or video frames that show the steps necessary to complete a task specified by a language instruction and an initial observation. By leveraging the extensive diversity of the training data encoded by video models, these methods circumvent the need for large-scale expert demonstrations or explicit dynamics models to solve a broad range of robot tasks.

Visual planning methods [244] generally optimize the generated video plans using sampling-based trajectory optimization methods, such as the gradient-free cross-entropy method, or gradient-based methods, e.g., gradient descent or Levenberg-Marquardt optimizers. The optimization routine is often embedded within a model predictive control (MPC) framework, facilitating the incorporation of new observations during planning via sensor feedback. Video-model-based visual planning methods can utilize *action-guided* or *action-free* approaches to create feasible robot trajectories.

Action-Guided Visual Planning. Action-guided visual planning methods utilize a three-step approach, which consists of: generating action proposals, synthesizing video trajectories using video models as dynamics prediction modules given these action proposals, and subsequently evaluating the resulting video trajectories based on an objective function. Broadly, the action proposals are typically generated by sampling-based approaches [39], learned approaches [15], or VLMs [14, 94]. The work in [39] uses the cross-entropy method to generate action proposals, optimizing the photometric/Euclidean error between a user-provided goal image or keypoints and the video frames generated by the video model conditioned on the proposed actions. The action samples are drawn by fitting a Gaussian distribution to the actions associated with the minimum objective value and sampling from the resulting Gaussian. Similarly, FLIP [15] uses a conditional variational autoencoder to generate action proposals and fine-tunes a language-image value network [245] to learn a value function over the generated video trajectories. The action that maximizes the discounted return is selected for execution. In contrast to these approaches, MindJourney [94] uses a VLM to propose candidate camera trajectories and to evaluate the generated video trajectories from a video model given these action proposals.

Likewise, the work in [14] uses a VLM for task decomposition, breaking down the language-specified task into subtasks in natural-language, which serve as text inputs for the video model. The VLM further analyzes the generated videos to expand and refine the subtasks using a tree-search-based approach. Subsequently, a goal-conditioned policy predicts robot actions from the best video plan. VLP [95] takes a similar approach, integrating a video model with an LLM, which analyzes the generated videos and selects a final plan for execution.

Action-Free Visual Planning. Action-free visual planning methods do not utilize action proposals for planning. Rather, these methods generate video plans directly from text-conditioned video models and use the video frames as image subgoals for planning. Prior work [96] uses goal-conditioned behavior cloning for extracting robot actions from the image subgoals. In contrast, CLOVER [40] trains an IDM that maps the current image observation and image subgoals to robot actions. The IDM is further conditioned on the error between the image embeddings of the current observation and image subgoals for stronger feedback. Similarly, UniPi [246] uses an IDM for action estimation but also introduces a super-resolution video generation phase that refines coarse video trajectories into finer video plans. In contrast, NovaFlow [13] extracts the object pose (represented by particles in the case of deformable objects) from generated videos, which serve as coarse robot actions. The resulting action plan serves as a reference trajectory that is refined using non-linear least-squares optimization with a pre-trained particle-based dynamics model.

4 Evaluating Video Models

In this section, we present standard metrics and benchmarks for evaluating video models across different dimensions, including perceptual quality, physical consistency, and semantic alignment with the input prompts.

4.1 Metrics for Evaluating Video Models

To assess video generation quality in accordance with human judgment, various metrics are needed to evaluate video models on visual quality, temporal coherence, diversity of generation, and physical commonsense. Although many traditional image quality metrics [97, 98, 247] exist, these metrics do not assess temporal consistency of generated videos. To address this limitation, recent work [101, 101] has introduced video-specific metrics that measure video quality both spatially and temporally. Additionally, application-focused metrics are equally important. For example, in policy evaluation, the usefulness of an action-conditioned video generation model depends on how well it can predict policy success rate, and in policy learning, whether the generated demonstration data results in more performant policies [12]. Here, we discuss frame-level metrics and spatiotemporal consistency metrics.

Frame-level Metrics. Traditional frame-level metrics from computer vision can be used to assess video generation quality, such as the peak signal-to-noise ratio (PSNR) [97] and structural similarity index (SSIM) [98]. Unlike PSNR, which is inversely proportional to the mean squared error of the pixel values, SSIM assesses image quality on luminance, contrast, and structure, which is more indicative of perceived similarity. Pixel-based metrics often fail to capture higher-order image structures that align with human perceptual judgments [98], which might be better represented in the learned feature spaces of deep models. For instance, the CLIP similarity score uses the cosine similarity between images in the embedding space [100] to assess semantic alignment between a pair of images. For generative models, the inception score [248] assesses if the model confidently generates diverse, yet semantically meaningful images by computing the expected KL-divergence between the predicted class distribution and the marginal distribution of all generated images. However, the inception score does not use real samples, depends on a fixed label space, and is not suited for image generation without a target object. The Fréchet Inception Distance (FID) [249] addresses these challenges by computing the Wasserstein-2 distance between multi-dimensional Gaussian distributions over the real and generated feature embeddings. Likewise, the Learned Perceptual Image Patch Similarity (LPIPS) [99] is a similarity score on feature embeddings from several layers of a deep image recognition network, which has been shown to be comparable to human judgments. Furthermore, recent work [247] has demonstrated that these perceptual metrics can be learned to further align with human judgments.

Spatiotemporal Metrics. While frame-level metrics focus on visual representation at any given video frame, assessing the temporal coherence of videos is also important for evaluating video generation quality. The

Fréchet Video Distance (FVD) [101] accomplishes this by extending the Fréchet Inception Distance temporally to video representations that capture motion features across frames as well as the quality of images per frame. Instead of assuming a Gaussian representation for the features, the Kernel Video Distance (KVD) [101] uses a kernel-based metric (maximum mean discrepancy), to capture higher-order variations. The Fréchet Video Motion Distance (FVMD) computes the Fréchet distance on motion features by extracting keypoints that can be tracked across multiple frames and computing their velocities and accelerations. Prior work has also employed optical flow [10, 102, 250] to assess temporal coherence and VLMs [12, 44] to evaluate physical consistency of generated videos.

4.2 Benchmarks for Evaluating Video Models

Despite their impressive capabilities, video models tend to generate videos that violate specific desired qualities, such as physical consistency, even when these videos are of high visual quality. Prior work [48, 251, 252] has introduced benchmarks to assess the performance of video models across different criteria, spanning visual quality, dynamic consistency, and instruction following. By evaluating video models across many dimensions, these benchmarks highlight critical areas for future research, in addition to identifying SOTA video models. Generally, existing benchmarks demonstrate that video models fail to follow physical laws, even after scaling these models, although their aesthetic quality and temporal consistency tend to improve with scale. While many existing benchmarks evaluate the overall quality or physical consistency of generated videos from video models, only a few benchmarks assess the safety of generated videos. These safety benchmarks [52, 53] provide an extensive evaluation of the safety of video models, demonstrating their tendency to generate illegal or unethical videos that violate their safety guidelines. In the subsequent discussion, we present benchmarks that examine the overall quality of video models broadly and those that focus on evaluating physical commonsense.

Broad Benchmarks. WorldModelBench [48] introduces a benchmark to evaluate the instruction following and physics adherence capabilities of video models, identifying physically inconsistent changes in the sizes of objects, which violates the law of mass conservation. Further, EvalCrafter [103] evaluates the quality of generated videos in terms of their aesthetic and motion quality as well as temporal consistency and text-to-video alignment. While visual quality is assessed using DOVER [253], motion quality is evaluated using action recognition methods, which are based on the activity classes in the Kinetics 400 dataset [254]. Temporal consistency and text-to-video alignment are measured using optical flow and CLIP, respectively. EvalCrafter shows that its evaluation criteria are well-aligned with human preferences. EWMBench [255] also evaluates video models along similar axes but uses the cosine-similarity metric with DINOv2 [198] embeddings to measure visual consistency. Furthermore, VBench [104] examines the performance of video models across sixteen fine-grained criteria, such as background consistency, subject consistency, and temporal flickering, in addition to aesthetic and semantic quality and instruction following. Like other benchmarks, VBench demonstrates that the results of each video model on each criterion is highly correlated with human preferences. Likewise, PAI-Bench [252] compares video models based on the temporal consistency, motion smoothness, and aesthetic quality of their generated videos. Beyond measuring overall video consistency, T2V-CompBench [105] evaluates object attribute consistency, such as color, shape, and texture, along with action consistency in generated videos. Similarly, WorldSimBench [47] assesses the physical consistency of motion, particularly the perception of a sense of depth, and changes in the velocity of objects in different media such as air and water.

Physical Commonsense. Other benchmarks focus primarily on evaluating the physical commonsense of video models [43, 108]. For example, Physics-IQ [43] assesses video models' understanding of the laws of physics, such as those on optics, thermodynamics, magnetism and fluid dynamics, demonstrating that video models lack a solid understanding of physical laws. Likewise, PhyGenBench [45] measures the commonsense knowledge of video models on 27 physical laws, including gravity, sublimation, solubility, and friction, across 160 prompts. VideoPhy [44] evaluates video models along similar axes, focusing more on object interactions. VP² [106] examines the alignment of video models with physical laws in the task of visual planning, demonstrating that strong performance on perceptual metrics is generally not indicative of alignment with physical consistency. Further, VP² [106] shows that although scaling the model size and training dataset improves performance, the resulting gains plateau relatively quickly.

5 Open Challenges and Future Directions

We identify open research challenges in robotics applications of video models and highlight directions for future research to address these challenges. We note that solutions to these challenges apply broadly beyond robotics, which could motivate novel applications of video models.

5.1 Hallucinations and Violations of Physics

Despite their impressive capabilities, video models often hallucinate, generating implausible video frames that are temporally inconsistent or misaligned with physical reality. In T2V generation, recent works [46, 256, 257] have explored different types of hallucinations, including vanishing subject, omission error, numeric variability, visual incongruity, and subject dysmorphia [256], and have proposed hallucination detectors. In robotics, the challenge of hallucination is especially important, given the critical role of accurate future prediction in policy evaluation and visual planning, among other application areas. Recent works have found that using multi-view frame inputs and particularly including a wrist camera view reduces hallucinations [17]. However, augmented conditioning inputs have limited effect on mitigating the violation of physics. Specifically, video models typically fail to follow the laws of physics governing object motion and interactions [107, 111]. Prior work [43, 44, 48] has demonstrated that generated videos from these models violate fundamental principles, such as Newton’s law of motion, conservation of energy and mass, and gravitational effects, revealing a lack of understanding of these laws. Further, these models tend to mimic the closest training example when presented with a task at inference, limiting their generalization to new (unseen) tasks. In this setting, video models exhibit a propensity to prioritize transferring the color, size, velocity, and shape of objects in the training dataset to the objects in the new task, in that particular order [108, 109].

Further, existing work [44, 45] shows that video models struggle with generating physically-realistic solid-solid interactions, demonstrating that video models do not understand the material properties of objects, the law of conservation of momentum, and the impenetrability of objects. Video models also show a fundamental lack of understanding of fluid mechanics and conservation of mass [43], generating unrealistic videos of liquid flows, e.g., pouring a drink into a cup without a corresponding change in the volume of liquid in the cup. However, generating physically realistic data is crucial in robotics, such as in robot learning where the generated data serves as expert demonstrations for training a policy, highlighting the need to impart physical understanding to video models. Moreover, prompt engineering and scaling techniques do not adequately resolve this challenge, suggesting that novel architectures and training techniques are required to address this problem. Next, we discuss potential directions for future research to improve the physical consistency of videos generated by video models.

Future Directions. Physical realism of generated videos from video models is essential in applications requiring trustworthy video generation, such as policy evaluation, planning, and policy learning, underscoring the importance of research on hallucination mitigation. To improve the physical consistency of generated videos, prior work [258–261] has explored integrating physics-based priors and physics-based simulation with video generation. Hamiltonian and Lagrangian approaches [258, 259] train models to predict the dynamics of system based on Hamiltonian or Lagrangian mechanics. By encoding the laws of physics as priors in the training process, the resulting models tend to adhere better to the physical laws. Other methods employ simulation engines to enforce physical laws. For example, PhysGen [260] extracts object segmentation masks and physical properties using VLMs and computes feasible trajectories for the annotated objects using rigid-body dynamics equations. Subsequently, the trajectories are applied to corresponding pixels for video generation. However, the resulting video often contains artifacts, which degrades its fidelity. PhysGen uses a video diffusion model to edit these artifacts to generate higher-quality videos [262]. Likewise, WonderPlay [261] constructs a 3D scene representation from the conditioning inputs and estimates the physical properties of objects in the scene using a VLM. The scene and objects’ physical properties are passed into a physics-based simulator, which computes a coarse trajectory conditioned on applied forces. The coarse trajectory from the simulator serve as conditioning inputs for a video model to generate future frames. Other methods [110] have utilized LLMs to refine video models’ input prompts to provide comprehensive descriptions of physical attributes and interactions to improve the physical accuracy of generated videos. Although these methods improve physical alignment, they do not eliminate violations of the laws of physics. Specifically, LLMs/VLMs are prone to hallucinations [263], which limits the effectiveness of the aforementioned methods. Moreover, these methods

rely on ad-hoc solutions, negatively impacting their generality and ease of implementation. We believe a promising future direction will be to explore efficient techniques for natively endowing video models with a fundamental understanding of physical laws, which might necessitate the design of novel training techniques and model architectures [264] that enforce physical laws.

Additionally, improving the ability of video models to understand feasible interaction modes could be critical to mitigating hallucinations. Prior work has explored identifying and localizing functional interaction cues from videos, e.g., how humans interact with objects and environments, which is referred to as affordance-based video understanding [265, 266]. Existing methods [267–270] localize interaction regions in videos and embed these cues into a latent space to predict the evolution of contact regions (hotspots) across future video frames. The resulting affordance maps [271–274] can serve as conditioning (guidance) signals in video synthesis to improve the physical consistency of generated videos. Developing effective strategies for incorporating these signals during video generation is an important area for future work.

5.2 Uncertainty Quantification

Uncertainty quantification (UQ) techniques are widely utilized with traditional deep neural networks to examine the trustworthiness of these difficult-to-interpret models. While the rapid development of LLMs has led to increased research in UQ of large generative models to address severe hallucinations (see [275] for a review of LLM UQ methods), UQ methods for image and video generation models remain largely underexplored. Meanwhile, extending existing UQ methods to video generation models faces significant challenges due to the complexity of spatial and temporal relationships. For example, generative video modeling fails to satisfy the central assumptions of standard Bayesian UQ methods, such as the assumption of independent, identically distributed samples, given the correlation between frames across multiple timesteps. Additionally, the significant computational cost associated with video generation impedes the application of ensemble-based UQ methods. Importantly, existing video models lack the ability to express or verbalize their confidence. As a result, inference-time UQ methods, e.g., black-box LLM UQ methods, cannot be directly applied to video models.

Future Directions. A few recent works have explored UQ techniques for controllable video generation, including text-conditioned and action-conditioned models. S-QUBED [46] quantifies uncertainty of T2V generation in the semantic space. However, this method only estimates task-level confidence on video generation. On the other hand, C^3 [111] trains video models for simultaneous video generation and uncertainty quantification in latent space. Specifically, C^3 enables video models to predict the uncertainty associated with each subpatch of the generated video, providing dense confidence estimates spatially and temporally. In general, these methods are only guaranteed to provide calibrated uncertainty estimates within the distribution of the training dataset, limiting their effectiveness in out-of-distribution use-cases. A promising direction for future work will be to explore more cost-effective methods for uncertainty quantification with provable guarantees both within and beyond the training distribution.

5.3 Instruction Following

Like early language models [276], text-conditioned video models struggle with following user instructions specified in the input prompts [44, 47], which poses a significant limitation. Although these models are generally trained with guidance for alignment with the conditioning inputs, existing guidance mechanisms do not provide sufficient supervision to produce videos consistent with the input prompt. In general, SOTA video models often fail to complete the specified task due to their inability to extract and transfer the intended action from the conditioning input to the specified actor (agent). Prior work [48] has shown that video models are generally able to correctly generate videos containing the agents stated in the input prompt but only partially follow the specified action and in some cases, completely fail to incorporate the specified action into the generated video.

Furthermore, video models typically fail to generate high-quality text (annotations) in videos [103], even in videos with otherwise high-fidelity components. This limitation becomes especially conspicuous when the input prompt specifically requests text annotations. Further, camera motion control via input prompts remains a major challenge for video models [103, 255]. Even when asked to generate videos with a static

camera viewpoint without panning, video models tend to mimic their training videos, which often contain camera motion, resulting in non-adherence to the input prompt.

These challenges limit robotics applications in data generation and policy learning, among others. For example, many robot data generation methods operate under the assumption of a static camera position for accurate 3D pose estimation of the robot’s end-effector pose through back-projection. Violation of this assumption results in inaccurate goal poses for tracking, degrading the robot’s task performance. Likewise, failure to generate videos that correctly follow the actions specified by the input prompt leads to training data corruption, limiting the effectiveness of imitation learning, which relies on high-quality (expert) demonstrations.

Future Directions. Recent work [112–114] has explored improving the instruction-following capability of video models through multimodal conditioning. ViMi [112] interleaves language and images into a single instruction prompt, which is passed into a VLM to extract a conditional embedding for video generation. Similarly, Aid [113] uses a VLM to predict the states of future video frames, which are fused with the text instruction to generate a conditional embedding for video synthesis. Other approaches [115, 116] enable fine-grained multimodal user inputs to more strongly guide video models in the generation process. With InteractiveVideo [115], users can control the content of generated videos through image, text, and trajectory prompts, describing the desired motion of different elements of the video scene. Similarly, ATI [116] enables localized control of deformations using keypoints and motion paths. Some other methods [117] have examined instruction fine-tuning using preference-based reward models to train video models that are better at following user instructions. The aforementioned approaches generally rely on VLMs or other learned models that are susceptible to hallucinations, limiting their practical effectiveness. To address this challenge, a promising research direction will be to explore intrinsic methods for improving task understanding and instruction following, e.g., through inference-time “reasoning” over the generated video patches and frames, similar to the approach used in reasoning language models [19, 277].

5.4 Evaluating Video Models

A unified framework for evaluating video models remains lacking, especially in the context of robotics applications. Existing metrics for evaluating video models generally assess either the perceptual quality [97, 98, 249] of their generated videos or their semantic consistency [100, 198]. While visual quality may be prioritized in content generation, physical consistency and predictive accuracy are more critical in robotics [106]. Given the lack of suitable metrics, researchers often resort to surrogate measures based on the downstream application, e.g., correlation between real and predicted policy success rates by video models, to approximate the performance of the video models [17]. Additionally, many works rely on human judgment to evaluate video model performance [118], which is qualitative, costly, and subject to bias. Designing effective evaluation metrics is critical in assessing the performance of video models, which could further motivate directions for future development.

Future Directions. Prior works have developed benchmarks for evaluating video generation in terms of alignment with downstream task performance [47, 106]. However, the environment complexity and visual quality of these benchmarks are fundamentally limited by the simulators. Recent works have explored benchmarking and evaluating T2V generation without ground-truth videos along many axes, such as overall video quality, text-to-video alignment, motion quality, and temporal consistency [103]. To evaluate the quality of video models as embodied world models, WorldModelBench [48] trains a VLM-based judge to assess video models in terms of instruction following, physics adherence, and commonsense. In general, these benchmarks still lack the ability to assess video generation quality in fine-grained robot manipulation tasks. A promising direction for future research will be to explore robotics-centric benchmarks and multi-dimensional metrics for quantitative, efficient, and task-relevant video model evaluation. Further, future research on evaluation pipelines that compare the physical consistency of generated videos based on the corresponding motion in the associated 3D scene reconstructions will be important.

5.5 Safe Content Generation

Many video models lack adequate safety guardrails, impeding their integration into many real-world applications. Prior work [52, 53] has demonstrated the propensity of video models to generate unsafe content,

containing crime, offensive activities, violence, or misinformation, which could hinder adoption in sensitive applications. Despite the importance of safety, only a few papers [119] have explored methods for improving the safety of video models. Addressing this challenge is essential to driving broader applications in robotics.

Future Directions. Enforcing the safety of video models is particularly challenging, given the broad diversity of unsafe video content. For tractability, prior work has utilized model guardrails to prevent the generation of potentially harmful content. While there is extensive literature on safeguarding LLMs [278], analogous techniques for video generation models are far less developed. Recent work (e.g., SAFEWatch [52]) introduces a mechanism for enforcing user-specified safety policies during video generation. However, these methods are task-specific which limits their amenability to more general applications, underscoring the need for more versatile safety guardrails. Additionally, there is a growing need for safety benchmarks for video models. Existing benchmarks [52, 53] evaluate video models on a limited range of criteria, e.g., crimes, hate content, privacy violations, and abusive content; however, a broader evaluation of safety is required for real-world use-cases in robotics. Developing more effective safety guardrails and introducing more comprehensive safety benchmarks will be critical to improving the overall safety of video models in video synthesis.

5.6 Safe Robot Interaction

Beyond safe video synthesis, robots must interact safely with other objects and agents in their environments. Safety in robotics can be broadly classified into two categories: (i) physical safety, which involves avoiding all forms of collisions; and (ii) semantic safety, which involves avoiding situations deemed potentially harmful by common-sense knowledge, such as tossing sharp objects at other agents. These forms of safety have been underexplored in robotics applications of video models. However, the success of many robotics tasks depends significantly on satisfying these safety constraints, e.g., in visual planning.

Future Directions. As embodied world models, video models enable robots to assess the safety of proposed actions without executing these actions in the real-world, which is critical to preserving the safety of robots, other agents, and their environments. To detect safety violations, some existing methods [30] generate video predictions from robot action proposals using video models. Other prior work [120, 279] perform robot safety filtering directly in the latent space of world models to predict failures and preempt their occurrence. Likewise, existing methods [121, 280] quantify uncertainty in the latent space to guard against unseen out-of-distribution (OOD) hazards and other user-specified constraint violations. While these works make notable steps toward safe robot control, they have primarily been limited to Markovian state-based world models. Extending these ideas to the spatiotemporal latent spaces of video world models remains a challenge, constituting an important direction for future research. Moreover, generalization beyond the training distribution remains a core challenge in long-tail or safety-critical scenarios because world models are inherently limited by the distribution of their training data.

5.7 Action Estimation

SOTA imitation-learned robot policies require high-quality data [209, 281, 282], which is often expensive to collect in the real-world. Although video generation models can address this challenge, the video generated by these models typically do not contain action-labeled frames, which is essential in learning robot policies. Some methods have explored estimating robot actions from videos; however, these methods [122] typically fail to achieve the high level of accuracy required in imitation learning in fine-grained tasks, hindering the effectiveness of current solutions that integrate video models in policy learning frameworks. We discuss a few limitations of latent action models and inverse-dynamics models, the two main approaches for action estimation from robot videos.

Latent action models [122, 123] estimate robot actions between a pair of video frames in a (discrete) latent space, defined by a fixed set of action codes (primitives). The expressiveness of the learned latent actions is strongly influenced by the size of the latent codebook. Scaling the size of the latent codebook is challenging in practice due to the significant training instabilities and higher compute cost associated with training latent action models with larger codebooks. Further, latent actions are generally difficult to interpret, which makes data curation and analysis more challenging. Additional real-world data is also required to fine-tune latent action models to predict actions that are compatible with physical robots. Inverse-dynamics models [124, 125]

suffer from similar challenges and require lots of training data to sufficiently cover the space of robot actions. Like other imitation-learned models, inverse-dynamics models exhibit limited generalization outside of the training distribution, hindering real-world applications.

Future Directions. For better interpretability, recent work [8] utilizes small latent codebooks, which facilitate mapping each latent action to interpretable conditioning inputs. However, this approach fails to scale to more complex robotics tasks which require larger codebooks to effectively learn latent actions. Exploring model architectures that induce interpretable latent actions, without compromising the expressiveness of the latent action space, will be critical to advancing the adoption of video models in robot policy learning. Likewise, the development of robust training procedures for latent action models will be essential to their generalization in robotics. Additionally, semi-supervised training techniques could enable efficient training of generalizable inverse-dynamics models with only a few human annotations, constituting a promising area for future work.

5.8 Long Video Generation

To serve as effective world models in robotics tasks, video models must predict sufficiently long future horizons that match the duration of robotic tasks, which are often minutes long. However, SOTA video models are limited to generating videos of only a few seconds in duration. For example, Veo 3.1 [9] generates 8-second long videos while Wan 2.5 [10] generates 10-second long videos. These durations are not long enough for informed decision-making in many robotics problems, such as visual planning. Current video generation pipelines require extending multiple short clips to create longer-duration videos; however, this approach often introduces artifacts that degrade the temporal coherence and physical consistency of the resulting videos. While SOTA video models excel in short-duration video generation tasks, scaling these models to longer horizons for robotics tasks remains an open challenge.

Future Directions. Several architectures attempt to address video consistency over long horizons. Broadly, these methods use frame compression, sampling schedule optimizations, or hierarchical frameworks to enable long video generation. For example, MALT [49] encodes past segments into a compact latent memory vector to facilitate autoregressive generation; however, this approach remains susceptible to error accumulation [283]. FramePack [50] mitigates drift by compressing frame contexts based on importance and establishing early endpoints to anchor the generation process. TTTVideo [127] and LaCT [128] utilize test-time training (TTT) to dynamically encode history into model weights or neural hidden states during inference. However, the quality of the generated videos degrades as video length increases. To improve video fidelity, Long-Context Tuning (LCT) [51] expands the context window to maintain dense attention across multi-shot scenes but is limited by the quadratic cost of self-attention, which imposes a computational ceiling on the maximum generation length. In contrast to these approaches, Mixture of Contexts (MoC) [284] circumvents compressing history entirely by recasting generation as an information retrieval task via a sparse attention routing mechanism. Diffusion Forcing [126] offers an alternative solution by training models to denoise tokens with independent noise levels, enabling variable-horizon generation that empirically improves stability in policy rollouts. On the other hand, NUWA-XL [285] utilizes a hierarchical “diffusion-over-diffusion” structure, where a global model generates sparse keyframes and local models recursively fill the intermediate gaps. Despite these improvements, existing methods still struggle to generate minutes-long videos, impeding the their effectiveness in real-world applications. A promising direction for future work will be to design efficient techniques for extending the memory (context window) of video models without a prohibitive increase in the computation cost to enable high-fidelity long-video generation.

5.9 Data Curation Costs

High-quality data is essential to training video models that are capable of synthesizing high-fidelity, physically-consistent videos across diverse tasks. Beyond video quality, diversity of the training data strongly influences the fidelity of generated videos [129, 136], especially for text-conditioned or action-conditioned video models, which require extensive data coverage for desirable results. Although large volumes of videos exist on the internet, many of these videos lack good visual quality and descriptive text annotations, posing a challenge. Specifically, many existing datasets, such as WebVideo-10M [286] and Panda-70M [130], have focused on scale rather than quality, aggregating tens of millions of videos along with their captions. As a result, these datasets suffer from inaccurate, non-descriptive video captions, blurry videos, and rapid shot changes between

temporally-inconsistent clips, which negatively impact training. SOTA methods [10, 11, 129, 136] typically rely on expensive data preprocessing pipelines to identify good-quality video data for training. This pipeline consists of three broad stages: (i) video splitting, (ii) video filtering, and (iii) video annotation. At the video splitting stage, candidate video data is temporally segmented into short continuous clips using classical shot detection tools. Videos that are too short are removed at this stage. The resulting clips are then processed by video filters using metrics that assess the visual quality, text quality, motion smoothness and jitter, among others, often with learned models. Subsequently, many methods [11, 136] utilize VLMs [130, 287, 288] for annotating the processed videos, pairing text descriptions with the video data for supervising video models. The VLMs are typically fine-tuned for higher-quality video captioning. These processes often require human supervision for evaluation, increasing the cost of data curation.

Future Directions. Recent video datasets, e.g., VidGen-1M [131] and OpenVid-1M [132], have explored different pre-processing techniques to filter videos using well-defined quality scores before training. These quality scores evaluate the aesthetics, temporal consistency, motion fidelity, and caption descriptiveness, identifying video clips that are more likely to be natural without unrealistic motion. Although these datasets generally provide higher-quality training data, their relatively small size impedes strong zero-shot generalization. Consequently, many SOTA video models [9–11] utilize proprietary curated datasets with dense annotations by VLMs and humans to ensure high quality control. However, VLMs are prone to hallucinations, and human-annotated data collection is expensive, posing significant challenges in high-fidelity video data collection. Exploring strategies for grounding VLMs to minimize the risk of hallucinations is a promising area for future work. Likewise, developing novel-view synthesis techniques to efficiently scale data collection to new scenes from a small set of high-quality videos will be essential to reducing the costs of data curation. Further, more accurate methods for splitting and filtering videos will be critical to curating highly diverse datasets with good temporal and spatial consistency, e.g., [133]. In robotics, high-fidelity future prediction in both successful and unsuccessful task rollout or demonstrations is essential for video models to serve as good proxies for real-world environments. Notably, failure demonstrations are important to train video models that faithfully execute actions output by the policy. Recent studies suggest that incorporating failure data from autonomous policy rollouts is critical for training world models that exhibit action controllability [29, 92, 93]. In the absence of such data, generated videos can exhibit an optimistic bias toward success, with hallucinations that reposition objects for easier grasping, over-estimate the feasibility of a grasp, and insufficiently model obstructions, all of which would cause real executions to fail [29].

5.10 Training and Inference Costs

SOTA video models require large amounts of compute resources for training and inference. Although the true cost of training video models is often confidential especially for closed-source models, the most cost-effective SOTA open-source video models require hundreds of thousands of dollars to train—e.g., \$200k for OpenSora 2.0 [136]. Video models typically have billions of parameters, which is a major contributing factor to their significant training costs. Although latent diffusion [135] reduces the number of parameters required by these models, the corresponding reduction in training costs is often not sufficient. As a result, research on training video models has broadly remained limited to large research groups with deep budgets. Moreover, recent developments such as classifier-free guidance [169, 174] for fine-grained input-conditioning introduce additional computational overhead. Reducing training and inference costs is critical to advancing broader applications of video models in robotics.

Additionally, high-fidelity video models [7, 9–11] are often limited by significantly slow inference speeds. For example, Veo 3 [9] generates about 12 video frames per second on an NVIDIA A100 GPU. Although sufficient in some use cases, the slow inference time presents an important challenge in many robotics applications, such as visual planning, where closed-loop execution requires real-time feedback to the planner for robustness. Existing video model planners often take a few seconds to generate feasible action trajectories for a single episode [134], which is not fast enough for real-time operation.

Future Directions. For faster training and inference, recent work [31, 136] has explored spatial and temporal compression techniques to reduce the number of costly attention operations during video generation. Dreamer 4 [31] applies temporal attention sparsely to every fourth video frame by decoupling spatial and temporal attention. Similarly, OpenSora uses deep compression autoencoders [289] to downsample input

tokens at greater ratios to speed up inference by an order of magnitude. Likewise, Wan [10] employs a feature cache mechanism to enable chunk-based video synthesis while preserving temporal continuity. Some other methods utilize shortcut models [137] for finer control over the number of sampling steps required for video generation without any significant degradation in video quality. Like shortcut models, consistency models [138, 290] enable efficient video diffusion using a single-step denoising process. Other video models utilize more classical speed optimization techniques for faster inference, e.g., quantization [291] and model distillation [292]. Further research on these topics is required to improve inference speeds for real-time applications.

6 Conclusion

This survey reviews video models and their applications as embodied world models in robotics, identifying prevailing model architectures, conditioning modalities, and key capabilities of video models. Specifically, we categorize existing robotics applications into four broad classes: robot data generation and action prediction in imitation learning, dynamics and rewards modeling in reinforcement learning, policy evaluation, and visual planning. We emphasize that these applications are underpinned by the remarkable ability of video models to learn fine-grained spatiotemporal relationships that govern the evolution of the state of real-world environments, which is essential for physically consistent future predictions. Furthermore, we identify critical open research challenges and propose directions for future research, seeking to motivate broader applications of video models.

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