FitVid: Overfitting in Pixel-Level Video Prediction

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Abstract

An agent that is capable of predicting what happens next can perform a variety of tasks through planning with no additional training. Furthermore, such an agent can internally represent the complex dynamics of the real-world and therefore can acquire a representation useful for a variety of visual perception tasks. This makes predicting the future frames of a video, conditioned on the observed past and potentially future actions, an interesting task which remains exceptionally challenging despite many recent advances. Existing video prediction models have shown promising results on simple narrow benchmarks but they generate low quality predictions on real-life datasets with more complicated dynamics or broader domain. There is a growing body of evidence that underfitting on the training data is one of the primary causes for the low quality predictions. In this paper, we argue that the inefficient use of parameters in the current video models is the main reason for underfitting. Therefore, we introduce a new architecture, named FitVid, which is capable of severe overfitting on the common benchmarks while having similar parameter count as the current state-of-the-art models. We analyze the consequences of overfitting, illustrating how it can produce unexpected outcomes such as generating high quality output by repeating the training data, and how it can be mitigated using existing image augmentation techniques. As a result, FitVid outperforms the current state-of-the-art models across four different video prediction benchmarks on four different metrics.

1 Introduction

Predicting what happens next is a cornerstone of intelligence and one of the key capabilities of humans, which we heavily rely on to make decisions in everyday life [7]. This capability enables us to anticipate future events and plan ahead to perform temporally extended tasks. While the machine learning literature has studied a wide range of prediction problems, one of the most direct challenges is to predict raw sensory inputs. In particular, prediction of future visual inputs conditioned on a context of past observations – i.e., pixel-level video prediction – encapsulates the challenges of visual perception, modeling of physical events, and reasoning about uncertain behaviors. Video prediction can be formulated as a self-supervised problem, enabling us to use a substantial amount of unla- beled data to provide autonomous systems with powerful predictive capabilities as well as learning rich representations for downstream tasks. Already, video models have

Figure 1: FitVid is capable of predicting high quality images of the future given the first few frames. Note the accurately predicted movement of the pushed object with preserved visual details as well as the lack of movement from the stationary object. Also, note the detailed shadows of the robotic arm that are correctly predicted.
Recently, it has been demonstrated that underfitting on video prediction is still considered to be extremely challenging. The current state-of-the-art methods are limited to low-resolution videos (typically 64×64 [95] and a maximum of 256×256 [59]) usually in a narrow domain such as a single human walking, or a robotic arm pushing objects in a stationary setting. Even in such limited domains, the quality of predicted frames tend to drop substantially after less than 10 seconds into the future [87]. A growing body of evidence suggests that underfitting is one of the primary reasons for low quality predictions. For example, Villegas et al. [95] demonstrate how scaling the model, by simply adding more parameters, can substantially improve the prediction quality. Similarly, Castrejon et al. [9] argue that blurry prediction of variational methods in video prediction is a sign of underfitting, exhibiting an improved test and train evidence lower bound as the network capacity increases. Wu et al. [108] also observed monotonic improvement as the number of modules in a hierarchical architecture increases. While scaling up models is a common trend in deep learning research to address underfitting, it comes at the cost of more computation, memory, and integration risks [107] as well as more complicated training regimes [108].

In this paper we take a step back and address underfitting by instead finding an architecture which uses its parameters more efficiently. More precisely, we propose FitVid, a model that – with the same parameter count as current state-of-the-art models – can significantly overfit to the video prediction datasets, including benchmarks that prior works have not been able to overfit to. To the best of our knowledge, this is the first time a video model reports substantial overfitting on theses benchmarks. Importantly, we also find that simple image augmentation techniques can mitigate this overfitting, leading to models that can both fit the training set and generalize well to held-out videos. As a result, FitVid achieves state-of-the-art on four challenging video datasets across a wide range of metrics. Furthermore, we find that with FitVid we can utilize a significantly simpler training recipe. Prior works on video prediction, particularly those that make use of variational methods to provide for stochasticity, typically require a number of delicate design decisions to train successfully: curriculum training [76, 30, 64, 10], a learned prior [17, 95, 9] and annealing of the weight on the VAE KL-divergence penalty [1]. In contrast to these approaches, we show that our method actually fits the training set well without any such components, training directly via optimizing the evidence lower bound with minimal hyperparameters. Videos generated by FitVid can be found in https://sites.google.com/view/fitvidpaper.

2 Related Work

Video prediction [82, 89] has been formulated in different ways such as generating videos from a single image [28, 75, 21, 114, 48] or no image [97, 86, 14], text to video generation [109], video-to-video translation [102, 101] and data-driven simulation [54, 59, 58]. In this paper, our focus is on conditional video prediction, which is to predict the future frames of a video conditioned on a few initial context frames and possibly the future actions of the agents [30, 1]. Conditional video prediction has a number of applications, including model-based reinforcement learning from pixels [39, 40, 54, 79] and robotics [4, 29, 55, 24, 25, 26, 111, 78, 73, 74].

Initially, video prediction was tackled using deterministic models [98, 30, 52, 112, 99, 66, 8, 96, 93, 68, 11, 69]. Later on, given the common randomness and partial observability in the real-life situations, various stochastic models were proposed to capture the stochasticity of the future. Generative adversarial networks (GANs) [37] are demonstrated to generate sharp predictions [71, 64, 14, 70, 46]; however, they tend to suffer from mode-collapse [35], particularly in conditional generation settings [117]. Autoregressive video prediction models [56, 83, 105] can predict sharp but noisy videos while suffering from high training and inference time, particularly for longer videos. Flow based generative models [19, 20] are also adopted for video prediction [63] which can generate high quality videos but their high dimensional latent space makes them hard to implement and train.

Variational auto-encoders (VAEs) [61] are widely used for conditional video prediction as well [88, 1, 17, 106, 95, 32, 9, 113, 80, 65, 108, 100]. Recently, it has been demonstrated that underfitting on training data plays a major role in low quality blurry predictions in VAE based models. Villegas et al. [95], Castrejon et al. [9] and Wu et al. [108] all reported improved prediction quality as the network capacity increases. However, larger networks require more computation and memory. In this paper, we are interested in addressing underfitting without increasing the capacity of the current models, and instead, find a more expressive architecture which uses its capacity more efficiently.
3 Background

Following prior work [30, 1, 17, 85, 77, 108], we define the problem of pixel-level video prediction as follows: given the first $c$ frame of a video $x_{<c} = x_0, x_1, \ldots, x_{c-1}$, our goal is to predict the future frames by sampling from $p(x_{c:T} | x_{<c})$. Optionally, the predictive model can be conditioned on additional given information $a_t$, such as the actions that the agents in the video are planning to take. This is typically called action-conditioned video prediction.

Variational video prediction follows the variational auto-encoder [61] formalism by introducing a set of latent variables $z$ to capture the inherent stochasticity of the problem. The latent variables can be fixed for the entire video [1] or vary over time [17]. In both cases, we can factorize the likelihood model to $\prod_{t=c}^{T} p_{\theta}(x_t | x_{<t}, z_{\leq t})$ which is parametrized in an autoregressive manner over time; i.e. at each timestep $t$ the video frame $x_t$ and the latent variables $z_t$ are conditioned on the past latent samples and frames. By multiplying the prior we can factorize the predictive model as

$$p(x_{c:T} | x_{<c}) = \prod_{t=c}^{T} p_{\theta}(x_t | x_{<t}, z_{t}) p(z_t | x_{<t}, z_{<t})$$

where the prior $p(z) = p(z_t | x_{<t}, z_{<t})$ can be either fixed [61, 1] or learned [13, 17, 9]. For inference, we need to compute a marginalized distribution over the latent variables $z$, which is intractable. To overcome this problem, we use variation inference [53] by defining an amortized approximate posterior $q(z | x) = \prod_{t} q(z_t | z_{<t}, x_{<t})$ that approximates the posterior distribution $p(z | x)$. The approximated posterior is commonly modeled with an inference network $q_\phi(z | x)$ that outputs the parameters of a conditionally Gaussian distribution $\mathcal{N}(\mu_\phi(x), \sigma_\phi(x))$. This network can be trained using the reparameterization trick [61], according to:

$$z = \mu_\phi(x) + \sigma_\phi(x) \times \epsilon, \quad \epsilon \sim \mathcal{N}(0, I)$$

Here, $\theta$ and $\phi$ are the parameters of the generative model and inference network, respectively. To learn these parameters, we can optimize the variational lower bound [61, 84]:

$$\mathcal{L}(x) = -E_{q_\phi(z | x)} \left[ \log p_{\theta}(x_{c:T} | x_{<t}, z) \right] + \beta D_{KL}(q_\phi(z | x) || p(z))$$

(1)

where $D_{KL}$ is the Kullback-Leibler divergence between the approximated posterior and the prior $p(z)$ which is fixed to $p(z) = \mathcal{N}(0, I)$. The hyper-parameter $\beta$ represents the trade-off between minimizing frame prediction error and fitting the prior [44, 43, 17].

4 The FitVid Architecture

Striving for simplicity, we propose the FitVid model for stochastic video prediction, a convolutional non-hierarchical variational model with a fixed prior of $\mathcal{N}(0, I)$. The architecture of FitVid is visualized in Figure 2.
Encoder and decoder. Following the recent advances in image generation, we use similar residual encoding and decoding cells as NVAE [92]. Each cell includes convolutional layers with batch-normalization [50] and swish [81, 27, 42] as the activation function, followed by Squeeze and Excite [47]. The encoder is made of four encoding blocks with two cells in each block. There is down-sampling after each encoder block using a strided convolution of size three in the spatial dimensions. The decoder also consists of four decoding blocks with two cells in each block, and a nearest neighbour up-sampling after each block. The number of filters in each encoding block is doubled while the number of filters in each decoding block is halved from the previous one. There is a residual skip connection between the encoder and the decoder after each cell which are fixed to the output from the last context frame. The statistics for batch-normalization is averaged across time.

Dynamics model. Similar to Denton and Fergus [17], the encoded frame $h_t$ is used to predict $h_{t+1}$ using two layers of LSTMs [45]. Likewise, $q(z_t|x_{<t})$ is also modeled using a single layer of LSTMs with $h_{t+1}$ as the input that outputs the parameters of a conditionally Gaussian distribution $\mathcal{N}(\mu_\phi(x_t), \sigma_\phi(x_t))$. During the training, $z$ is sampled from $q(z_t|x_{<t})$ while at the inference time $z$ is sampled from the fixed prior $\mathcal{N}(0, I)$. The input to the model is always the ground-truth image (which is usually referred to as teacher-forcing [36, 10]). At inference time, the predicted image in the previous time-step is used as input to predict the next frame.

Data augmentation. We find that FitVid can substantially overfit on some of the video prediction datasets (read Section 5 and 6). To prevent the model from overfitting we use augmentation. To the best of our knowledge, this is the first use of augmentation in video prediction, perhaps because prior state-of-the-art models tend to underfit already and therefore would not benefit from it. Given the rich literature in image augmentation, we augment the videos using RandAugment [15]. We randomize the augmentation per video but keep the randomization constant for frames of a single video. RandAugment substantially improves the overfitting, however not entirely, as it can be seen in Figure 3. We improve the augmentation by selecting a random crop of the video before resizing it to the desired resolution at the training time, called RandCrop. The combination of RandCrop and RandAugment successfully prevents the overfitting, leading to models that both fit the training set and generalize well to held-out videos.

What FitVid does not need. Prior works on variational video prediction [31, 1, 64, 95, 108], generally require a range of additional design decisions for effective training. Common design parameters include using curriculum training, commonly by scheduled sampling [3], to mitigate distributional shift between training and generation time [76, 30, 64, 10]; heuristically tuning $\beta$ in Eqn 1 to balance the prediction vs fitting the prior [17] by annealing it over the course of training [1, 64] or learned priors [17, 95, 9, 108]. Each of these design choices introduces hyperparameters, tuning burden, and additional work when applying a model to a new task. FitVid does not require any of these details: we simply train optimizing $\mathcal{L}(x)$ from Eqn 1 using Adam [60].

Check the appendix for more architecture details. The source code is available at https://github.com/google-research/fitvid.

5 Experiments

To evaluate FitVid, we test it on four different real-world datasets and compare its performance with prior state-of-the-art methods, with comparable parameter count, using four different metrics. Our main goal is to demonstrate that FitVid can in fact overfit on these datasets and illustrate how augmentation can prevent FitVid from overfitting, resulting in state-of-the-art prediction performance. Please visit https://sites.google.com/view/fitvidpaper to see samples of videos.

5.1 Experimentation Setup

Datasets: To test FitVid, we use four datasets that cover a variety of real-life scenarios. We use the Human3.6M dataset [51], which consists of actors performing various actions in a room to study the structured motion prediction. We also use the KITTI dataset [34] to evaluate FitVid’s ability to handle partial observability and dynamic backgrounds. For both datasets, we followed the pre-processing and testing format proposed by Wu et al. [108] and Villegas et al. [95], which is to predict 25-frames conditioned the previous five in a 64×64 resolution.
Table 1: The empirical comparison between FitVid (with 302M parameters), GHV AE [108] (with 599M parameters) and SVG [95] (with 298M parameters). To prevent FitVid from overfitting, we use augmentation for Human3.6M and KITTI. The green color highlights where FitVid achieved state-of-the-art result while the red color highlights otherwise.

| Dataset     | FVD↓ | PSNR↑ | SSIM↑ | LPIPS↓ |
|-------------|------|-------|-------|--------|
| RoboNet [16] |      |       |       |        |
| GHV AE [108] | 95.2 | 24.7  | 89.1  | 0.036  |
| SVG [95]     | 123.2| 23.9  | 87.8  | 0.060  |
| FitVid (ours)| 62.5 | 28.2  | 89.3  | 0.024  |

| Dataset     | FVD↓ | PSNR↑ | SSIM↑ | LPIPS↓ |
|-------------|------|-------|-------|--------|
| KITTI [34]  |      |       |       |        |
| GHV AE [108] | 552.9| 15.8  | 51.2  | 0.286  |
| SVG [95]     | 1217.3| 15.0  | 41.9  | 0.327  |
| FitVid (ours)| 884.5| 17.1  | 49.1  | 0.217  |

To evaluate FitVid in an action-conditioned setting, we use RoboNet dataset [16]. This large dataset includes more than 15 million video frames from 7 different robotic arms pushing objects in different bins. It contains a wide range of conditions, including different viewpoints, objects, tables, and lighting. Prior video prediction methods have a tendency to badly underfit on this dataset [16]. Unfortunately, RoboNet does not provide a standard train/test partition. Hence, we follow the same setup as Wu et al. [108] and randomly select 256 videos for testing. Similar to Wu et al. [108], we train FitVid to predict next ten frames given two context frames as well as the ten future actions.

Finally, to compare FitVid to a wider range of prior work, we use the BAIR robot pushing dataset [23], which is a widely-used benchmark in the video prediction literature. We follow the evaluation protocol of Rakhimov et al. [80], which predicts the next 16 frames given only one context frame and no actions. Given the high stochasticity of robotic arm movement in BAIR, particularly in the action-free setting, it is a great benchmark for evaluating the model’s ability to generate diverse outputs.

**Metrics:** We evaluate our method and prior models across four different metrics: Structural Similarity Index Measure (SSIM) [104], Peak Signal-to-noise Ratio (PSNR) [49], Learned Perceptual Image Patch Similarity (LPIPS) [116] and Fréchet Video Distance (FVD) [91]. FVD measures the overall visual quality and temporal coherence without reference to the ground truth video. PSNR, SSIM, and LPIPS measure pixel-wise similarity to the ground-truth with LPIPS most accurately representing human perceptual similarity. Given the stochastic nature of video prediction benchmarks, we follow the standard stochastic video prediction evaluation protocol [1, 95, 108]: we sample 100 future trajectories per video and pick the best one as the final score for PSNR, SSIM and LPIPS. For FVD, we use all 100 with a batch size of 256.

### 5.2 Results

**Comparisons:** First, we compare FitVid to GHV AE [108] and SVG [95]. We chose these two baseline because they both investigated overfitting by scaling the model, and achieve state-of-the-art results. However, SVG reported no overfitting even for their biggest model with 298M parameters [95] while GHV AE (with 599M parameters) reported "some overfitting" on smaller datasets [108]. At the same time, both of these models share a similar architecture to FitVid. GHV AE is a hierarchical variational video prediction model trained in a greedy manner. SVG is a large-scale variational video prediction model with learned prior and minimal inductive bias. As mentioned before, we compare against the largest version of SVG (M = 3, K = 5) which has 298 million parameters that is in the same ballpark as FitVid with 302 million parameters.

Table 1 contains the results of these experiments. As it can be seen in this table, FitVid outperforms both SVG and GHV AE across all metrics in Robobnet and Human3.6M. In KITTI, FitVid also consistently outperforms SVG while either improves or closely matches the performance of GHV AE which has more than twice as parameters. For qualitative results, see Figures 4, 5 and 6.

**Comparison to non-variational methods:** To compare the performance of FitVid with more prior methods, including non-variational models, we test it on BAIR robot pushing dataset [23]. As can be seen in Table 2, FitVid outperforms most of the previous models in this setting while performing comparably to Video Transformer [105] which contains 373M parameters.
6 Analysis

In this section, we take a closer look at the results from Section 5, to analyse the consequences of overfitting and the effect of regularization on the current benchmarks.

**On Human3.6M as a video prediction benchmark:** Human3.6M [51] is a common benchmark in video prediction literature [30, 1, 94, 103, 95, 67, 32, 38, 108, 110] which we also use to evaluate FitVid (Figure 6). At the first glance, it seems that the model is generating extremely detailed and human-like motions conditioned on the given context pose. However, on closer inspection, we observe that the human subject in the predicted video is changing. In fact, FitVid replaces the unseen human subject into a training subject which is particularly evident from the clothing. Actually, we can find similar video clips from the training data for each one of the predicted videos (see Figure 6). These frames are not exactly the same, but they look notably similar. This observation indicates that:

1. The model can **generalize** to unseen frames and subjects since the test context frames are new and unseen. FitVid detects the human and continues the video from there.
2. The model **memorized** the motion and the appearance of the training subjects. The model **morphs** the test human subject into a training one, and then **plays** a relevant video from the memory.

This means that FitVid fails to generalize to a new subject, while still generalizing to unseen frames. Given that the Human3.6M has five training and two test subjects [30, 94] this may not be surprising.

Nevertheless, this observation shows how the current low-resolution setup for Human3.6M is not suitable for large-scale video prediction. In fact, after this observation, we traced the same behaviour in other video prediction literature and, unfortunately, it seems this is a common and overlooked issue. For example, the same phenomena can be seen in Figure 6 from Franceschi et al. [32] that shows changing the test to a training subject by Struct-VRNN [72] and the proposed method by Franceschi et al. [32] (note the changed shirt). For others examples, see Figure 7 of Villegas et al. [95] and Figure 5 of Villegas et al. [94]. A copy of these figures can be seen in Figure 15 in the appendix.

**Overfitting and regularization:** As mentioned in Section 1, there is considerable evidence that current video prediction models tend to underfit when trained on large datasets [95, 9, 108]. Wu et al. [108], which is the current state-of-the-art model with 599 million parameters, reported "some overfitting" on smaller datasets such as Human3.6M and KITTI. However, we observe severe and clear overfitting with FitVid, despite having only 302 million parameters. Figure 7 visualizes the training and evaluation LPIPS metric while training FitVid on Human3.6M, without augmentation. This graph demonstrates that the training keeps getting better while the test quality starts to get worse after $\sim$15K iterations. We also observed similar behaviour on KITTI, as can be seen in Figure 7b. These results clearly shows that FitVid is overfitting on Human3.6M and KITTI, indicating that FitVid is using its parameters more efficiently. As mentioned in Section 4, to address overfitting, we use augmentation. As a result FitVid achieves state-of-the-art results as reported in Table 1.
Figure 4: FitVid on action-conditioned RoBoNet [16]. The model is conditioned on the first two frames and is predicting the next ten frames given the future actions of the robotic arm. These figures demonstrate how the predicted movements of the arm closely follows the ground truth given that the future actions is known. The model also predicts detailed movements of the pushed objects (visible in the left example) as well as filling in the previously unseen background with some random objects (look at the object that appear behind the robotic arm in the right). Also notice the wrong predictions of robot’s fingers in the right example. See Figure 11 for more frames from these video samples.

Figure 5: FitVid on KITTI dataset [34]. As it can be seen in this figure, the model generates high quality prediction of the future in a dynamic scene. Note how in the top example FitVid keeps predicting the movement of the shadow on the ground till it gets out of the frame. After that, the model still brings the background closer in each frame, implying driving forward. We noticed that the quality of predictions drop substantially faster when there are more objects in the scene e.g. the driving scenes inside a city as can be seen in the right example. This indicates the model still fails to generalize to more complex scenes with more moving subjects. See Figure 12 for more frames.

Figure 6: FitVid on Human3.6M [51]. This figures demonstrates extremely detailed and human-like motions predicted by FitVid, conditioned on the given context frames. However, on closer inspection, it can be seen that the human subject in the video is changing, from the test subject to a training subject. This is particularly evident from the cloths. This phenomena indicates that, although FitVid is capable of generalizing to the frames out of training distribution, however, it morphs the human subject into a familiar one from the training set and then plays the video from the memory. In fact, we can find similar videos in the training set as visualized in the last row. The highlighted frame is the one used for finding the closest training video. Check Figure 13 for more predicted frames.

More videos can be found at https://sites.google.com/view/fitvidpaper.
Overfitting on Robonet: We did not observe any overfitting on Robonet, which is expected given the fact that Robonet is much larger compared to the other benchmarks. Trying to find a model that can overfit on Robonet, we test a scaled version of FitVid with 500M parameters — which is still smaller compared to GHV-AE with 599M parameters and reported no overfitting on this dataset. This scaled version of FitVid overfits on Robonet, as demonstrated in Figure 7d. Note that we did not use this scaled version in the reported numbers of Table 1, which is generated using the 302M version. Our goal here was to demonstrate that a scaled version of FitVid can also use its parameters more efficiently, compared to prior models, leading to overfitting even on bigger datasets such as Robonet.

Effect of Augmentation on SVG There is a discrepancy between the input data for training the models in Section 5. FitVid is trained with augmentation while the baselines are trained without any augmentation which raises a question: can the better performance of FitVid be explained only by the augmentation? In other words, do the previous methods benefit from augmentation too? To answer this question, we retrain SVG with and without augmentation. As demonstrated in Table 3, SVG performs worse if trained with augmented data, supporting the claim that it is underfitting to the raw data. As a result, this experiment provides more support for FitVid truly overfitting on these datasets and therefore benefiting from augmentation. Please note that we included our SVG results without augmentation too, as we could not perfectly reproduce the numbers reported by Villegas et al. [95] used in Table 1.

Zero-shot Real Robot Performance Prior work indicate that improved video prediction translates to better performance in the downstream tasks [108, 2]. However, in these works, the training and test distribution are the same and there is almost no domain shift from training to testing. In this section, we are interested in investigating whether FitVid is capable of generalizing to a similar but visually different task with no training data for this new domain. Therefore, we setup a real-robot experiment, with a Franka Emika Panda robot arm, in which the goal is to push a specific object to a predetermined goal position. We train FitVid on Robonet and use cross-entropy method (CEM) [85, 12] for planning (please see Appendix for details). As can

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Table 3: SVG [95] with and without augmentation. This table shows that SVG does not benefit from augmentation as it is underfitting to the original data, as argued by Villegas et al. [94].

| Human3.6M [51] | FVD↓ | PSNR↑ | SSIM↑ | LPIPS↓ |
|----------------|------|-------|-------|--------|
| Without        | 389.55 | 27.4 | 93.7 | 0.041 |
| With           | 429.25 | 23.0 | 87.1 | 0.094 |

| KITTI [34] | FVD↓ | PSNR↑ | SSIM↑ | LPIPS↓ |
|------------|------|-------|-------|--------|
| Without    | 1612.62 | 14.8 | 38.7 | 0.330 |
| With       | 2051.67 | 14.4 | 36.0 | 0.333 |

Table 4: Zero-shot real robot performance. We use FitVid for planning future actions of a real robot pushing an object to a goal location with no training data from our setup. We train the model on visually different data (RoboNet) and the data from a closer domain (from Wu et al. [108]) with and without augmentation. While unable to directly adapt from RoboNet to the new domain, the results illustrate that fine-tuning on similar data and augmentation improve FitVid’s performance.

| Training Data | Success Rate |
|---------------|--------------|
| Baseline (random actions) | 28% |
| Robonet        | 17%          |
| Robonet + Wu et al. [108] | 56% |
| Robonet + Augmented Wu et al. [108] | 78% |
be seen in Table 4, this agent is unable to generalize to the new domain, achieving worse performance than a random agent. This may not be surprising given the fact that the videos in RoboNet have entirely different robots and visuals, although the robots are performing the same task (i.e. pushing objects in a bin using a robotic arm). We then try to bring the training and test domain closer to each other by fine-tuning FitVid on the data from Wu et al. [108]. This data contains 5000 autonomously collected videos of a Franka Emika Panda robot arm pushing objects around which look more similar to our setup compared to RoboNet, but still contain different lighting, camera angle, and target objects. This time, we observe that FitVid is relatively successful at generalizing to the new domain, succeeding in 56% of the trials. Finally, we find that adding data augmentation to the fine-tuning improves the generalization ability of the model, achieving 78% success rate. These results illustrate that while large distribution shift adaptation (RoboNet) remains difficult, by using data augmentation FitVid is capable of adapting to a relatively new domain (from Wu et al. [108] data).

7 Conclusion

We propose FitVid, a simple and scalable variational video prediction model that can attain a significantly better fit to current video prediction datasets even with a similar parameter count as prior models. In fact, while prior methods generally suffer from underfitting on these datasets, naïvely applying FitVid actually results in overfitting. We therefore propose a set of data augmentation techniques for video prediction that prevent overfitting, leading to state-of-the-art results across a range of prediction benchmarks.

To the best of our knowledge, this is the first time a model reports substantial overfitting on these benchmarks. This is particularly important because underfitting is usually cited as one the main reasons for low quality predictions of the future frames. We demonstrate how image augmentation techniques can prevent the model from overfitting, resulting in high quality images. As a result, FitVid outperformed the current state-of-the-art models across four different video prediction benchmarks on four different metrics. We also illustrate how a model that can properly fit the training data, can fool the current benchmarks and metrics resulting in undesired outcomes, which are often overlooked in the video prediction literature.

There are many ways that FitVid can be expanded. As mentioned in the text, one of the interesting features of our proposed method is that it is simple. It is non-hierarchical, convolutional, with no attention mechanism, no curriculum learning, and no training scheduling. Any of these features can potentially improve the results of FitVid in order to generate even higher quality images. Given the simplicity of FitVid, it can be easily built upon. Another interesting direction would be to introduce new training-aware metrics for video prediction and generation to signal when a model is generating high quality videos by repeating the training data.

Broader Impact

Videos are an abundant source of visual information about our physical world. They contain information about objects, humans and how they interact with each other. The goal of video prediction is to foremost learn a representation of the world, usable for downstream tasks by an agent. Second, is to predict what happens next, conditioned on the past and the future intents, which can be used for planning. Despite many recent advances in this field, the present day models are still relatively low-quality and limited to narrow domains which makes their applications limited. However, if improved, video prediction or representations learned by video prediction, can be a major step forward toward fully autonomous self-learning agents. This paper, we believe, takes an important step towards this goal by pushing state-of-the-art forward and simplifying it in a meaningful way. However, our model is vulnerable to the bias in the training data and if adopted widely, this can skew research in certain directions. For example, our results may lead to higher quality models which can be scaled to generate even higher quality results. These models will be harder to design and train and require more computational power, and potentially can be biased. Finally, the underlying techniques for video prediction can be misused for generating high-quality videos that are misleading, depicting deliberately false situations or persons, similar to the phenomenon of deepfakes [62]. However, we believe that our experiments are conducted in relatively specific narrow settings and conditions which will likely not generalize broadly. Specifically, it is especially challenging to generate high-quality realistic-looking videos even with such state of the art methods.
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A Appendix

A.1 Implementation Details

In this section we describe the details of FitVid’s architecture as well as training. Algorithm 1 and Algorithm 2 describe the high-level training and prediction process respectively. Look at Table 5 for the used hyper-parameters. We used the same set of hyper-parameters across all experiments. As mentioned in Section 4, all of the hyper-parameters are fixed during the training and there is no scheduling. Table 6 and Table 8 include the detailed architecture of the encoder and the decoder. Table 7 describes the structure of dynamic and posterior networks. Finally, Table 9 describes the augmentations details.

A.1.1 Computation Resources

We implement FitVid using Flax [41] library for JAX [5]. We train FitVid on $4 \times 4$ TPUs (32 co-processors). Each training step (with global batch size of 128 or local batch size of 4) takes $\sim 1020$ milliseconds (i.e. 0.98 step per second). In parallel, we evaluate the model every 1000 training steps on a single V100 GPU which takes about $\sim 850$ milliseconds for a batch size of 128. The models are trained for one million training iterations which takes $\sim 12$ days to complete.

Algorithm 1: FitVid training.

Input: Number of context frames $c$
Data: Training frames $x_{0:T}$ and actions $a_{0:T}$

// Encode all frames
1 for $t \leftarrow 0$ to $T$
2 \quad $h_t, C_t \leftarrow \text{Encoder}(x_t)$
3 end

// Prediction
4 $s_{0}, s_d \leftarrow 0, 0$ // Initialize states
5 for $t \leftarrow 0$ to $T$
6 \quad \{ $\mu_t, \sigma_t$ \}, $s_p \leftarrow \text{Posterior}(h_{t+1}, s_p)$
7 \quad $z_t \sim \mathcal{N}(\mu_t, \sigma_t)$ // Approximate posterior
8 \quad $\hat{h}_t, s_d \leftarrow \text{Dynamic}(\{ h_t, a_t, z_t \}, s_d)$ // Predict future state
9 end

// Decode all frames
10 for $t \leftarrow 0$ to $T$
11 \quad $\hat{x}_t \leftarrow \text{Decoder}(\hat{h}_t, C_c)$ // Use last available skip connection
12 end

// Optimize ELBO
13 $L \leftarrow ||x - \hat{x}||_2^2 + D_{KL}(\mathcal{N}(\mu, \sigma), \mathcal{N}(0, I))$
14 $w \leftarrow \text{Adam}(w, L)$

Algorithm 2: FitVid prediction.

Input: Context frames $x_{0:c}$
Input: All actions $a_{0:T}$
Output: $\hat{x}$

1 $s_d \leftarrow 0$ // Initialize states
2 $C \leftarrow \text{Encoder}(x_c)$ // Get last skips.
3 for $t \leftarrow 0$ to $T$
4 \quad $h_t, C_t \leftarrow \text{Encoder}(x_t)$ // Encode frame
5 \quad $z_t \sim \mathcal{N}(\mathcal{N}(0, I))$ // Sample from prior
6 \quad $\hat{h}_t, s_d \leftarrow \text{Dynamic}(\{ h_t, a_t, z_t \}, s_d)$ // Predict future state
7 \quad $\hat{x}_t \leftarrow \text{Decoder}(h_t, C_c)$ // Decode frame
8 end

Table 5: Hyper-parameters used for training FitVid. We used the same set of hyper-parameters across all experiments. As mentioned in Section 4, all of the hyper-parameters are fixed during the training and there is no scheduling.

| Hyper-parameter | Value |
|-----------------|-------|
| Optimizer (Adam[60]) | $1e^{-3}$ |
| Learning Rate ($\alpha$) | 128 |
| Batch Size | 0.9 |
| $\beta_1$ | 0.999 |
| $\beta_2$ | $1e^{-8}$ |
| $\epsilon$ | 100.0 |
| Gradient Clipping ($l_2$) | 1 |
| Latent ($z$)-dimension | 10 |
| Encoder ($h$) dimension | 128 |
| LSTM size | 256 |
Table 6: FitVid Encoder Architecture. We are using the same encoding cells as NVAE [92]. The strides are always $1 \times 1$ except when down-sampling which has strides of $2 \times 2$. (bn) is batch-normalization [50]. (swish) is the activation [81]. (s&e) is Squeeze and Excite [47]. There is a skip connection from the beginning of each cell to the end of it. In these skip connections, the number of input filters will be matched by the output using a $1 \times 1$ convolution.

| Cell | Input Size | Pre | Kernel | Filters | Post | Down Sampling |
|------|------------|-----|--------|---------|------|--------------|
| 1-1  | $64 \times 64$ | bn + swish | $3 \times 3$ | 64 | - | - |
| 1-1  | $64 \times 64$ | bn + swish | $3 \times 3$ | 64 s&e | - | - |
| 1-2  | $64 \times 64$ | bn + swish | $3 \times 3$ | 64 | - | - |
| 1-2  | $64 \times 64$ | bn + swish | $3 \times 3$ | 64 s&e | Yes | - |
| 2-1  | $32 \times 32$ | bn + swish | $3 \times 3$ | 128 | - | - |
| 2-1  | $32 \times 32$ | bn + swish | $3 \times 3$ | 128 s&e | Yes | - |
| 2-2  | $32 \times 32$ | bn + swish | $3 \times 3$ | 128 | - | - |
| 3-1  | $16 \times 16$ | bn + swish | $3 \times 3$ | 256 | - | - |
| 3-1  | $16 \times 16$ | bn + swish | $3 \times 3$ | 256 s&e | - | - |
| 3-2  | $16 \times 16$ | bn + swish | $3 \times 3$ | 256 | - | - |
| 3-2  | $16 \times 16$ | bn + swish | $3 \times 3$ | 256 s&e | Yes | - |
| 4-1  | $8 \times 8$ | bn + swish | $3 \times 3$ | 512 | - | - |
| 4-1  | $8 \times 8$ | bn + swish | $3 \times 3$ | 512 s&e | - | - |
| 4-2  | $8 \times 8$ | bn + swish | $3 \times 3$ | 512 | - | - |
| 4-2  | $8 \times 8$ | bn + swish | $3 \times 3$ | 512 s&e | - | - |

Table 7: FitVid Dynamics Architecture. We are using a similar dynamics as Denton and Fergus [17]. The encoded output is first averaged across spatial dimension and then decoded into h-size using a fully connected layer. Then, the dynamics are modeled by two LSTM layers. Finally, the output is mapped and reshaped to an image tensor before passing to the decoder. The posterior uses the exact same architecture except that only has one LSTM layer.

| Cell | Input Size | Pre | Layer | Size | Post |
|------|------------|-----|-------|------|------|
| -    | $8 \times 8$ | spatial average + flatten | dense | 256 | append $x$ and $a$ |
| -    | $128+$      | -   | LSTM  | 256 | -    |
| -    | $256$       | -   | LSTM  | 256 | -    |
| -    | $256$       | -   | dense | $8 \times 8 \times 512$ | sigmoid + reshape |

Table 8: FitVid Encoder Architecture. We are using the same encoding and decoding cells as NVAE [92]. The strides are always $1 \times 1$. For up-sampling we use nearest neighbour. (bn) is batch-normalization [50]. (swish) is the activation [81]. (s&e) is Squeeze and Excite [47]. There is a skip connection from the beginning of each cell to the end of it. There are also skip connections from each encoder block to the corresponding decoder block (look at Figure 2). In these skip connections, the number of input filters will be matched by the output using a $1 \times 1$ convolution.

| Cell | Input Size | Pre | Kernel | Filters | Post | Up Sampling |
|------|------------|-----|--------|---------|------|-------------|
| 1-1  | $8 \times 8$ | bn | $1 \times 1$ | 2048 | - | - |
| 1-1  | $8 \times 8$ | bn + swish | $5 \times 5$ | 2048 | - | - |
| 1-1  | $8 \times 8$ | bn + swish | $1 \times 1$ | 512 | bn + s&e | - |
| 1-2  | $8 \times 8$ | bn | $1 \times 1$ | 2048 | - | - |
| 1-2  | $8 \times 8$ | bn + swish | $5 \times 5$ | 2048 | - | - |
| 1-2  | $8 \times 8$ | bn + swish | $1 \times 1$ | 512 | bn + s&e | Yes |
| 2-1  | $16 \times 16$ | bn | $1 \times 1$ | 1024 | - | - |
| 2-1  | $16 \times 16$ | bn + swish | $5 \times 5$ | 1024 | - | - |
| 2-1  | $16 \times 16$ | bn + swish | $1 \times 1$ | 256 | bn + s&e | - |
| 2-2  | $16 \times 16$ | bn | $1 \times 1$ | 1024 | - | - |
| 2-2  | $16 \times 16$ | bn + swish | $5 \times 5$ | 1024 | - | - |
| 2-2  | $16 \times 16$ | bn + swish | $1 \times 1$ | 256 | bn + s&e | Yes |
| 3-1  | $32 \times 32$ | bn | $1 \times 1$ | 512 | - | - |
| 3-1  | $32 \times 32$ | bn + swish | $5 \times 5$ | 512 | - | - |
| 3-1  | $32 \times 32$ | bn + swish | $1 \times 1$ | 128 | bn + s&e | - |
| 3-2  | $32 \times 32$ | bn | $1 \times 1$ | 512 | - | - |
| 3-2  | $32 \times 32$ | bn + swish | $5 \times 5$ | 512 | - | - |
| 3-2  | $32 \times 32$ | bn + swish | $1 \times 1$ | 128 | bn + s&e | Yes |
| 4-1  | $64 \times 64$ | bn | $1 \times 1$ | 256 | - | - |
| 4-1  | $64 \times 64$ | bn + swish | $5 \times 5$ | 256 | - | - |
| 4-1  | $64 \times 64$ | bn + swish | $1 \times 1$ | 64 | bn + s&e | - |
| 4-2  | $64 \times 64$ | bn | $1 \times 1$ | 256 | - | - |
| 4-2  | $64 \times 64$ | bn + swish | $5 \times 5$ | 256 | - | - |
| 4-2  | $64 \times 64$ | bn + swish | $1 \times 1$ | 64 | bn + s&e | - |
| -    | $64 \times 64$ | - | $1 \times 1$ | 3 | sigmoid | - |
Table 9: To prevent FitVid from overfitting we use augmentation. First, at training time, we select a random crop of the video before resizing it to the desired resolution (64×64) at the training time, called RandCrop. This processes crops all the frames of a given video to include a minimum of $C$ percent of the frame’s height. Then we use RandAugment [15] to improve the augmentation. We use the same augmentation configuration for all the datasets. Per video, we use the same randomization across all the frames.

Algorithm 3: Video Augmentation.

Input: Video $x$
Input: Number of RandAugment transformations $N$
Input: RandAugment magnitude $M$
Input: RandCrop crop height minimum ratio $C$

1. $x ← RandCrop(x, C)$
2. for $i ← 0$ to $N$ do
   3. $f ← $ ChooseRandomTransformation()
   4. $x ← f(x, M)$
5. end
6. return $x$

Hyper-parameter | Value
--- | ---
RandAugment |  
No. of transformations $N$ | 1
Magnitude $M$ | 5
Transformations |  
identity - auto_contrast - equalize rotate - solarize - color - posterize contrast - brightness - sharpness shear_x - shear_y translate_x - translate_y
RandCrop |  
Crop height minimum ratio $C$ | 0.8

Table 10: Used datasets and their licenses.

| Dataset       | Reference       | License        |
|---------------|-----------------|----------------|
| RoboNet       | Dasari et al. [16] | MIT            |
| KITTI         | Geiger et al. [33] | Creative Commons |
| Human3.6M     | Ionescu et al. [51] | License        |
| BAIR robot pushing | Ebert et al. [24] | GitHub Default |

Figure 8: FitVid on BAIR robot pushing dataset [23] with no actions. The model is conditioned only on the first frame and is predicting the next 16 frames. Given that the future actions of the robotic arm is unknown, the prediction can diverge substantially from the ground truth video. However, the model predicts movements for the objects whenever the arm pushes the object in an imaginary scenario. It also fills the background with random objects.
A.2 Robot Experiment Details

A.2.1 Environment

The robot environment consists of a Franka Emika Panda robot operating over a bin which contains various objects. The robot's observations are $64 \times 64 \times 3$ RGB images, and its action space consists of 3 DOF delta position control of the end effector with action magnitudes in the range [-10cm, 10cm].

A.2.2 Data

The data used for finetuning the model used in robot experiments was taken directly from Wu et al. [108]. This data consists of different viewpoint, lighting conditions, and target objects than what is used in our evaluation.

A.2.3 Evaluation Details

During evaluation, the agent is specified to complete an object pushing task by a goal image. The agent has 50 timesteps to complete the task, and a trial is measured as successful if the majority of the object overlaps with its target position at some point in the episode. Each method is evaluated over 18 trials, of which 6 consist of objects in an “office” setting, 6 consist of objects in a “kitchen” setting, and 6 consist of objects in a “cleaning” setting (See Figure 9).

To execute the task, the agent performs visual model predictive control using the cross entropy method (CEM). Specifically, the agent takes in 1 frame, and predicts trajectories of 10 time-steps for 200 different sampled action sequences. Trajectories are ranked according to their negative mean squared error to the goal image, averaged across all 10 time-steps. The action distribution refits to the top 20 actions, and repeats for 3 iterations of CEM. Afterwards the best sequence of 10 actions is stepped in the environment in an open loop fashion. The process repeats 5 times until the end of the episode.
Figure 10: Example tasks for zero-shot object pushing using a robotic arm. The goal in each trial is to push the a specific object to a predetermined goal location. The trial is considered successful, if the robot pushes at least half of the object overlaps with its goal location at any point in the episode.
Figure 11: More detailed video from Figure 4 which illustrates FitVid on action-conditioned RoboNet [16]. The model is conditioned on the first two frames and is predicting the next ten frames given the future actions of the robotic arm. These figures demonstrate how the predicted movements of the arm closely follows the ground truth given that the future actions is known. The model also predicts detailed movements of the pushed objects (visible in the top example) as well as filling in the previously unseen background with some random objects (look at the object that appear behind the robotic arm in the bottom example). Also notice the wrong predictions of robots fingers in the bottom example.
Figure 12: More detailed video from Figure 5 which illustrates FitVid on KITTI dataset [34]. As it can be seen in this figure, the model generates high quality prediction of the future in a dynamic scene. Note how in the top example FitVid keeps predicting the movement of the shadow on the ground till it moves out of the frame. After that, the model keeps pushing the background closer in each frame, implying driving forward. We noticed that the quality of predictions drop substantially faster when there are more objects in the scene e.g. the driving scenes inside a city as can be seen in the bottom example. This indicates the model still fails to generalize to more complex scenes with more moving subjects.
Figure 13: More detailed video from Figure 6 which illustrates FitVid on Human3.6M [51]. This figure demonstrates extremely detailed and human-like motions predicted by FitVid, conditioned on the given context frames. However, on closer inspection, it can be seen that the human subject in the video is changing, from the test subject to a training subject. This is particularly evident from the cloths. This phenomena indicates that, although FitVid is capable of generalizing to the frames out of training distribution, however, it morphs the human subject into a familiar one from the training set and then plays the video from the memory.
Figure 14: More detailed video from Figure 8 which illustrates FitVid on BAIR robot pushing dataset [23] with no actions. The model is conditioned only on the first frame and is predicting the next 16 frames. Given that the future actions of the robotic arm is unknown, the prediction can diverge substantially from the ground truth video. However, the model predicts movements for the objects whenever the arm pushes the object in an imaginary scenario. It also fills the background with random objects.
Figure 15: These are copies of Figure 6 from Franceschi et al. [32], Figure 7 from Villegas et al. [95] and Figure 5 from Villegas et al. [94]. The proposed methods in these papers are also changing the human test subject into a training subject (mostly visible in the changed shirt). This seems to be a common issue which is typically overlooked in the video prediction literature.