

iVideoGPT: Interactive VideoGPTs are Scalable World Models

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<https://thuml.github.io/iVideoGPT>

Abstract

World models empower model-based agents to interactively explore, reason, and plan within imagined environments for real-world decision-making. However, the high demand for interactivity poses challenges in harnessing recent advancements in video generative models for developing world models at scale. This work introduces Interactive VideoGPT (iVideoGPT), a scalable autoregressive transformer framework that integrates multimodal signals—visual observations, actions, and rewards—into a sequence of tokens, facilitating an interactive experience of agents via next-token prediction. iVideoGPT features a novel compressive tokenization technique that efficiently discretizes high-dimensional visual observations. Leveraging its scalable architecture, we are able to pre-train iVideoGPT on millions of human and robotic manipulation trajectories, establishing a versatile foundation that is adaptable to serve as interactive world models for a wide range of downstream tasks. These include action-conditioned video prediction, visual planning, and model-based reinforcement learning, where iVideoGPT achieves competitive performance compared with state-of-the-art methods. Our work advances the development of interactive general world models, bridging the gap between generative video models and practical model-based reinforcement learning applications.

1 Introduction

Recent years have witnessed remarkable advancements in generative models of multimodal contents, including text [1], audio [8], and images [21], with video generation now emerging as a new frontier [10]. A particularly significant application of these generative video models, learned in an unsupervised way on diverse Internet-scale data, is to construct predictive world models [51, 27] at scale. These world models are expected to accumulate commonsense knowledge about how the world works, enabling the prediction of potential future outcomes (e.g., visual observations and reward signals) based on the actions of agents. By leveraging these world models, agents employing model-based reinforcement learning (RL) can imagine, reason, and plan inside world models [19, 28], thus acquiring new skills more safely and efficiently with a handful of trials in the real world.

Despite the fundamental connection, significant gaps remain between the development of generative models for video generation and world models for agent learning. One primary challenge is achieving the best of both interactivity and scalability. In the realm of model-based RL, world models predominantly utilize recurrent network architecture. This design naturally allows the transition of observations or latent states conditioned on actions in each step, facilitating interactive behavior learning [28, 77, 32]. However, these models mostly focus on games or simulated environments with visually simple data and have limited capability to model complex, in-the-wild data at scale. In

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Figure 1: Practical applications of iVideoGPT, which is designed to scale, allowing pre-training on millions of human and robotic manipulation trajectories. This results in a versatile foundation of interactive world models, adaptable to a wide range of downstream tasks.

contrast, Internet-scale video generative models [35, 6, 10] can synthesize realistic long videos that are controllable via text descriptions [104] or future action sequences [97]. Although such models allow for high-level, long-horizon planning [18], their trajectory-level interactivity does not provide sufficient granularity for agents to efficiently learn precise behavior as basic skills step-by-step.

In this work, we explore the development of world models that are both interactive and scalable within a GPT-like autoregressive transformer framework [86, 72]. Pioneering efforts have been made recently through diffusion models [98] and masked generative models [11]. Nevertheless, utilizing autoregressive transformers for world models offers distinct advantages such as seamless integration with the established Large Language Model (LLM) ecosystem [105] and greater flexibility in handling diverse conditions without the need for specific architectural modifications like adapter modules [74, 102]. We present *Interactive VideoGPT* (*iVideoGPT*), a scalable world model architecture that incorporates multimodal signals, including visual observations, actions, and rewards, in an interactively autoregressive manner. Unlike multimodal LLMs that discretize visual observations into tokens frame-by-frame using image tokenizers [53], a key innovation of iVideoGPT is to learn compressive tokenization for each observation conditioned on rich contextual observations, achieving an asymptotic $16\times$ reduction in token sequence length. We highlight that more compact video tokenization could not only facilitate more efficient training and generation but also enhance video quality. This is achieved by decoupling context from dynamics, allowing the model to focus on predicting the motion of objects while maintaining temporal consistency within the scene [95].

We demonstrate a series of practical applications of iVideoGPT for visual robotic manipulation, as illustrated in Figure 1. Mirroring the two-phase approach popularized by Large Language Models (LLMs), our methodology involves pre-training followed by domain-specific adaptation. During pre-training, iVideoGPT is scalable for action-free video prediction on a mixture of over one million trajectories from both robotic and human manipulation [67, 24]. The pre-trained iVideoGPT serves as a versatile foundation that can be adapted into interactive world models for various downstream tasks. These include action-conditioned video prediction [20, 15], visual planning [82], and visual model-based RL [101]. Furthermore, we showcase the pre-trained transformer’s preliminary capability in iVideoGPT for zero-shot video generation without fine-tuning, requiring only the tokenizer to be adapted to unseen domains.

The main contributions of this work can be summarized as follows:

- We introduce Interactive VideoGPT (iVideoGPT), an autoregressive transformer architecture for scalable world models, which features compressive tokenization for visual observations.
- We pre-train iVideoGPT on a large-scale dataset comprising millions of robotic and human manipulation trajectories and adapt it to domain-specific tasks. The pre-trained model weights will be made available to encourage further research.
- Extensive experiments covering video prediction, visual planning, and visual model-based RL demonstrate that iVideoGPT can simulate accurate and realistic experiences and provide competitive performance compared with state-of-the-art methods.

2 Problem Formulation

A world model is an internal model learned by the agent to simulate the environment. This environment is typically modeled as a *partially observable Markov decision process (POMDP)*

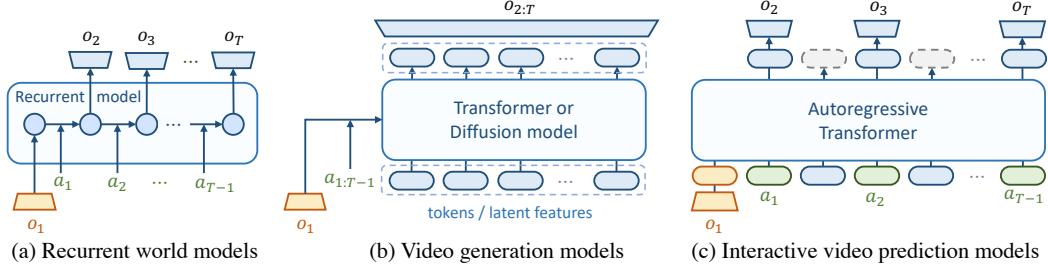


Figure 2: Conceptual comparison among architectures, illustrated using a single context frame ($T_0 = 1$) for simplicity. (a) Recurrent architectures for world models like Dreamer [28] and MuZero [77] provide step-level interactivity but limited scalability. (b) Recent video generation advancements like VideoGPT [97] and Stable Video Diffusion [7, 6] use non-causal temporal modules that can only offer trajectory-level interactivity. (c) Our model utilizes an autoregressive transformer that separately maps each step into a sequence of tokens, achieving both scalability and interactivity.

$(\mathcal{S}, \mathcal{O}, \phi, \mathcal{A}, p, r, \gamma)$. At each step, $s_t \in \mathcal{S}$ represents the underlying state of the environment, and $o_t = \phi(s_t)$ is the observation received by the agent, only providing incomplete information of s_t . After taking an action $a_t \in \mathcal{A}$, $p(s_{t+1}|s_t, a_t)$ defines the transition probability from state s_t to s_{t+1} . The agent also receives immediate rewards $r_{t+1} = r(s_t, a_t)$, and aim to learn a policy π such that $a_t \sim \pi(o_{1:t})$ maximizing the γ -discounted accumulated rewards $\mathbb{E}_{p, \pi}[\sum_t \gamma^{t-1} r_t]$.

While world models can be learned from many types of data, video is one modality that is task-agnostic, widely available, and embeds broad knowledge that can be learned in a self-supervised way. Thus, we formulate learning world models for visual control as an *interactive video prediction* problem [98, 11] where $\mathcal{O} = \mathbb{R}^{H \times W \times 3}$ is the space of video frames². Concretely, given a short history visual observations of T_0 frames $o_{1:T_0}$, at each step $t = T_0, \dots, T - 1$, the agent takes an action a_t based on its policy and previous imagined observations, and then the world model need to approximate and sample the transition $p(o_{t+1}, r_{t+1} | o_{1:t}, a_{T_0:t})$ to feedback the agent.

As depicted in Figure 2, a majority of advanced video generation models [97, 7, 100], including VideoGPT, can not deal with the interactive video prediction problem because they design non-causal modules fusing information along the temporal dimension. Existing world models in the literature of MBRL [28, 77], such as Dreamer, utilize recurrent architecture but lack scalability.

3 Interactive VideoGPT

In this section, we introduce Interactive VideoGPT, a scalable world model architecture with great flexibility to integrate multimodal signals, including visual observations, actions, rewards, and other potential sensory inputs. At its core, iVideoGPT consists of a compressive tokenizer to discretize video frames and an autoregressive transformer predicting subsequent tokens (Section 3.1). This model can acquire broad world knowledge through pre-training on diverse video data (Section 3.2) and then effectively transfer to downstream tasks incorporating additional modalities (Section 3.3).

3.1 Architecture

Compressive tokenization. Transformers particularly excel in operating over sequences of discrete tokens. VQGAN [21] is a commonly used visual tokenizer that converts from raw pixels to discrete tokens. Instead of using an image tokenizer to discretize each frame independently [53, 60, 26], leading to rapidly increasing sequence lengths, or using a 3D tokenizer that compresses videos spatiotemporally at the expense of interactivity [97, 100], we propose to tokenize videos with a novel conditional VQGAN consisting of dual encoders and decoders $\{(E_c, D_c), (E_p, D_p)\}$. As illustrated in Figure 3a, initial context frames $o_{1:T_0}$, rich in contextual information, are independently tokenized and reconstructed through N tokens: $z_t^{(1:N)} = E_c(o_t)$, $\hat{o}_t = D_c(z_t)$ for $t = 1, \dots, T_0$. In contrast, due to the temporal redundancy between context and future frames, only essential dynamics information, such as the position and pose of moving objects, needs to be encoded. This is achieved

²Due to this connection, we use the terms "video frame" and "visual observation" interchangeably.

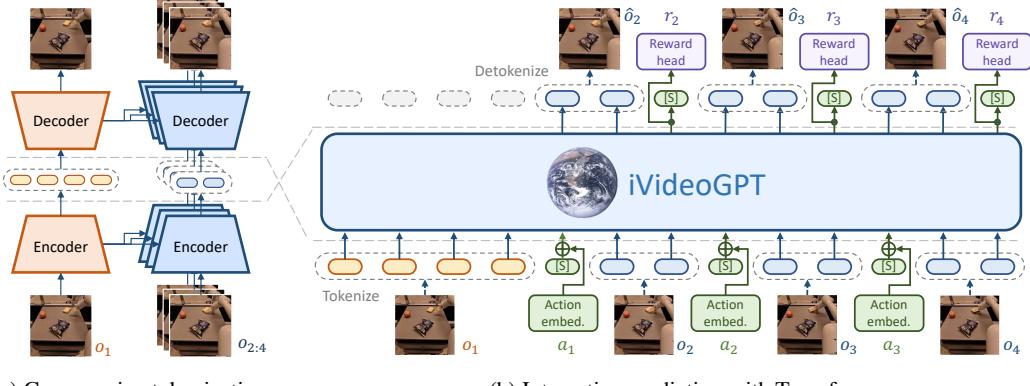


Figure 3: Architecture of iVideoGPT, simplified to show only a single context frame ($T_0 = 1$). (a) Compressive tokenization utilizes a conditional VQGAN that discretizes future frames conditioned on context frames to handle temporal redundancy, significantly reducing the number of video tokens. (b) An autoregressive transformer integrates multimodal signals—visual observations, actions, and rewards—into a sequence of tokens, enabling interactive agent experiences through next-token prediction. Actions and rewards are optional and not included in action-free video pre-training.

using a conditional encoder and decoder, which require a far smaller number of n tokens ($n \ll N$):

$$z_t^{(1:n)} = E_p(o_t | o_{1:T_0}), \hat{o}_t = D_p(z_t | o_{1:T_0}) \quad \text{for } t = T_0 + 1, \dots, T. \quad (1)$$

We implement this conditioning mechanism using cross-attention between multi-scale feature maps (see details in Appendix A.1). Overall, the proposed tokenizer is trained with the following objective:

$$\mathcal{L}_{\text{tokenizer}} = \sum_{t=1}^{T_0} \mathcal{L}_{\text{VQGAN}}(o_t; E_c(\cdot), D_c(\cdot)) + \sum_{t=T_0+1}^T \mathcal{L}_{\text{VQGAN}}(o_t; E_p(\cdot | o_{1:T_0}), D_p(\cdot | o_{1:T_0})), \quad (2)$$

where $\mathcal{L}_{\text{VQGAN}}(o; E, D)$ is a combination of a L_1 reconstruction loss, a commitment loss [85], a perceptual loss [42], and optionally an adversarial loss [21].

There are primarily two benefits of the proposed tokenization. First, it significantly reduces the sequence length of tokenized videos, which grows linearly with the number of frames but at a much smaller rate n . In this work, we set $N = 16 \times 16$ and $n = 4 \times 4$, resulting in an asymptotic reduction of $16\times$, facilitating faster rollouts for model-based planning and reinforcement learning. Second, by conditional encoding, transformers predicting subsequent tokens can maintain temporal consistency of the context much easier and focus on modeling essential dynamics information [95]. We discuss the assumptions and limitations of our tokenization in Section 6.

Interactive prediction with Transformers. After tokenization, the video is flattened into a sequence of tokens: $x = (z_1^{(1)}, \dots, z_1^{(N)}, [\text{S}], z_2^{(1)}, \dots, z_2^{(N)}, \dots, [\text{S}], z_{T_0+1}^{(1)}, \dots, z_{T_0+1}^{(n)}, \dots)$ with a length of $L = (N+1)T_0 + (n+1)(T-T_0) - 1$. Special slot tokens $[\text{S}]$ are inserted to delineate frame boundaries and facilitate the integration of extra low-dimensional modalities such as actions (see Section 3.3 for details). As Figure 3b, a GPT-like autoregressive transformer is utilized for interactive video prediction through next-token generation frame-by-frame. In this work, we take the model size of GPT-2 [73] but adopt the LLaMA architecture [83] in order to embrace the latest innovations for LLM architecture, such as rotary position embedding [81].

3.2 Pre-Training

Large language models can gain extensive knowledge from Internet text in a self-supervised way via next-word prediction. Similarly, the *action-free video pre-training* paradigm for world models [78, 95, 59] involves video prediction as a pre-training objective, providing Internet-scale supervision with physical world knowledge absent in LLMs. We pre-train iVideoGPT on this generic objective, applying a cross-entropy loss to predict subsequent video tokens:

$$\mathcal{L}_{\text{pre-train}} = - \sum_{i=(N+1)T_0+1}^L \log p(x_i | x_{<i}), \quad (3)$$

where L is the total sequence length and $(N + 1)T_0 + 1$ marks the first token index of the frames to be predicted. Notably, we do not train iVideoGPT to generate context frames, making its capacity focus on dynamics information, as previously discussed.

Pre-training data. While there are numerous videos available on the Internet, due to computational limitations, we specifically pre-train iVideoGPT for the robotic manipulation domain. We leverage a mixture of 35 datasets from the Open X-Embodiment (OXE) dataset [67] and the Something-Something v2 (SSv2) dataset [24], totaling 1.5 million trajectories (see Appendix A.2 for details). OXE is a diverse collection of robot learning datasets from a variety of robot embodiments, scenes, and tasks. These datasets are highly heterogeneous but can be easily unified in the action-free video prediction task. To further enhance the diversity, we also include SSV2, a dataset of human-object interaction videos, as previous work has demonstrated knowledge transfer from these human manipulation videos for learning a world model for robotic manipulation tasks [95, 59].

3.3 Fine-Tuning

Action conditioning & reward prediction. Our architecture is designed to flexibly incorporate additional modalities for learning interactive world models, as illustrated in Figure 3b. Actions are integrated by linear projection and adding to the slot token embeddings. For reward prediction, instead of learning independent reward predictors, we add a linear head to the last token’s hidden state of each observation. This multi-task learning approach can enhance the model’s focus on task-relevant information, thereby improving prediction accuracy for control tasks [55]. We use a mean-squared error loss for reward prediction in addition to the cross-entropy loss in Eq. (3).

Tokenizer adaptation. We choose to update the full model, including the tokenizer, for downstream tasks, finding this strategy more effective than parameter-efficient fine-tuning methods [37]. This is likely due to the limited diversity of our pre-trained data compared to Internet-scale images, which, while extensive, may also not adequately cover specific real-world applications like robotics. Minimal literature explores adapting a VQGAN tokenizer to domain-specific data. In this work, as our tokenization decouples dynamics information from context conditions, we hypothesize that while our model may encounter unseen objects like different robot types in downstream tasks, the fundamental knowledge of physics—such as motions and interactions—learned by the transformer from diverse scenes is commonly shared. This hypothesis is supported by our experiments transferring iVideoGPT from mixed pre-training data to the unseen BAIR dataset [20], where the pre-trained transformer can zero-shot generalize to predict natural motions, requiring only the tokenizer to be fine-tuned for unseen robot grippers (see Figure 7). This property is particularly important for scaling GPT-like transformers to large sizes, enabling lightweight alignment across domains while keeping the transformer intact. We leave an in-depth analysis of tokenizer adaptation for future work.

4 Experiments

In this section, we evaluate iVideoGPT on three different settings and compare its performance with prior state-of-the-art methods. We demonstrate that iVideoGPT is versatile to provide competitive performance across a range of tasks (Section 4.1, 4.2, and 4.3) and conduct in-depth analysis to understand the prediction ability, data efficiency, model scaling, and computational efficiency (Section 4.4). Experimental details can be found in Appendix A.

4.1 Video Prediction

Setup. The BAIR robot pushing dataset [20] consists of 43k training and 256 test videos, where we predict 15 frames from a single initial frame, a standard protocol of prior works. The RoboNet dataset [15] contains 162k videos across 7 robotic arms. Following prior works, we use 256 videos for testing, predicting 10 frames from two frames. Notably, RoboNet overlaps with our pre-training data OXE, from which we have carefully filtered test videos. We compare against a variety of video prediction models, including variational [87, 94, 3], diffusion [89], masked [100, 26], and autoregressive models [97], across four metrics: FVD [84], PSNR [38], SSIM [93], and LPIPS [103].

Results. As shown in Table 1, iVideoGPT provides competitive performance compared to state-of-the-art methods, MAGVIT [100] for BAIR and FitVid [3] for RoboNet, while achieving both

Table 1: Video prediction results on the BAIR robot pushing and RoboNet datasets. We report the mean and standard deviation for each metric calculated over three runs. “-” marks that the value is not reported in the original papers. LPIPS and SSIM scores are scaled by 100 for convenient display.

BAIR [20]	FVD↓	PSNR↑	SSIM↑	LPIPS↓	RoboNet [15]	FVD↓	PSNR↑	SSIM↑	LPIPS↓					
<i>action-free & 64×64 resolution</i>														
<i>action-conditioned & 64×64 resolution</i>														
VideoGPT [97]	103.3	-	-	-	MaskViT [26]	133.5	23.2	80.5	4.2					
MaskViT [26]	93.7	-	-	-	SVG [87]	123.2	23.9	87.8	6.0					
FitVid [3]	93.6	-	-	-	GHVAE [94]	95.2	24.7	89.1	3.6					
MCVD [89]	89.5	16.9	78.0	-	FitVid [3]	62.5	28.2	89.3	2.4					
MAGViT [100]	62.0	19.3	78.7	12.3	iVideoGPT (ours)	75.0_{±0.20}	20.4_{±0.01}	82.3_{±0.05}	9.5_{±0.01}					
iVideoGPT (ours)	75.0_{±0.20}	20.4_{±0.01}	82.3_{±0.05}	9.5_{±0.01}	<i>action-conditioned & 256×256 resolution</i>									
<i>action-conditioned & 64×64 resolution</i>														
MaskViT [26]	70.5	-	-	-	MaskViT [26]	211.7	20.4	67.1	17.0					
iVideoGPT (ours)	60.8_{±0.08}	24.5_{±0.01}	90.2_{±0.03}	5.0_{±0.01}	iVideoGPT (ours)	197.9_{±0.66}	23.8_{±0.00}	80.8_{±0.01}	14.7_{±0.01}					

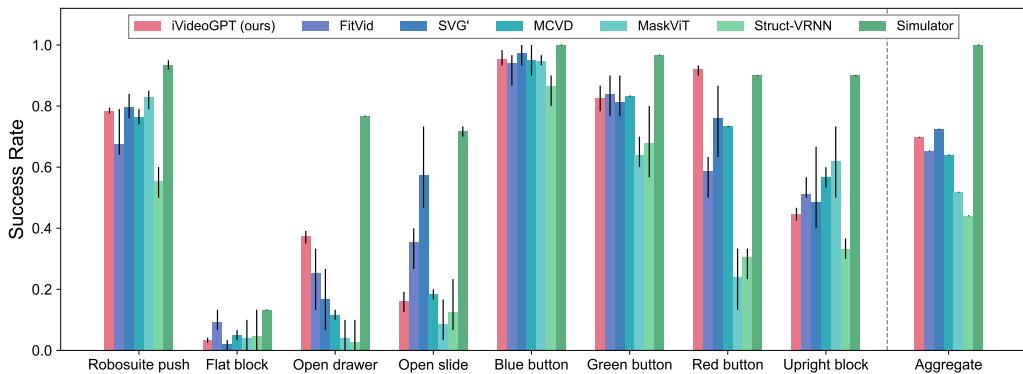


Figure 4: Visual MPC results on the VP² benchmark. We report the mean and min/max performance of iVideoGPT over 3 control runs. On the right, we show the mean scores averaged across all tasks except flat block due to low simulator performance, normalized by the performance of the simulator.

interactivity and scalability in its architecture. Initially pre-trained action-free, our model flexibly allows for action-conditioning, which notably improves FVD for BAIR by almost 20%. Although primary experiments are at a low resolution of 64×64, iVideoGPT can be easily extended to 256×256 for RoboNet. We highlight that MaskViT, a prior method leveraging per-frame tokenization, suffers from temporal inconsistency and flicker artifacts in VQGAN reconstructions. Our model, which employs compressive tokenization conditioned on consistent contextual information, improves this and significantly outperforms MaskViT. For qualitative results, refer to Figure 9.

4.2 Visual Planning

Setup. VP² is a control-centric benchmark [82] that evaluates video prediction models for visual model-predictive control (MPC) [23, 19] across four Robosuite [112] and seven RoboDesk tasks [45]. Each environment’s training dataset includes noisy scripted interaction trajectories. Following the protocol from the original benchmark paper, we trained iVideoGPT on 5K trajectories for Robosuite and 35K for RoboDesk, comparing our models with established baselines.

Results. Figure 4 presents the success rates of iVideoGPT compared to baseline models. While Tian et al. [82] observed that excellent perceptual metrics do not always correlate with effective control performance, iVideoGPT outperforms all baselines in two RoboDesk tasks with a large margin and achieves comparable average performance to the strongest model, SVG' [87]. In Appendix B.2, we analyze iVideoGPT’s suboptimal performance on the open slide task, which is attributed to the uncertainty inherent in low-resolution observations, exacerbated by the discrete tokenization.

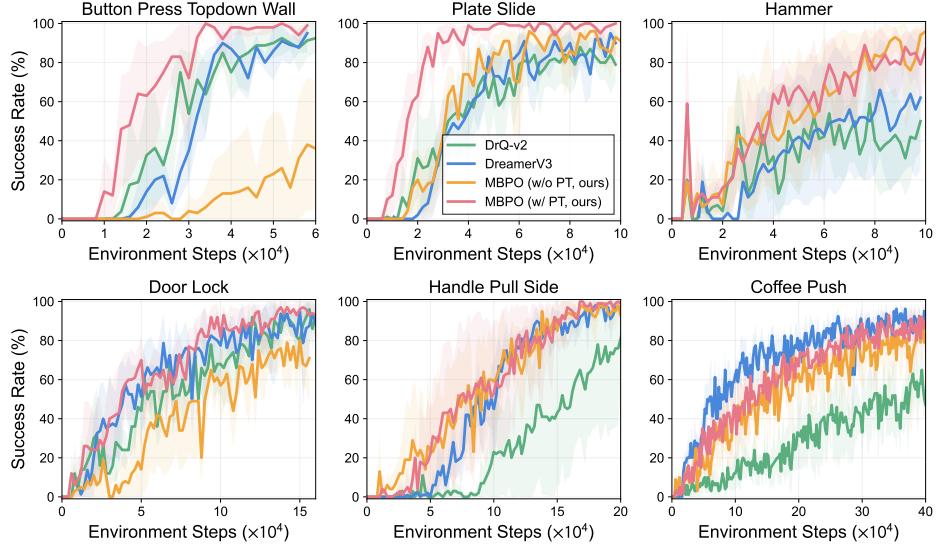


Figure 6: Visual model-based RL on Meta-world. We report the mean and 95% confidence interval across five runs, measuring success rates over 20 evaluation episodes. *PT* denotes pre-training.

4.3 Visual Model-based Reinforcement Learning

Setup. We conduct experiments on six robotic manipulation tasks of varying difficulty from MetaWorld [101]. Leveraging iVideoGPT as interactive world models, we have developed a model-based RL method adapted from MBPO [40], which augments the replay buffer with synthetic rollouts to train a standard actor-critic RL algorithm (see Appendix A.5 for the pseudo-code). Our implementation builds upon DrQ-v2 [99], a state-of-the-art visual model-free RL method. We also compare against a state-of-the-art model-based RL algorithm, DreamerV3 [31].

Results. Figure 6 shows that our model-based algorithm not only remarkably improves the sample efficiency over its model-free counterpart but also matches or exceeds the performance of DreamerV3. To our knowledge, this marks the *first successful application of MBPO to visual continuous control tasks*. These results highlight the opportunity, with powerful world models, to eliminate the need for latent imagination—a common strategy used in advanced MBRL systems to train policies on rollouts of latent states within world models [28, 77] (see comparison in Figure 5). Our development of performant MBRL algorithms decoupling model and policy learning can substantially simplify the design space, thereby greatly enhancing the practicality and effectiveness of MBRL algorithms in real-world applications.

4.4 Model Analysis

Zero-shot prediction. We first analyze the zero-shot video prediction ability of large-scale pre-trained iVideoGPT on the unseen BAIR dataset. Interestingly, we observe in the second row of Figure 7 that iVideoGPT, without fine-tuning, predicts a natural movement of a robot gripper—albeit a different one from our pre-training dataset. This indicates that while, due to insufficient diversity of pre-training data, our model has a limited ability of zero-shot generalization to completely unseen robots, it effectively separates scene context from motion dynamics. In contrast, with an adapted tokenizer, the transformer that is not fine-tuned itself successfully transfers the pre-trained knowledge and predicts movements for the new robot type in the third row, providing a similar perceptual quality as the fully fine-tuned transformer in the fourth row. Quantitative results can be found in Figure 8a.

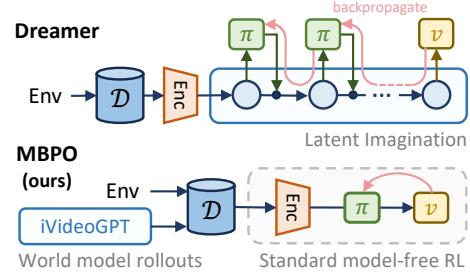


Figure 5: Powerful iVideoGPTs enable a simple yet performant MBRL algorithm, decoupling model rollouts and policy learning.

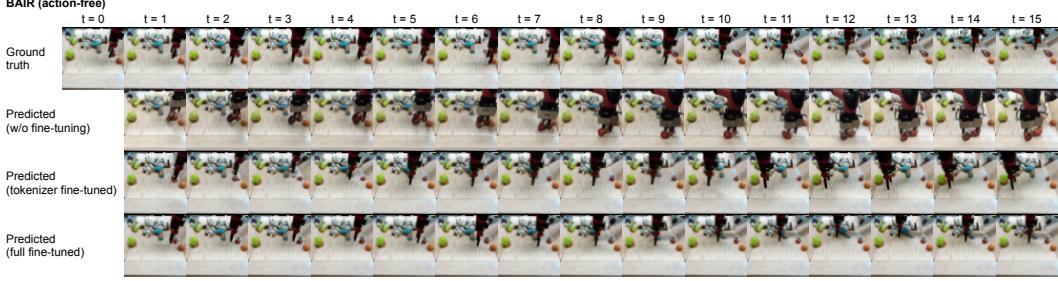


Figure 7: Zero-shot prediction by pre-trained transformer in iVideoGPT. Without fine-tuning, the transformer predicts natural movements of a different robot gripper using the pre-trained tokenizer (*second row*) but accurately predicts for the correct gripper type with an adapted tokenizer (*third row*).

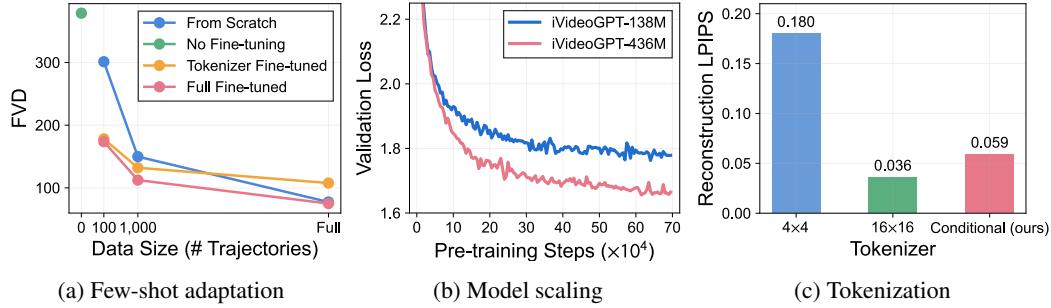


Figure 8: Model analysis. (a) Video prediction results with various fine-tuning strategies and data sizes on BAIR. (b) Validation losses for the 138M and 436M models on the pre-training dataset. (c) Reconstruction quality of different tokenizers on RoboNet (64 × 64 resolution).

Few-shot adaptation. Large-scale pre-trained models have proven effective, especially in data-scarce scenarios. Figure 8a shows iVideoGPT’s performance when fine-tuned with various data sizes on the BAIR dataset. We observe that pre-training offers minimal benefits when full downstream data is available, yet the advantages become significant under data scarcity (with 100 or 1,000 trajectories). The fast adaptation ability with a handful of data is particularly crucial in model-based RL. As presented in Figure 6, world models trained from scratch may generate inaccurate predictions, thereby degenerating the sample efficiency that is vital for model-based agents.

Model scaling. All previous experiments are conducted using an iVideoGPT with 12 transformer layers and 768-dimensional hidden states (138M parameters). To initially investigate the scaling behavior of our model, we trained a larger iVideoGPT with 24 layers and 1024-dimensional hidden states (436M parameters). Figure 8b illustrates the validation loss curves on the pre-trained dataset. It shows that (1) the validation loss (perplexity) continues to decrease regardless of model size, and (2) increasing the model size accelerates the loss decrease. These results align with our expectation that larger model sizes and increased computation [46] can build more powerful iVideoGPTs.

Tokenization. Finally, we evaluate the effectiveness of our compressive tokenization by comparing it against standard VQGAN tokenizers that independently convert each frame into 16×16 and 4×4 tokens. We train three tokenizers from scratch on RoboNet for the same number of steps. As Figure 8c, the tokenizer with 4×4 tokens suffers from low reconstruction quality due to its insufficient capacity. Our proposed tokenization method slightly compromises reconstruction quality compared to the standard 16×16 tokenizer but can provide more consistent contextual information, which is beneficial for video prediction tasks. Additionally, it significantly enhances computational efficiency by 16× measured by the number of an autoregressive transformer’s forward passes.

5 Related Work

World models for visual control. Learning general world models in visual domains remains a significant challenge in model-based reinforcement learning. A straightforward method involves

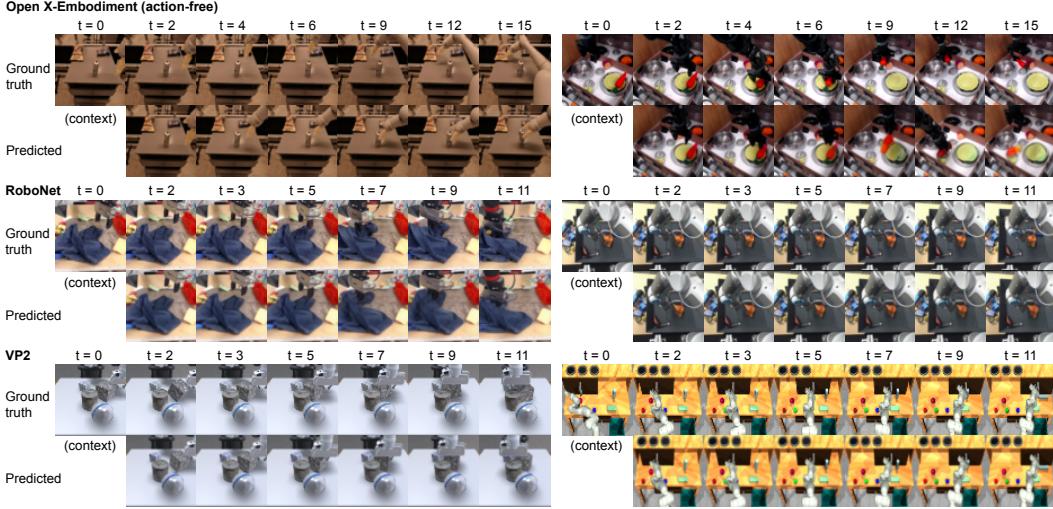


Figure 9: Qualitative evaluation: video prediction results of iVideoGPT on Open X-Embodiment, RoboNet, and VP². Zoom in for details. Extended examples can be found in Appendix B.1.

learning action-conditioned video prediction models [66, 43]. Advanced model-based RL algorithms [28, 30, 31, 77, 32] utilize latent imagination for more efficient and accurate rollouts but complicate themselves by tightly coupling model and policy learning. We show that this complexity can be reduced with powerful world models that have accumulated generalizable knowledge beyond specific tasks. Recent efforts to facilitate this include leveraging scalable architectures like transformers [60] and pre-training from large-scale data [95, 59]. Of particular relevance to our work are UniSim [98] and Genie [11], which have developed extensively trained world models with diffusion and masked models, respectively, though neither is publicly available. Our work distinguishes itself by utilizing a generic autoregressive transformer framework, advancing the flexibility of scalable world models.

Video generation and prediction. Recent developments in Internet-scale video generation models now enable the synthesis of realistic videos conditioned on class labels, text descriptions, and initial frames—the latter also known as the video prediction problem. Various models have been developed, including deterministic RNNs [80, 92], variational autoencoders [17, 2, 29, 3], diffusion [36, 10], masked [100, 26], and autoregressive models [97, 48, 53]. However, most recent works do not treat video prediction as a dynamics modeling problem and perform spatiotemporal compression [97, 7], thus providing limited interactivity to serve as world models. We achieve both compressive tokenization and interactivity by context-aware representation, employing cross-attention mechanisms with minimal inductive bias. This method diverges from previous techniques that rely on motion vectors [41] or optical flows [50] and offers a more generic form of video tokenization.

6 Discussion

We introduced Interactive VideoGPT (iVideoGPT), a generic and efficient world model architecture that leverages a scalable autoregressive transformer to integrate multimodal signals into a sequence of tokens, providing an interactive agent experience via next-token prediction. iVideoGPT has been pre-trained on millions of human and robotic manipulation trajectories and adapted to a wide range of downstream tasks. As a powerful foundation of world models, it enables accurate and generalizable video prediction as well as simplified yet performant model-based planning or reinforcement learning.

Limitations and future work. While iVideoGPT marks significant progress, there is substantial room for improvement. We found limited diversity in publicly available robotic data, including the large-scale Open X-Embodiment dataset, and initiated efforts to transfer knowledge from human videos [24]. We believe iVideoGPT should be pre-trained on more extensive data [25] to bridge knowledge between humans and robots. This requires iVideoGPT to incorporate more modalities, such as multi-view observations, proprioceptive robot states, and actions, within the unified formulation beyond action-free video prediction. Specifically, to process high-dimensional visual observations, our compressive tokenization assumes that initial frames provide sufficient contexts for

future frames, which works for low-level control tasks as model-based agents often foresee tens of steps, but may falter in scenarios with long videos and significant camera motion. This issue can be mitigated by keyframe extraction [49] but leaves an important future avenue of exploration.

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A Implementation and Experimental Details

The main hyperparameters of our experiment are detailed in Tables 2, 3, and 5. In this section, we provide a comprehensive explanation of all experimental details.

A.1 Architecture

Table 2: Hyperparameters of iVideoGPT architectures.

VQGAN	Low-resolution	High-resolution
Parameters	114M	310M
Resolution	64×64	256×256
Down blocks	3	5
Down layers per block	2	2
Down channels	[128, 256, 512]	[128, 256, 256, 512, 768]
Mid block attention	False	False
Up blocks	3	5
Up layers per block	3	3
Up channels	[512, 256, 128]	[768, 512, 256, 256, 128]
Embedding dim	64	64
Codebook size	8192	8192
Norm	GroupNorm	GroupNorm
Norm group	32	32
Activation	SiLU	SiLU
Max cross-att. resolution	16	32
Transformer	Small	Medium
Parameters	138M	436M
Layers	12	24
Heads	12	16
Hidden dim	768	1024
Feedforward dim	3072	4096
Dropout	0.1	0.1
Activation	SiLU	SiLU

Tokenizer. As illustrated in Figure 3, we use a conditional VQGAN for compressive tokenization. This comprises two encoder-decoder pairs: (E_c, D_c) for context frames (referred to as the *context encoder-decoder*) and (E_p, D_p) for future frames (referred to as the *prediction encoder-decoder*). Both pairs share the same architecture (detailed in Table 2), but the prediction encoder-decoder has a tighter bottleneck, focusing solely on encoding dynamic information. Specifically, it uses a 4×4 convolution to downsample 16×16 embeddings into 4×4 before looking up the codebook. Consequently, the prediction encoder-decoder needs to be conditioned on the features of the context encoder-decoder to incorporate rich contextual information. This conditioning is implemented via a multi-scale cross-attention mechanism, similar to ContextWM [95].

The intuition behind the multi-scale cross-attention across feature maps is as follows: the context encoder extracts contextual features at varying levels of abstraction, while the prediction encoder uses cross-attention to adaptively filter out contextual information and distill dynamics information. During decoding, the prediction decoder blocks employ cross-attention to retrieve contextual information at corresponding levels, facilitating the gradual reconstruction of the scene. This framework enhances the model’s ability to understand and manipulate complex scenes by focusing on dynamic changes, rather than being overwhelmed by irrelevant visual details.

Specifically, at the end of each encoder block, let $F_c^l \in \mathbb{R}^{c \times h \times w}$ be the feature map of a context frame, and $F_p^l \in \mathbb{R}^{c \times h \times w}$ be the feature map of a future frame. Before being processed by the next

Table 3: Hyperparameters of iVideoGPT training and evaluation.

VQGAN	Pre-train	Low-resolution (64×64)			High-resolution (256×256)	
		BAIR	RoboNet	VP ²	Pre-train	RoboNet
GPU days	17	2	8	4	16	9
Training steps	1×10^6	2×10^5	6×10^5	2×10^5	2.5×10^5	1.5×10^5
Disc. start	-	-	-	-	-	1×10^5
Batch size	64	64	64	64	8	8
Sequence length	16	16	12	12	16	12
Context frames	2	1	2	2	2	2
Sampled future frames	6	7	6	6	6	6
Learning rate	5×10^{-4}	5×10^{-4}	5×10^{-4}	5×10^{-4}	5×10^{-4}	1×10^{-4}
LR Schedule	Constant					
Weight decay	0.0					
Grad clip	1.0					
Warmup steps	500					
Loss balancing	Equal weights					
Optimizer	AdamW					
Mixed precision	bf16					
Transformer	Pre-train	BAIR	RoboNet	VP ²	Pre-train	RoboNet
GPU days	19	1.5	10	3	9	26
Training steps	7×10^5	1×10^5	6×10^5	2×10^5	3.5×10^5	5×10^5
Batch size	64	64	64	64	16	32
Sequence length	16	16	12	12	16	12
Context frames	2	1	2	2	2	2
Learning rate	1×10^{-4}					
LR Schedule	Cosine					
Weight decay	0.01					
Grad clip	1.0					
Warmup steps	5000					
Loss balancing	N/A or equal weights					
Optimizer	AdamW					
Mixed precision	bf16					
Sampling temperature	1.0					
Sampling top- <i>k</i>	100					

block, F_p^l is augmented with F_c^l as follows:

$$\begin{aligned} F_c^{l+1} &= \text{EncBlock}_c^{l+1}(F_c^l) \\ F_p^{l+1} &= \text{EncBlock}_p^{l+1}(\text{Augment}(F_p^l, F_c^l)) \end{aligned} \quad (4)$$

This is achieved by performing cross-attention between the $2hw$ positions of the feature maps:

$$\begin{aligned} \text{Flatten: } Q &= \text{Norm}(\text{Reshape}(F_p^l)) + \text{PosEmb}^Q \in \mathbb{R}^{hw \times c} \\ K = V &= \text{Norm}(\text{Reshape}(F_c^l)) + \text{PosEmb}^{KV} \in \mathbb{R}^{hw \times c} \\ \text{Cross-Attention: } R &= \text{Attention}(QW^Q, KW^K, VW^V) \in \mathbb{R}^{hw \times c} \\ \text{Residual-Connection: } &\text{Augment}(F_p^l, F_c^l) = \text{SiLU}(F_p^l + \text{Reshape}(R)) \in \mathbb{R}^{c \times h \times w}. \end{aligned} \quad (5)$$

To reduce memory usage, we apply the cross-attention mechanism only when the feature map size is below a certain threshold (16×16 for a 64×64 original resolution and 32×32 for a 256×256 resolution). This mechanism is symmetrically performed across the context and prediction decoder.

Since attention mechanisms can flexibly handle varied input lengths, the conditioning mechanism can be easily extended to accommodate different numbers of context frames. Each context frame is

independently processed by the context encoder and decoder, and their feature maps are concatenated to serve as inputs for cross-attention in the prediction encoder and decoder.

Our VQGAN for 256×256 resolution is initialized from the pretrained model from aMUSEd³ [70]. We do not use discriminators for 64×64 resolution, effectively converting the VQGAN into a vanilla VQVAE with an additional perceptual loss.

Transformer. We flatten a video into a sequence of tokens:

$$x = (z_1^{(1)}, \dots, z_1^{(N)}, [\text{S1}], z_2^{(1)}, \dots, z_2^{(N)}, \dots, [\text{S2}], z_{T_0+1}^{(1)}, \dots, z_{T_0+1}^{(n)}, \dots), \quad (6)$$

where we use two types of slot tokens [S1] and [S2] before the start of context frames and future frames, respectively. Context and future frames do not share token IDs, resulting in a transformer vocabulary of 16,386 tokens: the first 8,192 for context frames, the next 8,192 for future frames, and the last two for slot tokens. We adopt the autoregressive transformer architecture from LLaMA [83], but instantiate it to smaller models matching the size of GPT-2. We considered two model sizes, listed in Figure 2. Most of our experiments utilize a 138M parameter transformer, while preliminary scaling analysis is conducted using a 436M model.

A.2 Action-free Video Pre-training

Data mixture. We pre-trained iVideoGPT using 35 datasets from the Open X-Embodiment Dataset (OXE) [67] and Something-Something-v2 (SSv2) [24]. To construct our training dataset from OXE, we implement a filtering and weighting process similar to Octo [64]. Initially, we exclude datasets lacking image streams and those derived from mobile robots. Subsequently, datasets exhibiting excessive repetition or possessing low image resolutions are eliminated. The remaining datasets were categorized as either "large" or "small," and each was assigned a weight based on its size and diversity. For a comprehensive breakdown of the mixture, refer to Table 4. We selected 1% of samples from each subset as validation data and used the rest for training.

Training details. During training, we sample sequences of frames by first randomly selecting a training video and then uniformly sampling a segment of a specified length and step size, i.e., neighboring frames in the segment are spaced a certain number of steps apart in the original video. We observe that datasets are collected at different frequencies. To maintain consistency, we adjust sampling with varied step sizes, aligning each with its respective dataset frequency, as listed in Table 4. For tokenizer training, the initial frames of the segment are used as context frames, and from the remaining frames, we randomly sample a subset as future frames to reduce memory requirements and increase batch size. For transformer training, we use the full segment of frames. The number of frames in minibatches for each dataset is detailed in Table 3. We use a mixture of OXE and SSv2 for training the tokenizer to ensure visual diversity, while only OXE is used for training the transformer. For data augmentation, we apply random resized crop and color jitter, ensuring consistency across the sequence. During both tokenizer and transformer training, we blend different losses with equal weights. Unless specified otherwise, we follow the same implementation details when fine-tuning iVideoGPT on downstream tasks.

License. The Open X-Embodiment dataset follows the Apache license. RoboNet is licensed under Creative Commons Attribution 4.0, while BAIR follows Creative Commons BY 4.0. The Something-Something-V2 dataset is subject to the Data License Agreement.

A.3 Video Prediction

Evaluation metrics. We evaluate our model across four different metrics⁴: Structural Similarity Index Measure (SSIM) [93], Peak Signal-to-noise Ratio (PSNR) [38], Learned Perceptual Image Patch Similarity (LPIPS) [103] and Fréchet Video Distance (FVD) [84]. Following prior works

³<https://github.com/huggingface/amused> under openrail++ license

⁴We use public implementations of metrics: <https://github.com/francois-rozet/piqa> under MIT license for SSIM and PSNR, <https://github.com/richzhang/PerceptualSimilarity> under BSD-2-Clause license for LPIPS, and <https://github.com/universome/stylegan-v> under NVidia license for FVD.

Table 4: iVideoGPT pre-training data mixture from the Open X-Embodiment [67] and Something-Something-V2 [24] datasets.

Dataset	Num of trajectories	Step size	Sampling weight
Fractal [9]	87,212	1	12.8%
Bridge [90]	28,935	2	12.8%
BC-Z [39]	43,264	3	12.8%
RoboNet [15]	82,649	1	12.8%
Kuka [44]	580,392	3	8.5%
Language Table [54]	442,226	3	4.2%
Stanford MaskViT [26]	9,200	1	4.2%
UIUC D3Field [91]	768	1	2.2%
Taco Play [75, 58]	3,603	5	0.5%
Jaco Play [16]	1085	3	0.5%
Roboturk [56]	1,995	3	0.5%
Viola [110]	150	7	0.5%
Toto [106]	1,003	10	0.5%
Columbia Cairlab Push Real [13]	136	3	0.5%
Stanford Kuka Multimodal Dataset [52]	3,000	7	0.5%
Stanford Hydra Dataset [5]	570	3	0.5%
Austin Buds Dataset [111]	50	7	0.5%
NYU Franka Play Dataset [14]	456	1	0.5%
Furniture Bench Dataset [33]	5,100	3	0.5%
UCSD Kitchen Dataset [96]	150	1	0.5%
UCSD Pick and Place Dataset [22]	1,355	1	0.5%
Austin Sailor Dataset [62]	240	7	0.5%
UTokyo PR2 Tabletop Manipulation [65]	240	3	0.5%
UTokyo Xarm Pick and Place [57]	102	3	0.5%
UTokyo Xarm Bimanual [57]	70	3	0.5%
KAIST Nonprehensile [47]	201	3	0.5%
DLR SARA Pour [69]	100	3	0.5%
DLR SARA Grid [68]	107	3	0.5%
DLR EDAN Shared Control [88, 71]	104	3	0.5%
ASU Table Top [108, 107]	110	4	0.5%
UTAustin Mutex [79]	1,500	7	0.5%
Berkeley Fanuc Manipulation [109]	415	3	0.5%
CMU Playing with Food [76]	174	3	0.5%
CMU Play Fusion [12]	576	2	0.5%
CMU Stretch [4, 59]	135	3	0.5%
Something-Something-V2 [24]	193,690	1	15.0%
Total	1,491,063	-	100.0%

[2, 87, 3, 100], we account for the stochastic nature of video prediction by sampling 100 future trajectories per test video and selecting the best one for the final PSNR, SSIM, and LPIPS scores. For FVD, we use all 100 samples.

A.4 Visual Planning

We use the official repository⁵ to evaluate our model on the VP² benchmark. The reported baseline results are provided by the authors of the benchmark. For the Robosuite tasks, a cost below 0.05 is considered a success.

A.5 Visual Model-based Reinforcement Learning

Environments. Meta-world [101], following MIT License, is a benchmark of 50 robotic manipulation tasks. We select six tasks for our experiments: Button Press Topdown Wall, Plate Slide, Hammer, Door Lock, Handle Pull Side, and Coffee Push. We set the maximum episode length to 200 environment steps with an action repeat of 2 across these tasks and adjust the number of training steps to match the varying difficulty levels. During experiments, we observed that high rewards do not consistently correlate with high success rates in the original Meta-world implementation. This discrepancy presents a challenge to the learning stability of agents. To address this, we introduce an additional bonus for task success $r_{\text{bonus}} = 10.0$ alongside the original task reward r_{task} :

$$r = r_{\text{task}} + r_{\text{bonus}} \cdot \mathbb{I}_{\text{task success}}. \quad (7)$$

Moreover, Meta-world features hard-exploration tasks, resulting in significant variance in the learning curves, which poses challenges to the accurate evaluation of RL algorithm performance. To mitigate this issue, we initialize the replay buffer of all compared methods, with 5 successful demonstration trajectories for all tasks except Door Lock. This strategy, commonly used to accelerate reinforcement learning [34], helps stabilize the training process and provides a more reliable evaluation.

Implementation Details. We have developed a simple model-based RL algorithm using iVideoGPT as a world model within the MBPO [40] framework, with DrQ-v2 [99] as the base actor-critic RL algorithm. Please refer to Algorithm 1 for the pseudo-code. Our implementation is based on the official DrQ-v2 code⁶, using the same hyperparameters and architecture for actor-critic learning. Hyperparameters specific to model-based RL are listed in Table 5. We use a symlog transformation [31] for reward prediction in iVideoGPT.

Algorithm 1 Model-Based Policy Optimization (MBPO), adapted from [40]

```

1: Initialize actor-critic  $\pi_\phi, v_\psi$ , world model  $p_\theta$ 
2: Initialize real replay buffer  $\mathcal{D}_{\text{real}}$  with random policy
3: Initially train model  $p_\theta$  on  $\mathcal{D}_{\text{real}}$ 
4: Initialize imagined replay buffer  $\mathcal{D}_{\text{imag}}$  with random rollouts using  $p_\theta$ 
5: for  $N$  steps do
6:   // Training
7:   if model update step then
8:     Update world model  $p_\theta$  on a mini-batch from  $\mathcal{D}_{\text{real}}$ 
9:   end if
10:  Update actor-critic  $\pi_\phi, v_\psi$  with model-free objectives on a mini-batch from  $\mathcal{D}_{\text{imag}} \cup \mathcal{D}_{\text{real}}$ 
11:  // Data collection
12:  if model rollout step then
13:    Sample a mini-batch of  $o_t$  uniformly from  $\mathcal{D}_{\text{real}}$ 
14:    Perform  $k$ -step model rollout starting from  $o_t$  using policy  $\pi_\phi$ ; add to  $\mathcal{D}_{\text{imag}}$ 
15:  end if
16:  Take action in environment according to  $\pi_\phi$ ; add to  $\mathcal{D}_{\text{real}}$ 
17: end for

```

⁵<https://github.com/s-tian/vp2>

⁶<https://github.com/facebookresearch/drqv2> under MIT License

Table 5: Hyperparameters of model-based RL with iVideoGPT.

Model-based RL	Hyperparameter	Value
Model rollout	Init rollout batch size	640
	Interval	200 env. steps
	Batch size	32
	Horizon	10
Model training	Init training steps	1000
	Tokenizer training interval	40 env. steps
	Transformer training interval	10 env. steps
	Batch size	16
	Sequence length	12
	Context frames	2
	Sampled future frames (tokenizer)	5
	Learning rate	1×10^{-4}
	Weight decay	0
Model-based RL	Optimizer	Adam
	Real data ratio	0.5

B Additional Experimental Results

B.1 Qualitative Evaluation

We present additional examples of video predictions by iVideoGPT on various datasets in Figures 10, 12, 13, 14, 15, and 16. We also include an additional showcase of zero-shot predictions by the pre-trained transformer in iVideoGPT in Figure 11, supplementing Figure 7 of the main text.

B.2 Failure Case Analysis for Visual Planning

Our model performs sub-optimally on the RoboDesk open slide task from the VP² benchmark, and in this section, we investigate the underlying causes.

Despite achieving excellent overall video prediction metrics, such as mean square error and perceptual loss, on the validation set for the open slide task, our model predicts wrong outcomes on a few trajectories. We visualize these trajectories in Figure 17 and find that while the observation is limited to 64×64 resolution, the task of opening the slide requires the model to capture subtle changes, particularly whether the robot's gripper has made contact with the slide handle. Actually, even humans struggle to discriminate this detail with low-resolution inputs. Due to this uncertainty, the model may incorrectly predict a sequence of imprecise actions as successful. This overconfidence [63] can be exacerbated in the process of model predictive control, which samples a large number of action candidates and selects the "best" one according to the model. Our analysis provides an explanation to the observation by Tian et al. [82] that overall excellent perceptual metrics do not always correlate with effective control performance, as the worst-case scenarios are critical in model-predictive control.

Furthermore, we hypothesize that our two-stage architecture of tokenization and prediction can exacerbate the aforementioned uncertainty, as discrete tokenization inevitably results in some loss of information from the observations. This hypothesis is supported by the fact that end-to-end models like SVG' [87] and FitVid [3] perform significantly better than two-stage models, including ours and others like MaskViT [26], which uses a visual tokenizer, and Struct-VRNN [61], which employs a keypoint-based representation.

We anticipate that training and evaluating our model at a higher resolution, such as 256×256 , could mitigate these issues and enhance control performance. However, we currently conduct experiments at a lower resolution to ensure a fair comparison with other models.

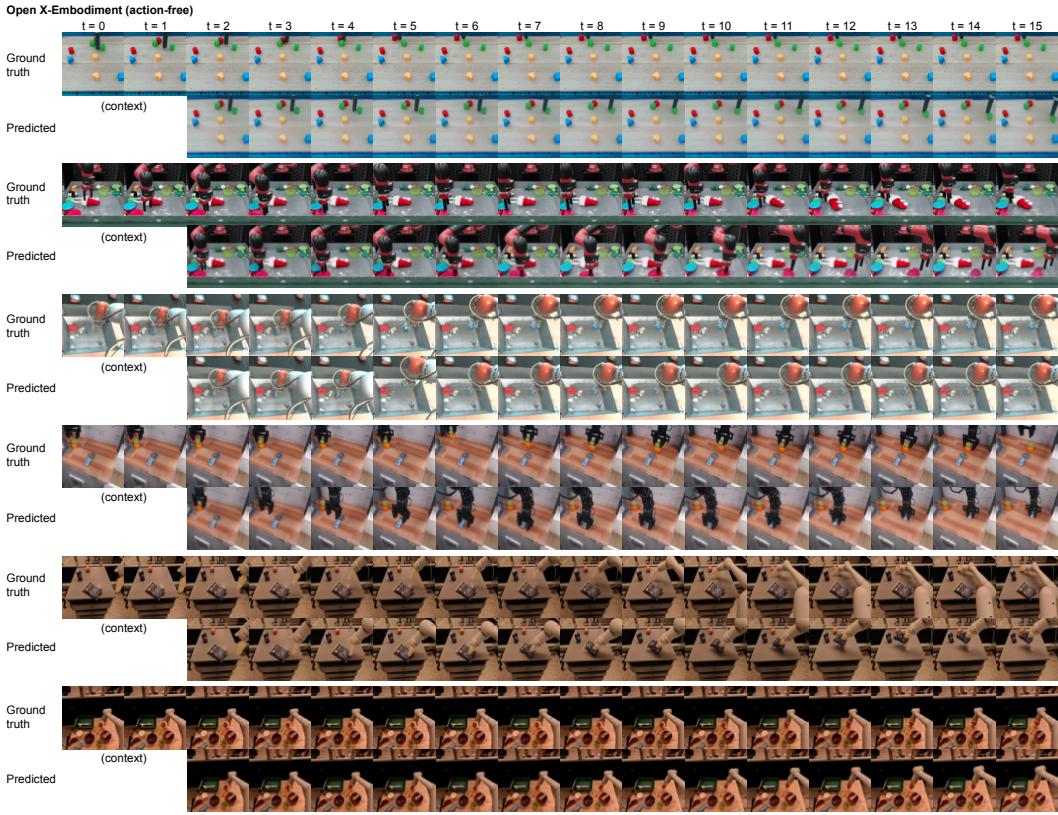


Figure 10: Additional qualitative evaluation on the Open X-Embodiment dataset.

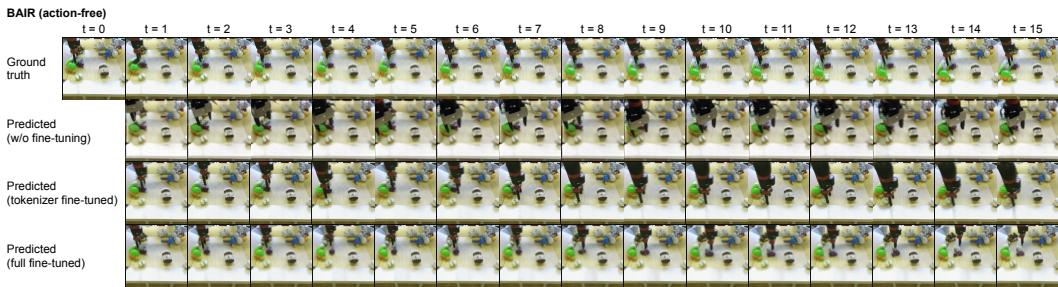


Figure 11: Additional zero-shot prediction by the pre-trained transformer in iVideoGPT, supplementing Figure 7 of the main text.

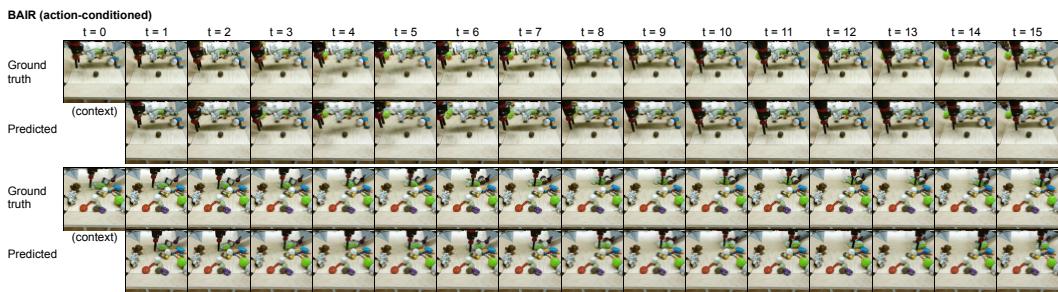


Figure 12: Additional qualitative evaluation on the BAIR dataset, given future actions.

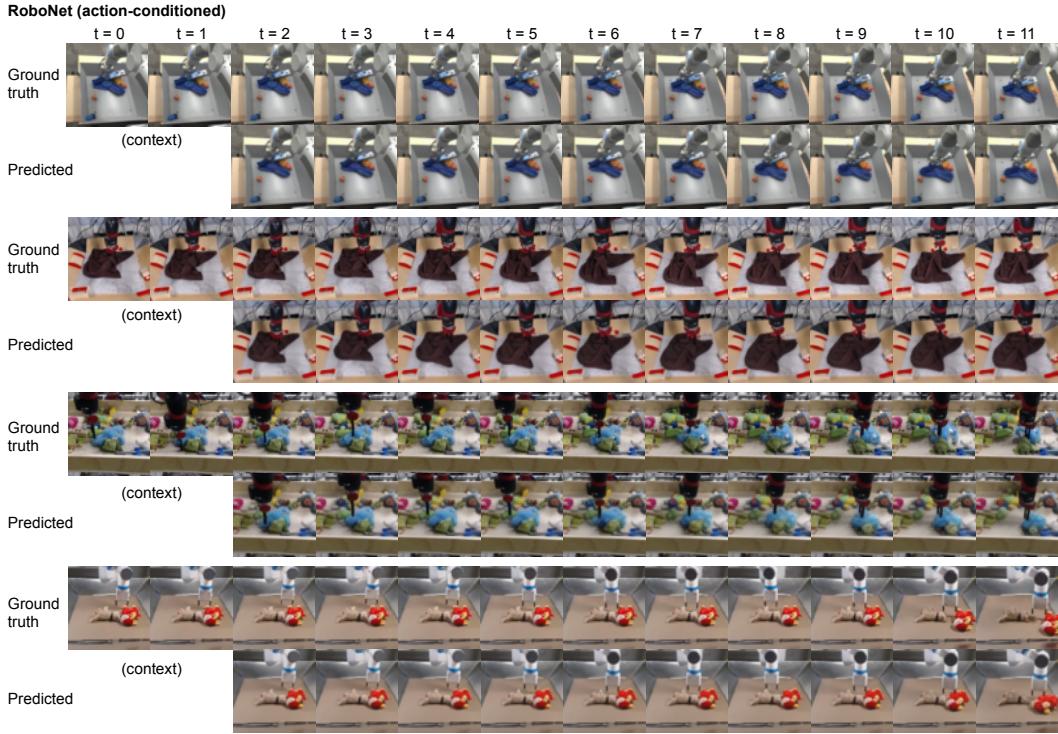


Figure 13: Additional qualitative evaluation on the RoboNet dataset, highlighting accurate movements of the pushed objects.

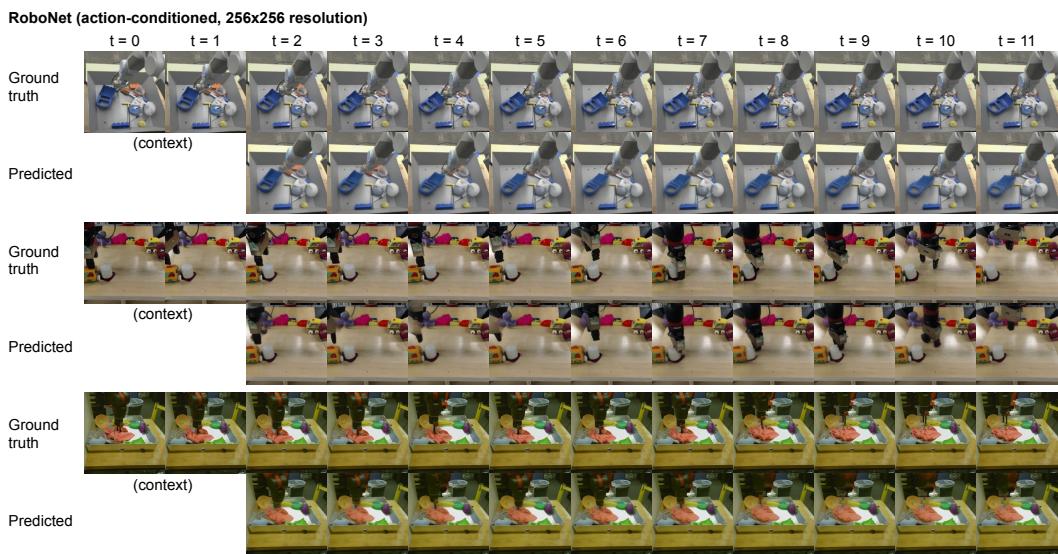


Figure 14: Additional qualitative evaluation on the RoboNet dataset, in high resolution (256×256).

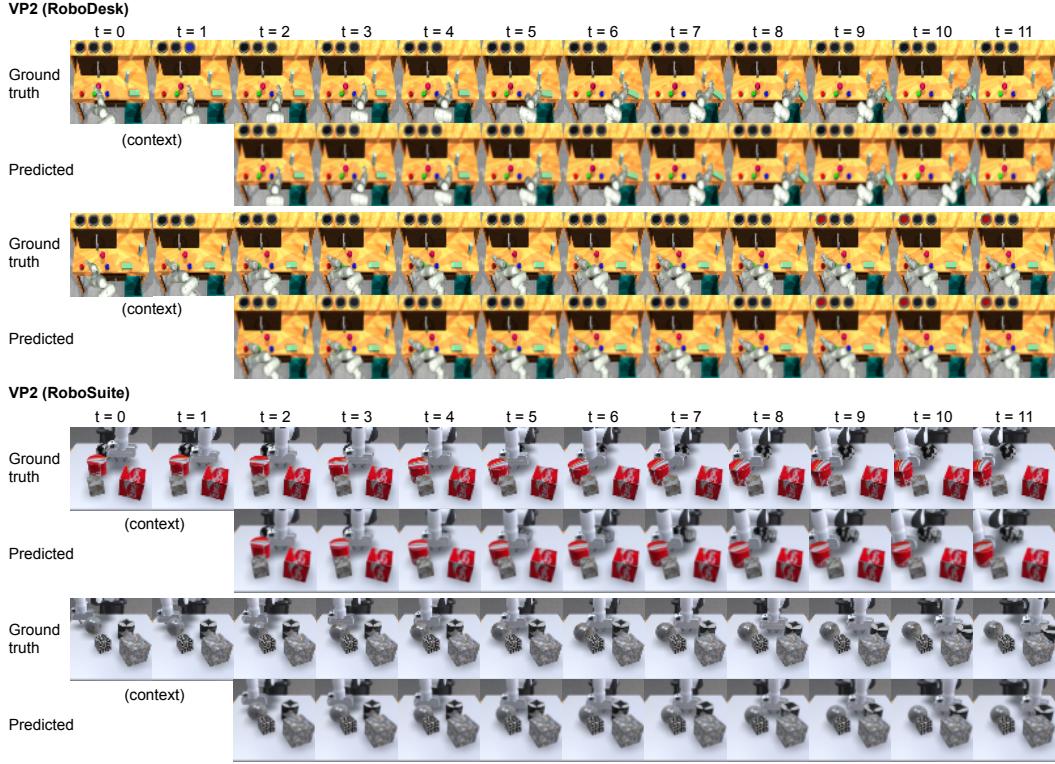


Figure 15: Additional qualitative evaluation on the VP^2 benchmark.

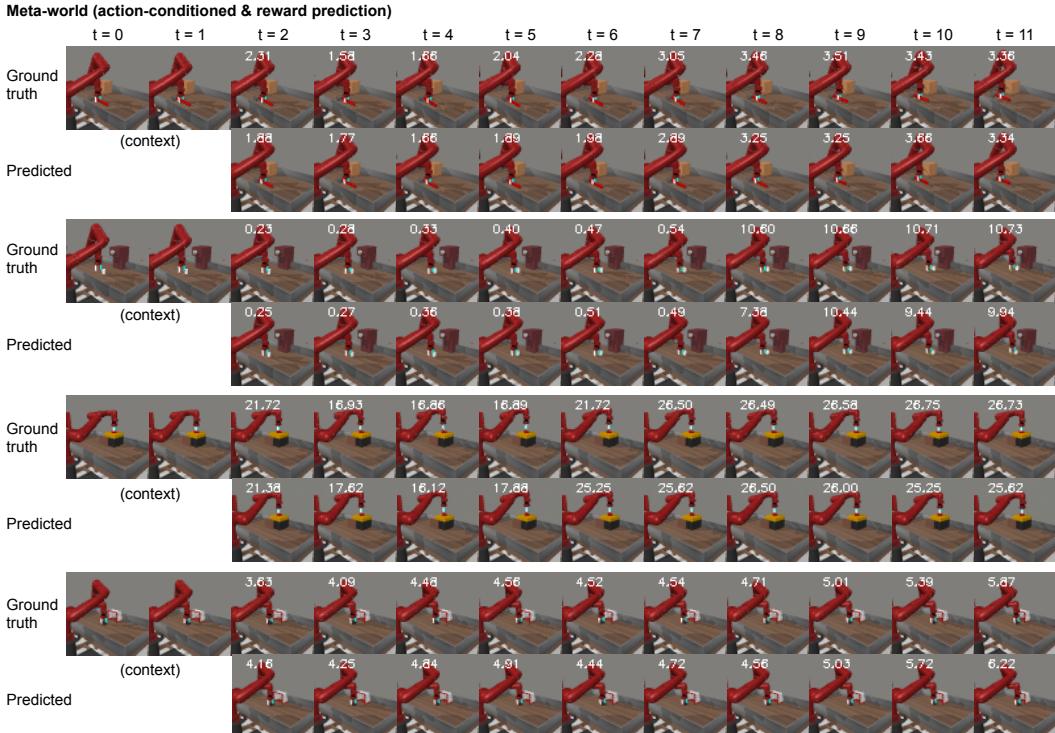


Figure 16: Additional qualitative evaluation on Meta-world tasks. True and predicted rewards are labeled at the top left corner. Zoom in for details.

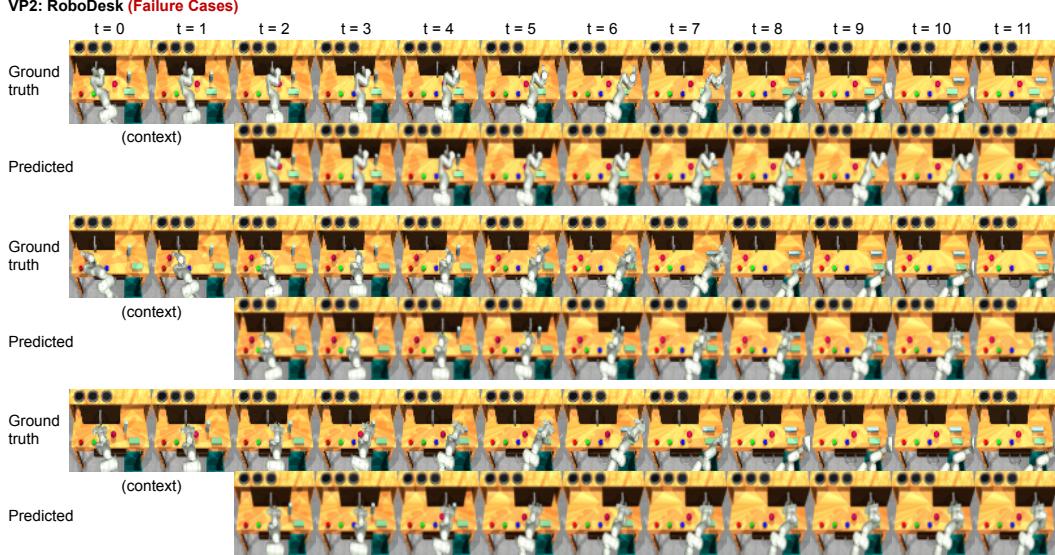


Figure 17: Failure case analysis on the RoboDesk open slide task from the VP² benchmark, where, due to the low resolution of observations, our model fails to discriminate between subtle changes, particularly whether the robot’s gripper has made contact with the slide handle.

C Computational Resources

We implement iVideoGPT in PyTorch, using the `diffusers`⁷ and `transformers`⁸ libraries. Our models are trained and evaluated on an A100 and RTX 3090 GPU cluster. Each experiment utilizes 4 GPUs in parallel, with 16 data loader workers per device. GPU days required for training are reported in Table 2. Experiments at 64×64 resolution can be conducted with 24 GB of GPU memory per device, while 256×256 resolution requires 40 GB. The Open X-Embodiment dataset is particularly large, occupying about 5TB of disk space.

⁷<https://github.com/huggingface/diffusers> under Apache License

⁸<https://github.com/huggingface/transformers> under Apache License