Preserve Your Own Correlation: A Noise Prior for Video Diffusion Models

Songwei Ge* — University of Maryland
Seungjun Nah — NVIDIA
Guilin Liu — NVIDIA
Tyler Poon — University of Chicago
Andrew Tao — NVIDIA
Bryan Catanzaro — NVIDIA
David Jacobs — University of Maryland
Jia-Bin Huang — University of Maryland
Ming-Yu Liu — NVIDIA
Yogesh Balaji — NVIDIA

A very happy fuzzy panda dressed as a chef eating pizza in the New York street food truck.

The supernova explosion of a white dwarf in the universe, photo realistic.

A high-quality 3D render of hyperrealist, super strong, multicolor stripped, and fluffy bear with wings, highly detailed.

Figure 1: Given a text description, our approach can faithfully generate videos that are consistent with the input text while being photorealistic and temporally consistent. *Best viewed with Acrobat Reader. Click the images to play the video clips.*

Abstract

Despite tremendous progress in generating high-quality images using diffusion models, synthesizing a sequence of animated frames that are both photorealistic and temporally coherent is still in its infancy. While off-the-shelf billion-scale datasets for image generation are available, collecting similar video data of the same scale is still challenging. Also, training a video diffusion model is computationally much more expensive than its image counterpart. In this work, we explore finetuning a pretrained image diffusion model with video data as a practical solution for the video synthesis task. We find that naively extending the image noise prior to video noise prior in video diffusion leads to sub-optimal performance. Our carefully designed video noise prior leads to substantially better performance. Extensive experimental validation shows that our model, Preserve Your Own COrrelation (PYoCo), attains SOTA zero-shot text-to-video results on the UCF-101 and MSR-VTT benchmarks. It also achieves SOTA video generation quality on the small-scale UCF-101 benchmark with a 10× smaller model using significantly less computation than the prior art. The project page is available at https://research.nvidia.com/labs/dir/pyoco/.

*Work done during an internship at NVIDIA.

1. Introduction

Large-scale diffusion-based text-to-image models [38, 42, 2] have demonstrated impressive capabilities in turning complex text descriptions into photorealistic images. They can generate images with novel concepts unseen during training. Sophisticated image editing and processing tasks can easily be accomplished through guidance control and embedding techniques. Due to the immense success in several applications [30, 67, 5], these models are established as pow-

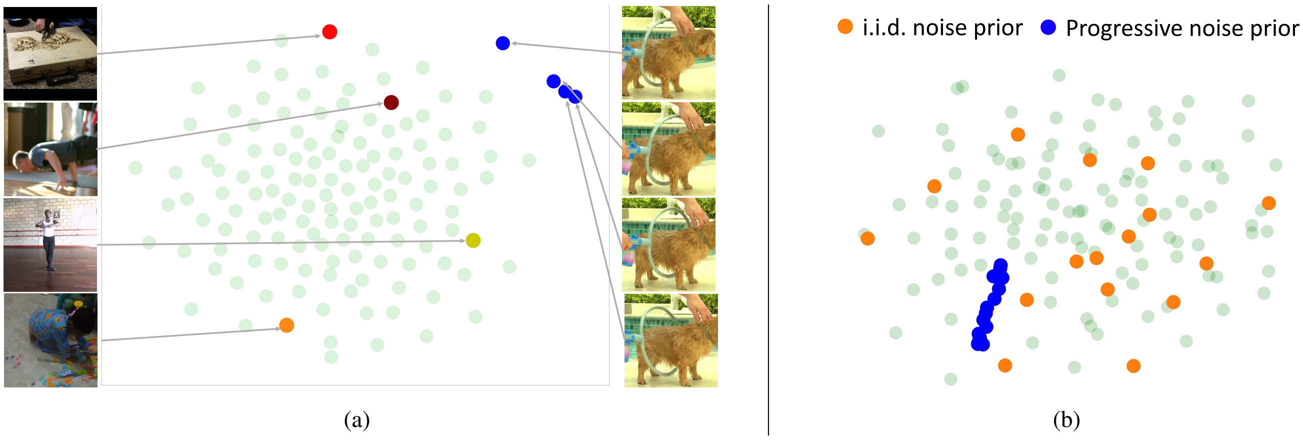


Figure 2: **Visualizing the noise map correlations**. (a) visualizes the t-SNE plot of the noise maps corresponding to input frames randomly sampled from videos. These noise maps are obtained by running a diffusion ODE [49, 48] on the input frames using a trained text-to-image model, but in the opposite direction of image synthesis ($\sigma : 0 \rightarrow \sigma_{\text{max}}$). The green dots in the background denote the reference noise maps sampled from an i.i.d. Gaussian distribution. The red dots and yellow dots are noise maps corresponding to input frames coming from different videos. We found they are spread out and share no correlation. On the other hand, the noise maps corresponding to the frames coming from the same video (shown in blue dots) are clustered together. (b) Using an i.i.d. noise model (orange dots) for finetuning text-to-image models for video synthesis is not ideal since temporal correlations between frames are not modeled. To remedy this, we propose a progressive noise model in which the correlation between different noise maps is injected along the temporal axis. Our progressive noise model (blue dots) aptly models the correlations present in the video noise maps.

erful image synthesis tools for content generation. As image synthesis is largely democratized with the success of these text-to-image models, it is natural to ask whether we can repeat the same success in video synthesis with large-scale diffusion-based text-to-video models.

Multiple attempts have been made to build large-scale video diffusion models. Ho *et al.* [17] proposed a UNet-based architecture for the video synthesis task that is trained using joint image-video denoising losses. Imagen video [14] extends the cascaded text-to-image generation architecture of Imagen [42] for video generation. In both works, the authors directly train a video generation model from scratch. While these approaches achieve great success and produce high-quality videos, they are inherently expensive to train, requiring hundreds of high-end GPUs or TPUs and several weeks of training. After all, video generators not only need to learn to form individual images but should also learn to synthesize coherent temporal dynamics, which makes the video generation task much more challenging. While the formation of individual frames is a shared component in an image and video synthesis, these works disregard the existence of powerful pretrained text-to-image diffusion models and train their video generators from scratch.

We explore a different avenue for building large-scale text-to-video diffusion models by starting with a pretrained text-to-image diffusion model. Our motivation is that most of the components learned for the image synthesis task can effectively be reused for video generation, leading to knowledge transfer and efficient training. A similar idea is adopted by several recent works [46, 69, 4]. Without exception, when finetuning, they naively extend the image diffusion noise prior (i.i.d. noise) used in the text-to-image model to a video diffusion noise prior by adding an extra dimension to the 2D noise map. We argue that this approach is not ideal as it does not utilize the natural correlations in videos that are already learned by the image models. This is illustrated in Figure 2, where we visualize the t-SNE plot of noise maps corresponding to different input frames as obtained from a pretrained text-to-image diffusion model. The noise maps corresponding to different frames coming from the same video (blue dots in Figure 2a are clustered together, exhibiting a high degree of correlation. The use of i.i.d. noise prior does not model this correlation, which would impede the finetuning process. Our careful analysis of the video diffusion noise prior leads us to a noise prior that is better tailored for finetuning an image synthesis model to the video generation task. As illustrated in Figure 2b, our proposed noise prior (shown in blue dots) aptly captures the correlations in noise maps corresponding to video frames.

We then proceed to build a large-scale diffusion-based text-to-video model. We leverage several design choices from the prior works, including the use of temporal attention [17], joint image-video finetuning [17], a cascaded generation architecture [14], and an ensemble of expert denoisers [2]. Together with these techniques and the proposed video noise prior, our model establishes a new state-of-the-art for video generation outperforming competing methods on several benchmark datasets. Figure 1 shows our model can achieve high-quality zero-shot video synthesis capability with SOTA photorealism and temporal consistency.

In short, our work makes the following key contributions.

1. We propose a video diffusion noise tailored for finetuning text-to-image diffusion models for text-to-video.
2. We conduct extensive experimental validation and verify the effectiveness of the proposed noise prior.
3. We build a large-scale text-to-video diffusion model by finetuning a pretrained eDiff-I model with our noise prior and achieve state-of-the-art results on several benchmarks.

2. Related Work

Diffusion-based text-to-image models: Diffusion models have significantly advanced the progress of text-based photorealistic, compositional image generation [38, 42]. Given the nature of the iterative denoising process that requires massive numbers of score function evaluations, earlier diffusion models focused on generating low-resolution images, e.g., 64×64 [15, 48]. To generate high-resolution images, two common approaches have been used. The first approach applies cascaded super-resolution models in the RGB space [32, 16, 42, 38], while the second approach leverages a decoder to exploit latent space [40, 11]. Based on these models, advanced image and video editing have been achieved through finetuning the model [41, 67, 5, 23, 61, 29] or controlling the inference process [30, 13, 34, 10, 35, 7, 31, 3]. Here, we study the problem of using large-scale diffusion models for text-to-video generation.

Video generation models: Generating realistic and novel videos have long been an attractive and essential research direction [58, 39, 65]. Previously studies have resorted to different types of generative models such as GANs [58, 43, 54, 52, 45], Autoregressive models [51, 63, 25, 9, 18], and implicit neural representations [47, 66]. Recently, driven by the tremendous success of applying the diffusion model to image synthesis, multiple works have proposed to explore diffusion models for conditional and unconditional video synthesis [57, 12, 69, 61, 4, 22, 19, 57, 64, 33, 28, 1, 59]. For example, Singer *et al*. extend the unCLIP framework [38] to text-to-video generation, which allows training without video captions [46]. Ho *et al*. [17] extend the Imagen framework [42] by repeatedly up-scaling low-resolution small-fps videos in both spatial and temporal directions with multiple models [14]. Our work also falls into this line of work which uses a diffusion model. We focus on augmenting an image diffusion model for video and study the design choice of the diffusion noise priors for such an image-to-video finetuning task.

Leverage knowledge from images for text-to-video generation: Like text-to-image models, text-to-video models require massive amounts of data to learn caption-relatedness, frame photorealism, and temporal dynamics. But in contrast to the abundant image data resource, video data are more limited in style, volume, and quality. To resolve such scarcity issue of text-video data, previous works have resorted to different strategies to leverage knowledge from image data for text-to-video generation, including joint training on the text-image data from scratch [17, 14, 56, 60], first training a text-to-image model and then finetuning partially [18, 4, 61, 29] or entirely [46, 8] on the video dataset, and using CLIP image features as the conditional information [46, 69]. In this paper, we propose a new video diffusion noise prior that is tailored for finetuning a pretrained diffusion-based image generation model for the video generation task. We reuse several design choices in the prior work by finetuning jointly on text-image and text-video datasets. As a result, we can build a text-to-video generation system that achieves state-of-the-art zero-shot performances.

3. Preliminaries

Diffusion models generate data by iteratively denoising samples drawn from a noise distribution. In the case of text-to-video models, text embeddings obtained from a pre-trained text encoder are used as additional inputs in the denoising process. Formally, let $D(\mathbf{x}, \mathbf{e}, \sigma)$ denote a denoising network that operates on the noisy input video $\mathbf{x} \in \mathbb{R}^{b \times n_s \times 3 \times h \times w}$ where $\mathbf{e}$ is the text embedding, and σ is the noise level. Here n_s is the sequence length of the input video, b is the batch size, and $h \times w$ is the spatial resolution. The model D is trained to denoise the input $\mathbf{x}$.

Training We follow the EDM formulation of Karras *et al*. [21] to optimize the denoiser D using the following objective

$$\mathbb{E}_{p_{\text{data}}(\mathbf{x}_{\text{clean}}, \mathbf{e}), p(\epsilon), p(\sigma)} \left[\lambda(\sigma) \| D(\mathbf{x}_{\text{noise}}; \mathbf{e}, \sigma) - \mathbf{x}_{\text{clean}} \|_2^2 \right] \tag{1}$$

$$\text{where} \quad \mathbf{x}_{\text{noise}} = \mathbf{x}_{\text{clean}} + \sigma\epsilon$$

Here, $\mathbf{x}_{\text{noise}}$ is the noisy sample obtained by corrupting the clean video $\mathbf{x}$ with noise $\sigma\epsilon$, where $p(\epsilon) = \mathcal{N}(\mathbf{0}, \mathbf{I})$ and σ is a scalar for the noise level drawn from $p(\sigma)$. The loss weight, $\lambda(\sigma)$, is a function of σ given by $\lambda(\sigma) = (\sigma^2 + \sigma_{\text{data}}^2)/(\sigma \cdot \sigma_{\text{data}})^2$. Eq. (1) is a simple denoising objective in which the denoiser D is trained to estimate the clean video $\mathbf{x}_{\text{clean}}$ from the noisy input $\mathbf{x}_{\text{noise}}$. Following EDM, we use a log-normal distribution for σ i.e., $\ln(p(\sigma)) = \mathcal{N}(P_{\text{mean}}, P_{\text{std}}^2)$ with $P_{\text{mean}} = -1.2$ and $P_{\text{std}} = 1.2$.

To train the denoising model, EDM uses preconditioning terms in its objective function to properly scale the inputs and output of the denoiser model D. More specifically, the denoising model D is written as

$$D(\mathbf{x};\mathbf{e},\sigma) := \left(\frac{\sigma_{\text{data}}}{\sigma^*}\right)^2 \mathbf{x} + \frac{\sigma \cdot \sigma_{\text{data}}}{\sigma^*} F_\theta\left(\frac{\mathbf{x}}{\sigma^*}; \mathbf{e}, \frac{\ln(\sigma)}{4}\right)$$

Here, F_θ is a neural network with parameters θ and $\sigma^* = \sqrt{\sigma^2 + \sigma^2_{\text{data}}}$. We use $\sigma_{\text{data}} = 0.5$.

Sampling Once the denoising model is trained, sampling can be performed by solving the following ODE [21]

$$\frac{d\mathbf{x}}{d\sigma} = -\sigma \nabla_{\mathbf{x}} \log p(\mathbf{x}|\mathbf{e}, \sigma) = \frac{\mathbf{x} - D(\mathbf{x}; \mathbf{e}, \sigma)}{\sigma} \qquad (2)$$

for σ flowing backwards from $\sigma = \sigma_{\max}$ to $\sigma = 0$. The initial value for $\mathbf{x}$ is obtained by sampling from the prior distribution $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \sigma^2_{\max}\mathbf{I})$. Over the recent years, several samplers have been proposed for sampling from the trained diffusion models [68, 48, 26, 27, 15]. In this paper, we use DEIS [68] and its stochastic variant [21] for synthesizing samples from our model.

4. Method

Training text-to-video models is much more challenging than training text-to-image diffusion models due to practical difficulties in collecting billion-scale video datasets and securing enough computational resources. Additionally, generating videos is much more challenging since individual frames need to be both photorealistic and temporally coherent. Prior works leverage large-scale image datasets to mitigate these difficulties by either joint training on the image datasets [60, 17, 14] or finetuning a text-to-image model on the video datasets [18, 46]. Here, we are interested in finetuning text-to-image diffusion models jointly on image and video datasets. We postulate that naively extending the image noise prior to video diffusion is not ideal. We carefully explore the design space of noise priors and propose one that is well suited for our video finetuning task, which leads to significant performance gains.

Correlated noise model An image diffusion model is trained to denoise independent noise from a perturbed image. The noise vector ϵ in the denoising objective (1) is sampled from an i.i.d. Gaussian distribution $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$. However, after training the image diffusion model and applying it to reverse real frames from a video into the noise space in a per-frame manner, we find that the noise maps corresponding to different frames are highly correlated. This is illustrated in Figure 2, where the t-SNE plot of noise maps corresponding to different video frames are plotted. When the input frames come from the same video (shown in blue dots in Figure 2a, noise maps are clustered. The use of i.i.d. sampling (shown in orange dots in Figure 2b does not capture these correlations. This is also depicted quantitatively in Table 1 where we compute the average pairwise cosine similarity between noise corresponding to (a) same video and (b) different video. (a) is much higher than (b). As a result, the video diffusion model trained with i.i.d. noise is coerced to forget such correlation among the noise between different frames, making it difficult to preserve knowledge from the image diffusion model. Motivated by this observation, we propose to modify the noise process to preserve the correlation between different frames. To this end, we investigate two noising strategies - mixed and progressive noising.

Table 1: **Cosine similarity of the reversed noise.** The noise maps corresponding to the frames sampled from the same videos have a higher similarity than those sampled from different videos.

	Cosine Similarity
(a) Same video noise	0.206±0.156
(b) Different video noise	0.001±0.009

Mixed noise model: Let $\epsilon^1, \epsilon^2, \dots \epsilon^{n_s}$ denote the noise corresponding to individual video frames i.e., ϵ^i corresponds to the i^{th} element of the noise tensor ϵ. In the mixed noise model, we generate two noise vectors ϵ_{shared} and ϵ_{ind}. ϵ_{shared} is a common noise vector shared among all video frames, while ϵ_{ind} is the individual noise per frame. The linear combination of both these vectors is used as the final noise.

$$\epsilon_{\text{shared}} \sim \mathcal{N}\left(\mathbf{0}, \frac{\alpha^2}{1+\alpha^2}\mathbf{I}\right), \epsilon^i_{\text{ind}} \sim \mathcal{N}\left(\mathbf{0}, \frac{1}{1+\alpha^2}\mathbf{I}\right) \qquad (3)$$
$$\epsilon^i = \epsilon_{\text{shared}} + \epsilon^i_{\text{ind}}$$

Progressive noise model: In the progressive noise model, the noise for each frame is generated in an autoregressive fashion in which the noise at frame i is generated by perturbing the noise at frame $i-1$. Let ϵ^i_{ind} denote the independent noise generated for frame i. Then, progressive noising can be formulated as

$$\epsilon^0 \sim \mathcal{N}(\mathbf{0}, \mathbf{I}) \quad \epsilon^i_{\text{ind}} \sim \mathcal{N}(\mathbf{0}, \frac{1}{1+\alpha^2}\mathbf{I}) \qquad (4)$$
$$\epsilon^i = \frac{\alpha}{\sqrt{1+\alpha^2}}\epsilon^{i-1} + \epsilon^i_{\text{ind}}$$

In both these models, α controls how much noise is shared among different video frames. The higher the value of α, the more correlation exists among the noise maps corresponding to different frames. As $\alpha \to \infty$, all frames would have the same noise which results in generating a frozen video. On the other hand, $\alpha = 0$ corresponds to i.i.d. noise.

As shown in Figure 2b, the use of progressive noise sampling (blue dots) better models the correlations between different noise maps by obtaining similar clustering patterns to the noise maps of real video frames embedded by a pretrained text-to-image model in Figure 2a (blue dots).

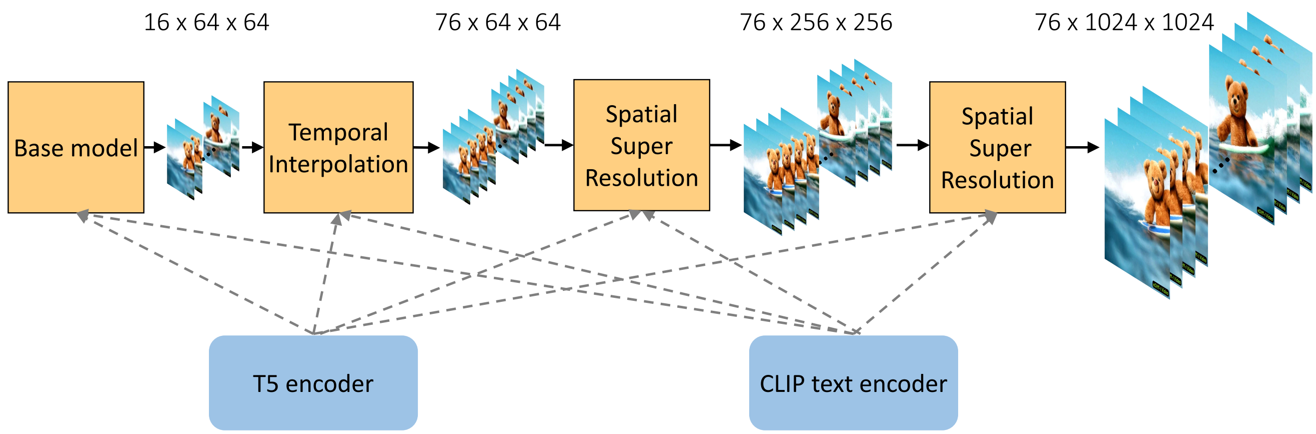


Figure 3: **Model architecture.** Our pipeline consists of a cascade of four networks — a base model and three upsampling models. All four models take inputs as the text embeddings obtained from the T5 encoder and the CLIP text encoder. The base model produces 16 video frames of spatial resolution 64×64 with a frameskip of 5. The first upsampling model performs a temporal interpolation, resulting in videos of size $76 \times 64 \times 64$ while the subsequent two super-resolution models perform spatial super-resolution to produce videos of sizes $76 \times 256 \times 256$ and $76 \times 1024 \times 1024$.

Model architecture As visualized in Figure 3, our model consists of a cascade of four networks — a base network and three upsampling stacks. The base network generates an output video of dimension $16 \times 64 \times 64$ with a frameskip of 5. It generates the frames $\{1, 6, 11, \ldots 76\}$. The first upsampling network performs a temporal interpolation to produce a video of size $76 \times 64 \times 64$. The second and the third super-resolution network performs spatial upsampling to produce the outputs of sizes $76 \times 256 \times 256$ and $76 \times 1024 \times 1024$. We utilize eDiff-I [2], a state-of-the-art text-to-image diffusion model, to initialize our base and spatial super-resolution models. Similar to prior works [17, 46], we adapt the image-based U-Net model for the video synthesis task by making the following changes: (1) Transforming 2D convolutions to 3D by adding a dimension 1 to temporal axis and (2) Adding temporal attention layers. Please refer to the supplementary material for more details.

Similar to Ho *et al.* [17], we jointly finetune the model on video and image datasets by concatenating videos and images in the temporal axis and applying our temporal modules only on the video part. Similarly to eDiff-I, our model uses both T5 text embeddings [37] and CLIP text embeddings [36]. We drop each of the embeddings independently at random during training, as in eDiff-I.

5. Experiments

In this section, we evaluate our proposed strategy of training diffusion models for video synthesis on two sets of experiments. We first comprehensively analyze our proposed noise model on the small-scale UCF-101 dataset. We then scale up our experiments to the challenging large-scale text-to-video synthesis task.

5.1. Experimental Setups

We conduct ablation experiments in a small-scale unconditional video generation setting and pick the best configuration for our large-scale text-to-video generation run.

Datasets We train our model on the UCF-101 dataset [50] for the small-scale experiments, where we follow the protocol defined in Ho *et al.* [17] to generate videos of size $16 \times 64 \times 64$. UCF-101 dataset contains $13,320$ videos. We randomly sample frames from these videos to train our image synthesis model. For our large-scale experiments, we use a combination of public and proprietary datasets for text-to-image and text-to-video finetuning. Most of the videos are of 2K resolution with 16:9 aspect ratio. All data was filtered using a preset CLIP and aesthetic scores* to ensure high quality. Our final image dataset contains around 1.2 billion text-image pairs and 22.5 million text-video pairs.

Training details In the unconditional generation experiment on the UCF-101 dataset, to do an ablation study on the model size, we design 3 models where each model has 69M, 112M, and 253M parameters, respectively. As a comparison, the baseline Video Diffusion Model (VDM) [17] contains 1.2B parameters. In the large-scale text-to-video experiment, our base and temporal interpolation models contain 1.08B parameters. Our super-resolution model adapted from the efficient U-Net [42] architecture with temporal convolution layers [14, 46] contains 313M parameters. Please refer to the supplementary material for more training details.

*https://github.com/christophschuhmann/improved-aesthetic-predictor

A cute corgi wearing a red robe holding a sign that says "Merry Christmas". There is a Christmas tree in the background. *An epic tornado attacking above a glowing city at night, the tornado is made of smoke, highly detailed.* *Small boat sailing in the ocean, giant Cthulhu monster coming out a dense mist in the background, giant waves attacking.* *A golden retriever puppy holding a green sign that says "NVIDIA ROCKS". Background is a classroom.*

A cute funny robot dancing, centered, award winning watercolor pen illustration. *A cartoon white wolf is giving puppy-dog eyes, detailed fur, very cute kid's film character.* *A lightning striking atop of eiffel tower, dark clouds in the sky, slow motion.* *An anime girl looks at the beautiful nature through the window of a moving train, well rendered.*

A skull burning while being held up by a skeletal hand. *A huge dinosaur skeleton walking in a golden wheat field on a bright sunny day.* *A cute rabbit is eating grass, wildlife photography.* *Tomato sauce pouring over fries.*

Figure 4: Sample generations. *Please check our project website to view the videos.*

Evaluation For the small-scale experiments on UCF-101 dataset, we follow the protocol defined in the prior approaches [52, 47, 17] and report the Inception Score (IS) [44] calculated by a trained C3D model [53] and Fréchet Video Distance (FVD) [55] by a trained I3D model [6]. For the large-scale text-to-video experiments, we perform the zero-shot evaluation of the video generation quality on the UCF-101 and MSR-VTT datasets following Make-A-Video [46]. We carefully discuss the evaluation process below.

UCF-101 experiment We use IS and FVD for evaluation in our small-scale experiments. UCF-101 is a categorical video dataset designed for action recognition. When sampling from the text-to-video model, we devise a set of prompts for each class name to be used as the conditional input. This is necessary as some class names (such as *jump rope*) are not descriptive. We list all the prompts we use in the supplementary material. We sample 20 videos for each prompt to compute the IS metric. For FVD, we follow the

Table 2: Zero-shot text to video generation on UCF-101. Our approach gives significant performance gains compared to the prior baselines both in inception score and FVD metrics.

Method	IS (↑)	FVD (↓)
CogVideo [18] (Chinese)	23.55	751.34
CogVideo [18] (English)	25.27	701.59
Make-A-Video [46]	33.00	367.23
MagicVideo [69]	-	655.00
Video LDM [4]	33.45	550.61
VideoFactory [59]	-	410.00
PYoCo	**47.76**	**355.19**

Table 3: Text conditional zero-shot generation on MSRVTT. Our approach with the base config achieves the best results, and using an ensemble further improves the FIDs.

Method	CLIP-FID (↓)	FID (↓)
NUWA [60] (Chinese)	47.68	-
CogVideo [18] (Chinese)	24.78	-
CogVideo [18] (English)	23.59	-
Make-A-Video [46]	13.17	-
MagicVideo [69]	-	36.50
Latent-Shift [1]	15.23	-
PYoCo (Config-A)	10.21	25.39
PYoCo (Config-B)	9.95	24.28
PYoCo (Config-C)	9.91	24.54
PYoCo (Config-D)	**9.73**	**22.14**

prior work [25, 52] and sample $2,048$ videos for evaluation.

MSR-VTT experiment MSR-VTT [62] test set contains $2,990$ videos as well as $59,794$ captions. All the videos have the same resolution of 320×240. We generate a $76 \times 256 \times 256$ video for each $59,794$ caption and save the videos in an *mp4* format with a high bit rate. To compare with Make-A-Video, we compute FID using a ViT-B/32 model [24]. We also report a more common FID metric computed by an Inception-V3 model. We also examine the idea of ensemble denoiser [2] by finetuning the level-1 experts of each model. We denote Config-A as the configuration of using only baseline models and Config-B to Config-D as incrementally changing super-resolution model, temporal interpolation model, and base model with the corresponding ensemble models.

5.2. Main Results

Large-scale text-to-video synthesis We quantitatively compare our method against Make-A-Video [46], NUWA [60], CogVideo [18], and several concurrent works [4, 69, 4, 59, 1]. Table 2 shows that our method

Table 4: Unconditional UCF-101 generation results. Our approach achieves the state-of-the-art inception score and FVD, while having considerably smaller parameter count compared to other diffusion-based approaches such as VDM (1B parameters).

Method	IS (↑)	FVD (↓)
TGAN [43]	$15.83_{\pm.18}$	-
LDVD-GAN [20]	$22.91_{\pm.19}$	-
VideoGPT [63]	$24.69_{\pm.30}$	-
MoCoGAN-HD [52]	32.36	838
DIGAN [66]	$29.71_{\pm.53}$	$655_{\pm22}$
CCVS [25]	$24.47_{\pm.13}$	$386_{\pm15}$
StyleGAN-V [47]	$23.94_{\pm.73}$	-
VDM [17]	$57.00_{\pm.62}$	-
TATS [9]	$57.63_{\pm.73}$	$430_{\pm18}$
PYoCo (112M)	$57.93_{\pm.24}$	$332_{\pm13}$
PYoCo (253M)	$\mathbf{60.01}_{\pm.51}$	$\mathbf{310}_{\pm13}$

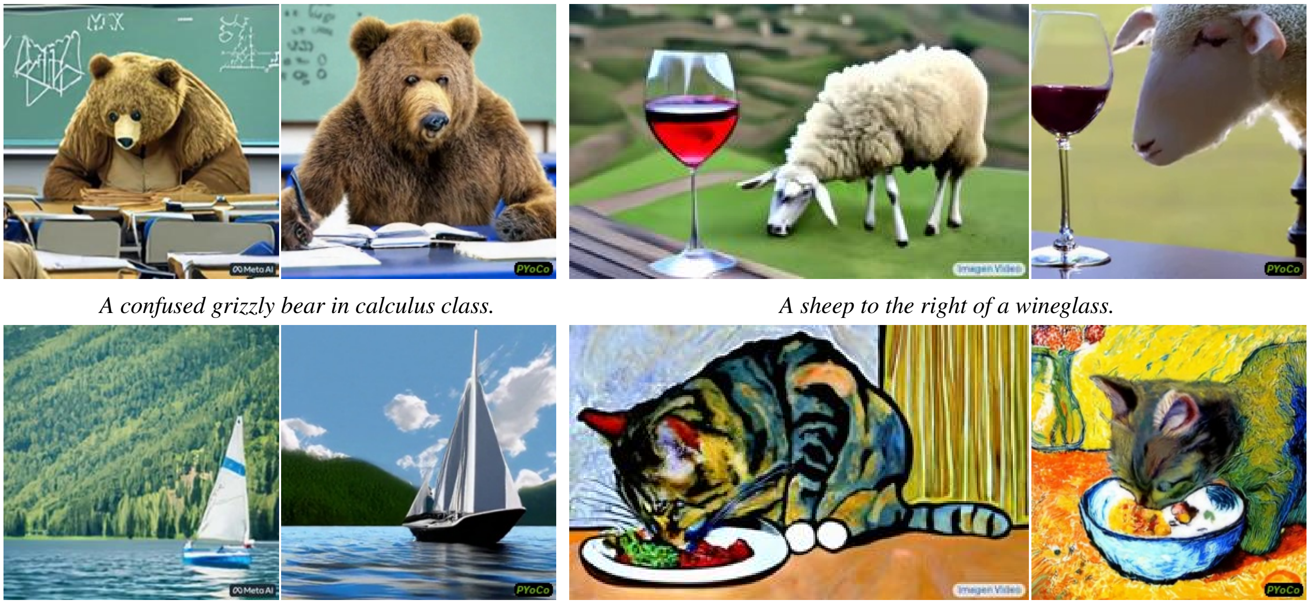
outperforms all the baselines on the UCF-101 dataset and improves the zero-shot Inception Score from 33.45 to 47.76. In Table 3, we show that our baseline model achieves a new state-of-the-art CLIP-FID score [24] of 10.21, while using ensemble models further improves both CLIP-FID and FID scores. In Figure 4, we qualitatively visualize the synthesis capability of our approach. Our model achieves high-quality zero-shot video synthesis capability with good photorealism and temporal coherency. We also provide a qualitative comparison with Make-A-Video [46] and Imagen Video [14] in Figure 5. We observe that our model is able to produce videos with better details than both approaches, as shown in the animal videos. We also produce better-stylized videos than Imagen Video.

Small-scale unconditional video synthesis We report IS and FVD scores on UCF-101 dataset in Table 4 and compare our model with multiple unconditional video generation baselines. Note that using class labels as conditional information could lead to sizeable improvement in IS and FVD scores [9], which we do not consider as the comparison. Our method attains state-of-the-art unconditional video generation quality. Compared with previous diffusion-based unconditional generation model [17], our model is $\sim 10\times$ smaller and has $\sim 14\times$ less training time (75 GPU-days vs. 925 GPU-days).

5.3. Ablation Study

We quantitatively compare several training strategies for video diffusion models. Then, we perform ablation on the correlation ratio in the Equations 3 and 4, a key hyper-parameter in our approach.

Make-A-Video [46] PYoCo Imagen Video [14] PYoCo



A confused grizzly bear in calculus class. *A sheep to the right of a wineglass.*

Sailboat sailing on a sunny day in a mountainlake. *A cat eating food out of a bowl, in style of Van Gogh.*

Figure 5: Qualitative comparison with baseline approaches. The two panels on the left show the comparison of our approach with Make-A-Video [46], while those on the right show the comparison with Imagen Video [14]. PYoCo achieves better photorealism compared to the two approaches.

Table 5: Quantitative results of different training strategies on UCF-101 dataset.

	IS(↑)	FVD (↓)	FID (↓)
Image Diffusion (ID)	-	-	30.05
Training from scratch	28.25	903.37	124.75
Finetuning from ID	41.25	566.67	56.43
+ Mixed Noise	52.71	**337.40**	**31.57**
+ Progressive Noise	**53.52**	339.67	31.88

Training strategies We compare training from scratch, a simple finetuning baseline, finetuning with mixed noising, and progressive noising using IS, FVD, and averaged frame FID metrics on the UCF-101 dataset in Table 5. We first find that finetuning from an image diffusion model is much more effective than training from scratch. For finetuning from the image model, the correlated noise model produces better video generation quality than the independent noise model. In addition, we notice that the correlated noise better preserves the image quality learned by the pretrained image model and produces a lower frame FID. This is particularly desired in large-scale text-to-video training to fulfill the goal of inheriting the knowledge from the image model missing in the video datasets. Specifically, most videos contain realistic scenes captured by cameras and have infrequent media types like paintings, illustrations, sketches, etc. Moreover, the video data is much smaller in volume, and the scenes are less diverse than image datasets. As shown in Figure 4, our model can preserve properties learned from image datasets that are not presented in our video dataset, such as the artistic styles, and generate faithful motion on them.

Correlation ratio The hyperparameter α in the Equations 3 and 4 controls the correlation between the noise of different frames. A larger α injects more correlation into the noise. The correlation disappears when $\alpha \to 0$, and the mixed and progressive noise models reproduce the vanilla noise model. To find optimal α, we train our UCF-small model (69M parameters) using $\alpha \in \{0, 0.1, 0.2, 0.5, 1, 1, 2, 5, 10, \infty\}$ and report FVD in Figure 7. For each α value, we repeat the experiment 3 times and report the mean. Note that $\alpha = 0$ indicates finetuning with the independent frame noise, and $\alpha = \infty$ indicates using identical noise maps for all the frames, which produces frozen videos during the inference time. Finetuning an image diffusion model almost consistently outperforms the training-from-scratch baseline with different αs. Using $\alpha = 1$ for mixed noising and $\alpha = 2$ for progressive noising produces similar best results. We also show qualitative results for models trained with $\alpha = 0, 1, 10$ in Figure 6. When α is too small, we notice a degradation in visual quality in the generated video frames and a reduced video diversity. For example, we notice many repeated samples and black borders in almost every video generated with

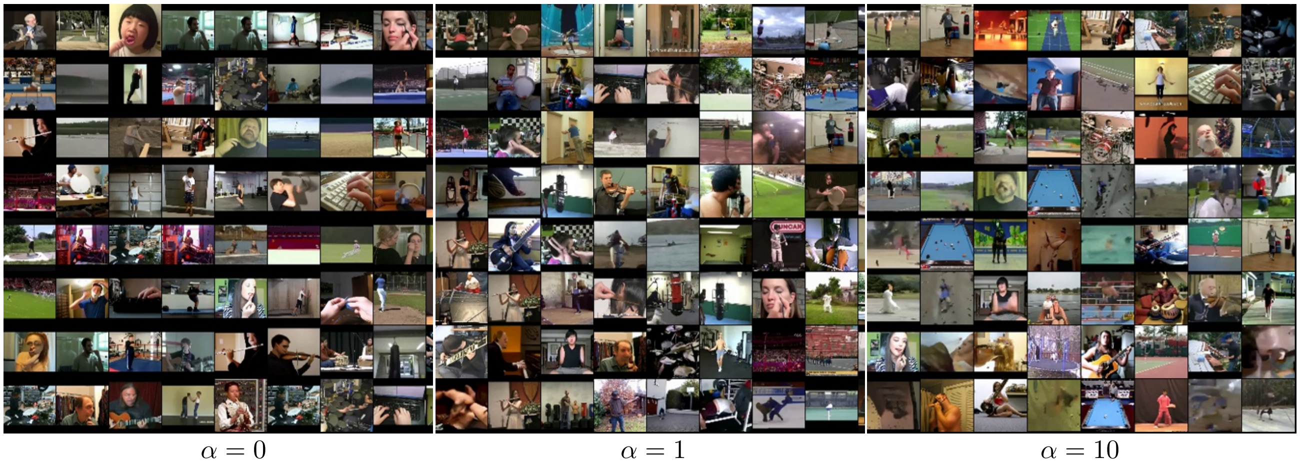


Figure 6: **Visual ablation on α.** Small $\alpha = 0$ reduces video quality and diversity and large $\alpha = 10$ yields motion artifacts.

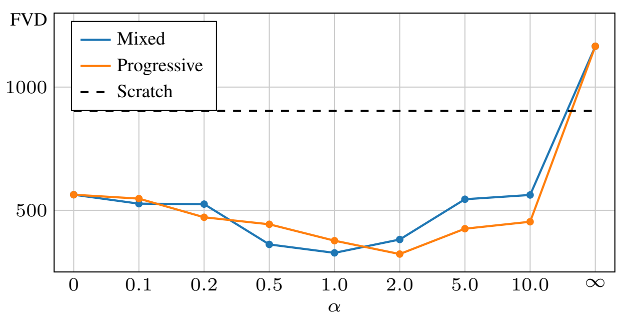


Figure 7: **Quantitative ablation on hyperparameter α.** Finetuning with temporally correlated prior improves over training from scratch. Using a too-large or too-small α leads to inferior results. $\alpha = 1$, $\alpha = 2$ each works the best for mixed and progressive noising, respectively.

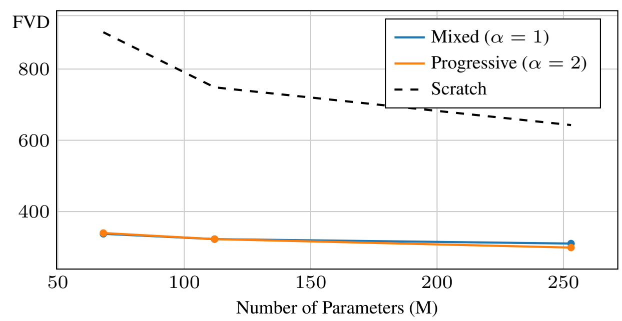


Figure 8: **Ablation on model size.** Larger models consistently improve the performance of both finetuning and training from scratch. Finetuning from image model consistently outperforms training from scratch.

$\alpha = 0$. On the other hand, when α is too large, the model has difficulty generating proper motions.

Model size We pick the best α for the mixed and progressive noise models and compare them with the model trained from scratch on models with different numbers of parameters, 69M, 112M, and 253M. Figure 8 shows that our mixed and progressive models outperform the baseline consistently by a large margin in terms of FVD. Overall, mixed and progressive noising provide similar performance. In our large large-scale experiments, we choose progressive noising with $\alpha = 2$ due to its autoregressive nature.

6. Conclusion

We proposed a new efficient way of training text-to-video generation models. By observing that the noise maps generating the frames of a video are clustered together, we study mixed and progressive noise priors well-suited for sequential video frame generation. We apply our progressive noise prior to finetuning a state-of-the-art diffusion-based text-to-image model to achieve a state-of-the-art large-scale text-to-video model. The high quality of the generated videos and the state-of-the-art Inception and FID scores demonstrate the strength of our approach.

Acknowledgment. We would like to thank Amanda Moran, John Dickinson, Sivakumar Arayandi Thottakara, David Page, Ranjitha Prasanna, Venkata Karri, and others in NGC and PBSS team for the computing infrastructure support. We also give thanks to Qinsheng Zhang, Zekun Hao, Tsung-Yi Lin, Ajay Jain, and Chen-Hsuan Lin for useful discussions and feedback. Thanks also go to Yin Xi and Thomas Hayes for clarifying the evaluation protocol of Make-A-Video and to Ming Ding for the details of CogVideo. We thank the ICCV PCs, ACs, and reviewers for their service and valuable feedback. This work is partly supported by NSF grants No. IIS-1910132 and IIS-2213335.

References

[1] Jie An, Songyang Zhang, Harry Yang, Sonal Gupta, Jia-Bin Huang, Jiebo Luo, and Xi Yin. Latent-shift: Latent diffusion with temporal shift for efficient text-to-video generation. *arXiv preprint arXiv:2304.08477*, 2023. 3, 7

[2] Yogesh Balaji, Seungjun Nah, Xun Huang, Arash Vahdat, Jiaming Song, Qinsheng Zhang, Karsten Kreis, Miika Aittala, Timo Aila, Samuli Laine, Bryan Catanzaro, et al. eDiff-I: Text-to-image diffusion models with an ensemble of expert denoisers. *arXiv preprint arXiv:2211.01324*, 2022. 1, 3, 5, 7

[3] Omer Bar-Tal, Dolev Ofri-Amar, Rafail Fridman, Yoni Kasten, and Tali Dekel. Text2live: Text-driven layered image and video editing. In *ECCV*, pages 707–723. Springer, 2022. 3

[4] Andreas Blattmann, Robin Rombach, Huan Ling, Tim Dockhorn, Seung Wook Kim, Sanja Fidler, and Karsten Kreis. Align your latents: High-resolution video synthesis with latent diffusion models. In *CVPR*, 2023. 2, 3, 7

[5] Tim Brooks, Aleksander Holynski, and Alexei A Efros. Instructpix2pix: Learning to follow image editing instructions. *CVPR*, 2023. 1, 3

[6] Joao Carreira and Andrew Zisserman. Quo vadis, action recognition? a new model and the kinetics dataset. In *CVPR*, pages 6299–6308, 2017. 6

[7] Duygu Ceylan, Chun-Hao Huang, and Niloy J. Mitra. Pix2video: Video editing using image diffusion. *arXiv:2303.12688*, 2023. 3

[8] Patrick Esser, Johnathan Chiu, Parmida Atighehchian, Jonathan Granskog, and Anastasis Germanidis. Structure and content-guided video synthesis with diffusion models. *arXiv preprint arXiv:2302.03011*, 2023. 3

[9] Songwei Ge, Thomas Hayes, Harry Yang, Xi Yin, Guan Pang, David Jacobs, Jia-Bin Huang, and Devi Parikh. Long video generation with time-agnostic vqgan and time-sensitive transformer. *arXiv preprint arXiv:2204.03638*, 2022. 3, 7

[10] Songwei Ge, Taesung Park, Jun-Yan Zhu, and Jia-Bin Huang. Expressive text-to-image generation with rich text. *arXiv preprint arXiv:2304.06720*, 2023. 3

[11] Shuyang Gu, Dong Chen, Jianmin Bao, Fang Wen, Bo Zhang, Dongdong Chen, Lu Yuan, and Baining Guo. Vector quantized diffusion model for text-to-image synthesis. In *CVPR*, pages 10696–10706, 2022. 3

[12] William Harvey, Saeid Naderiparizi, Vaden Masrani, Christian Weilbach, and Frank Wood. Flexible diffusion modeling of long videos. *arXiv preprint arXiv:2205.11495*, 2022. 3

[13] Amir Hertz, Ron Mokady, Jay Tenenbaum, Kfir Aberman, Yael Pritch, and Daniel Cohen-Or. Prompt-to-prompt image editing with cross attention control. *arXiv preprint arXiv:2208.01626*, 2022. 3

[14] Jonathan Ho, William Chan, Chitwan Saharia, Jay Whang, Ruiqi Gao, Alexey Gritsenko, Diederik P Kingma, Ben Poole, Mohammad Norouzi, David J Fleet, et al. Imagen video: High definition video generation with diffusion models. *arXiv preprint arXiv:2210.02303*, 2022. 2, 3, 4, 5, 7, 8

[15] Jonathan Ho, Ajay Jain, and Pieter Abbeel. Denoising diffusion probabilistic models. *NeurIPS*, 33:6840–6851, 2020. 3, 4

[16] Jonathan Ho, Chitwan Saharia, William Chan, David J Fleet, Mohammad Norouzi, and Tim Salimans. Cascaded diffusion models for high fidelity image generation. *JMLR*, 23:47–1, 2022. 3

[17] Jonathan Ho, Tim Salimans, Alexey Gritsenko, William Chan, Mohammad Norouzi, and David J Fleet. Video diffusion models. *arXiv preprint arXiv:2204.03458*, 2022. 2, 3, 4, 5, 6, 7

[18] Wenyi Hong, Ming Ding, Wendi Zheng, Xinghan Liu, and Jie Tang. Cogvideo: Large-scale pretraining for text-to-video generation via transformers. *arXiv preprint arXiv:2205.15868*, 2022. 3, 4, 7

[19] Tobias Höppe, Arash Mehrjou, Stefan Bauer, Didrik Nielsen, and Andrea Dittadi. Diffusion models for video prediction and infilling. *arXiv preprint arXiv:2206.07696*, 2022. 3

[20] Emmanuel Kahembwe and Subramanian Ramamoorthy. Lower dimensional kernels for video discriminators. *Neural Networks*, 2020. 7

[21] Tero Karras, Miika Aittala, Timo Aila, and Samuli Laine. Elucidating the design space of diffusion-based generative models. *arXiv preprint arXiv:2206.00364*, 2022. 3, 4

[22] Levon Khachatryan, Andranik Movsisyan, Vahram Tadevosyan, Roberto Henschel, Zhangyang Wang, Shant Navasardyan, and Humphrey Shi. Text2video-zero: Text-to-image diffusion models are zero-shot video generators. *arXiv preprint arXiv:2303.13439*, 2023. 3

[23] Nupur Kumari, Bingliang Zhang, Richard Zhang, Eli Shechtman, and Jun-Yan Zhu. Multi-concept customization of text-to-image diffusion. *arXiv preprint arXiv:2212.04488*, 2022. 3

[24] Tuomas Kynkäänniemi, Tero Karras, Miika Aittala, Timo Aila, and Jaakko Lehtinen. The role of imagenet classes in fréchet inception distance. In *ICLR*, 2023. 7

[25] Guillaume Le Moing, Jean Ponce, and Cordelia Schmid. Ccvs: Context-aware controllable video synthesis. *NeurIPS*, 2021. 3, 7

[26] Luping Liu, Yi Ren, Zhijie Lin, and Zhou Zhao. Pseudo numerical methods for diffusion models on manifolds. *arXiv preprint arXiv:2202.09778*, 2022. 4

[27] Cheng Lu, Yuhao Zhou, Fan Bao, Jianfei Chen, Chongxuan Li, and Jun Zhu. Dpm-solver++: Fast solver for guided sampling of diffusion probabilistic models. *arXiv preprint arXiv:2211.01095*, 2022. 4

[28] Zhengxiong Luo, Dayou Chen, Yingya Zhang, Yan Huang, Liang Wang, Yujun Shen, Deli Zhao, Jingren Zhou, and Tieniu Tan. Videofusion: Decomposed diffusion models for high-quality video generation. In *CVPR*, 2023. 3

[29] Yue Ma, Yingqing He, Xiaodong Cun, Xintao Wang, Ying Shan, Xiu Li, and Qifeng Chen. Follow your pose: Pose-guided text-to-video generation using pose-free videos. *arXiv preprint arXiv:2304.01186*, 2023. 3

[30] Chenlin Meng, Yutong He, Yang Song, Jiaming Song, Jiajun Wu, Jun-Yan Zhu, and Stefano Ermon. SDEdit: Guided image synthesis and editing with stochastic differential equations. In *ICLR*, 2022. 1, 3

[31] Eyal Molad, Eliahu Horwitz, Dani Valevski, Alex Rav Acha, Yossi Matias, Yael Pritch, Yaniv Leviathan, and Yedid Hoshen.

Dreamix: Video diffusion models are general video editors. *arXiv preprint arXiv:2302.01329*, 2023. 3

[32] Alex Nichol, Prafulla Dhariwal, Aditya Ramesh, Pranav Shyam, Pamela Mishkin, Bob McGrew, Ilya Sutskever, and Mark Chen. Glide: Towards photorealistic image generation and editing with text-guided diffusion models. *arXiv preprint arXiv:2112.10741*, 2021. 3

[33] Yaniv Nikankin, Niv Haim, and Michal Irani. Sinfusion: Training diffusion models on a single image or video. *arXiv preprint arXiv:2211.11743*, 2022. 3

[34] Gaurav Parmar, Krishna Kumar Singh, Richard Zhang, Yijun Li, Jingwan Lu, and Jun-Yan Zhu. Zero-shot image-to-image translation. *arXiv preprint arXiv:2302.03027*, 2023. 3

[35] Chenyang Qi, Xiaodong Cun, Yong Zhang, Chenyang Lei, Xintao Wang, Ying Shan, and Qifeng Chen. Fatezero: Fusing attentions for zero-shot text-based video editing. *arXiv preprint arXiv:2303.09535*, 2023. 3

[36] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision. In *ICML*, 2021. 5

[37] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *JMLR*, 21(140):1–67, 2020. 5

[38] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. Hierarchical text-conditional image generation with clip latents. *arXiv preprint arXiv:2204.06125*, 2022. 1, 3

[39] MarcAurelio Ranzato, Arthur Szlam, Joan Bruna, Michael Mathieu, Ronan Collobert, and Sumit Chopra. Video (language) modeling: a baseline for generative models of natural videos. *arXiv preprint arXiv:1412.6604*, 2014. 3

[40] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *CVPR*, pages 10684–10695, 2022. 3

[41] Nataniel Ruiz, Yuanzhen Li, Varun Jampani, Yael Pritch, Michael Rubinstein, and Kfir Aberman. Dreambooth: Fine tuning text-to-image diffusion models for subject-driven generation. *arXiv preprint arXiv:2208.12242*, 2022. 3

[42] Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily Denton, Seyed Kamyar Seyed Ghasemipour, Burcu Karagol Ayan, S Sara Mahdavi, Rapha Gontijo Lopes, et al. Photorealistic text-to-image diffusion models with deep language understanding. *arXiv preprint arXiv:2205.11487*, 2022. 1, 2, 3, 5

[43] Masaki Saito, Eiichi Matsumoto, and Shunta Saito. Temporal generative adversarial nets with singular value clipping. In *ICCV*, 2017. 3, 7

[44] Masaki Saito, Shunta Saito, Masanori Koyama, and Sosuke Kobayashi. Train sparsely, generate densely: Memory-efficient unsupervised training of high-resolution temporal gan. *IJCV*, 2020. 6

[45] Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. Mostgan-v: Video generation with temporal motion styles. In *CVPR*, 2023. 3

[46] Uriel Singer, Adam Polyak, Thomas Hayes, Xi Yin, Jie An, Songyang Zhang, Qiyuan Hu, Harry Yang, Oron Ashual, Oran Gafni, et al. Make-a-video: Text-to-video generation without text-video data. *arXiv preprint arXiv:2209.14792*, 2022. 2, 3, 4, 5, 6, 7, 8

[47] Ivan Skorokhodov, Sergey Tulyakov, and Mohamed Elhoseiny. Stylegan-v: A continuous video generator with the price, image quality and perks of stylegan2. *arXiv preprint arXiv:2112.14683*, 2021. 3, 6, 7

[48] Jiaming Song, Chenlin Meng, and Stefano Ermon. Denoising diffusion implicit models. In *ICLR*, 2021. 2, 3, 4

[49] Yang Song, Jascha Sohl-Dickstein, Diederik P Kingma, Abhishek Kumar, Stefano Ermon, and Ben Poole. Score-based generative modeling through stochastic differential equations. In *ICLR*, 2021. 2

[50] Khurram Soomro, Amir Roshan Zamir, and Mubarak Shah. Ucf101: A dataset of 101 human actions classes from videos in the wild. *arXiv preprint arXiv:1212.0402*, 2012. 5

[51] Nitish Srivastava, Elman Mansimov, and Ruslan Salakhudinov. Unsupervised learning of video representations using lstms. In *ICML*, 2015. 3

[52] Yu Tian, Jian Ren, Menglei Chai, Kyle Olszewski, Xi Peng, Dimitris N. Metaxas, and Sergey Tulyakov. A good image generator is what you need for high-resolution video synthesis. In *ICLR*, 2021. 3, 6, 7

[53] Du Tran, Lubomir Bourdev, Rob Fergus, Lorenzo Torresani, and Manohar Paluri. Learning spatiotemporal features with 3d convolutional networks. In *ICCV*, 2015. 6

[54] Sergey Tulyakov, Ming-Yu Liu, Xiaodong Yang, and Jan Kautz. Mocogan: Decomposing motion and content for video generation. In *CVPR*, June 2018. 3

[55] Thomas Unterthiner, Sjoerd van Steenkiste, Karol Kurach, Raphael Marinier, Marcin Michalski, and Sylvain Gelly. Towards accurate generative models of video: A new metric & challenges. *ICLR*, 2019. 6

[56] Ruben Villegas, Mohammad Babaeizadeh, Pieter-Jan Kindermans, Hernan Moraldo, Han Zhang, Mohammad Taghi Saffar, Santiago Castro, Julius Kunze, and Dumitru Erhan. Phenaki: Variable length video generation from open domain textual description. *arXiv preprint arXiv:2210.02399*, 2022. 3

[57] Vikram Voleti, Alexia Jolicoeur-Martineau, and Christopher Pal. Masked conditional video diffusion for prediction, generation, and interpolation. *arXiv preprint arXiv:2205.09853*, 2022. 3

[58] Carl Vondrick, Hamed Pirsiavash, and Antonio Torralba. Generating videos with scene dynamics. *NIPS*, 2016. 3

[59] Wenjing Wang, Huan Yang, Zixi Tuo, Huiguo He, Junchen Zhu, Jianlong Fu, and Jiaying Liu. Videofactory: Swap attention in spatiotemporal diffusions for text-to-video generation. *arXiv preprint arXiv:2305.10874*, 2023. 3, 7

[60] Chenfei Wu, Jian Liang, Lei Ji, Fan Yang, Yuejian Fang, Daxin Jiang, and Nan Duan. Nüwa: Visual synthesis pre-training for neural visual world creation. In *ECCV*, pages 720–736. Springer, 2022. 3, 4, 7

[61] Jay Zhangjie Wu, Yixiao Ge, Xintao Wang, Weixian Lei, Yuchao Gu, Wynne Hsu, Ying Shan, Xiaohu Qie, and Mike Zheng Shou. Tune-a-video: One-shot tuning of image diffusion models for text-to-video generation. *arXiv preprint arXiv:2212.11565*, 2022. 3

[62] Jun Xu, Tao Mei, Ting Yao, and Yong Rui. Msr-vtt: A large video description dataset for bridging video and language. In *CVPR*, 2016. 7

[63] Wilson Yan, Yunzhi Zhang, Pieter Abbeel, and Aravind Srinivas. Videogpt: Video generation using vq-vae and transformers. *arXiv preprint arXiv:2104.10157*, 2021. 3, 7

[64] Ruihan Yang, Prakhar Srivastava, and Stephan Mandt. Diffusion probabilistic modeling for video generation. *arXiv preprint arXiv:2203.09481*, 2022. 3

[65] Lijun Yu, Yong Cheng, Kihyuk Sohn, José Lezama, Han Zhang, Huiwen Chang, Alexander G Hauptmann, Ming-Hsuan Yang, Yuan Hao, Irfan Essa, et al. Magvit: Masked generative video transformer. *arXiv preprint arXiv:2212.05199*, 2022. 3

[66] Sihyun Yu, Jihoon Tack, Sangwoo Mo, Hyunsu Kim, Junho Kim, Jung-Woo Ha, and Jinwoo Shin. Generating videos with dynamics-aware implicit generative adversarial networks. In *ICLR*, 2021. 3, 7

[67] Lvmin Zhang and Maneesh Agrawala. Adding conditional control to text-to-image diffusion models. *arXiv preprint arXiv:2302.05543*, 2023. 1, 3

[68] Qinsheng Zhang and Yongxin Chen. Fast sampling of diffusion models with exponential integrator. In *ICLR*, 2023. 4

[69] Daquan Zhou, Weimin Wang, Hanshu Yan, Weiwei Lv, Yizhe Zhu, and Jiashi Feng. Magicvideo: Efficient video generation with latent diffusion models. *arXiv preprint arXiv:2211.11018*, 2022. 2, 3, 7