REVISITING HIERARCHICAL APPROACH FOR PERSISTENT LONG-TERM VIDEO PREDICTION

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ABSTRACT

Learning to predict the long-term future of video frames is notoriously challenging due to the inherent ambiguities in a distant future and dramatic amplification of prediction error over time. Despite the recent advances in the literature, existing approaches are limited to moderately short-term prediction (less than a few seconds), while extrapolating it to a longer future quickly leads to destruction in structure and content. In this work, we revisit the hierarchical models in video prediction. Our method generates future frames by first estimating a sequence of dense semantic structures and subsequently translating the estimated structures to pixels by video-to-video translation model. Despite the simplicity, we show that modeling structures and their dynamics in categorical structure space with stochastic sequential estimator leads to surprisingly successful long-term prediction. We evaluate our method on two challenging video prediction scenarios, *car driving* and *human dancing*, and demonstrate that it can generate complicated scene structures and motions over a very long time horizon (*i.e.,* thousands frames), setting a new standard of video prediction with orders of magnitude longer prediction time than existing approaches. Video results are avaiable at https://bit.ly/2EyDSem.

1 INTRODUCTION

Video prediction aims to generate future frames conditioned on a short video clip. It has received much attention in recent years as forecasting the future of visual sequence improves the planning for model-based reinforcement learning (Finn et al., 2016; Hafner et al., 2019; Ha & Schmidhuber, 2018) and has immediate applications (Hoai & Torre, 2013; Ryoo, 2011; Lan et al., 2014). Many previous approaches have formulated video prediction as conditional image generation problem by recursively synthesizing future frames using Generative Adversarial Networks (GANs) (Lee et al., 2018; Vondrick et al., 2016; Tulyakov et al., 2018) or Variational Autoencoders(VAEs) (Denton & Fergus, 2018; Babaeizadeh et al., 2018; Castrejon et al., 2019; Villegas et al., 2019). These approaches have made meaningful progress in predicting a short-term future. However, those methods have not been successful in synthesizing convincing long-term future due to the complexity of spatio-temporal variations in high-dimensional data, and due to the difficulty of extrapolating from short sequences to much longer future. As the prediction errors are easily propagated and amplified through time, the quality of the predicted frames quickly degrades over time.

One way to reduce the error propagation is to extrapolate in a low dimensional structure space instead of directly estimating pixel-level dynamics in a video. Therefore, many hierarchical modeling approaches are proposed (Villegas et al., 2017b; Wichers et al., 2018; Liang et al., 2017; Yan et al., 2018; Walker et al., 2017; Kim et al., 2019). These approaches first generate a sequence using low-dimensional structure representation, and subsequently generate appearance conditioned on the predicted structures. Hierarchical approaches are potentially promising for long-term prediction since learning structure-aware dynamics allows the model to generate semantically accurate motion and content in the future. However, previous approaches often employed too specific and incomprehensive structures such as human body joints (Villegas et al., 2017b; Yan et al., 2018; Yang et al., 2018; Walker et al., 2017; Kim et al., 2019) or face landmarks (Yan et al., 2018; Yang et al., 2018). Moreover, they also made oversimplified assumptions on the future by using deterministic loss or assuming homogeneous content. We therefore argue that the benefit of the hierarchical model has been underestimated and its impact on long-term video prediction has not been properly demonstrated.

In this paper, we propose a hierarchical model with general structure representation (i.e., *dense semantic label map*) for long-term video prediction with complex scenes. We abstract the scene as

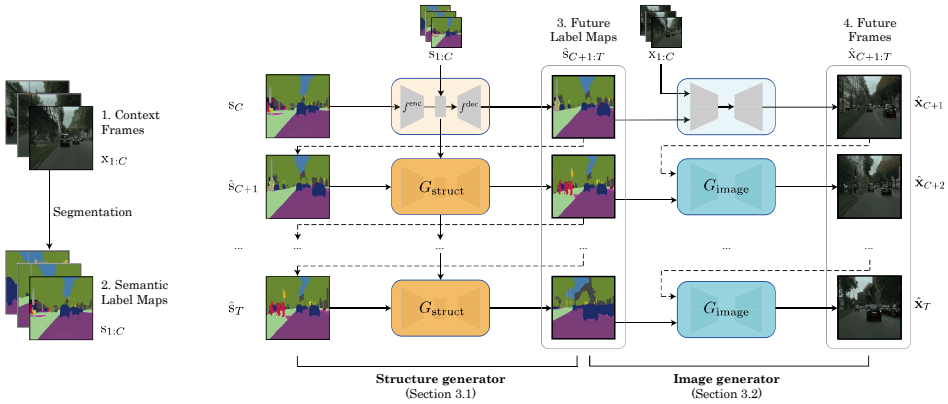

Figure 1: The overall framework of the proposed hierarchical approach. Given the context frames and its label maps extracted by the segmentation network, our model predicts the future frames by estimating the semantic label maps using stochastic sequence estimator (Section 2.1) and converting the predicted labels to the RGB frames by conditional image sequence generator (Section 2.2).

categorical labels for each pixel and then predict the motion and content change in this label space using variational sequence models. Given the context frames and the predicted label maps, we then generate the textures by translating the sequence of label maps to actual RGB frames. As dense label map is generic and universal, we can learn comprehensive scene dynamics including foreground object motion and global camera motion. Moreover, we can also capture the multi-modal dynamics in the dense label space with the stochastic prediction of the variational sequence model. Consequently, we are able to generate long term videos from driving scene to human dancing, including motion of multiple objects and even an evolution of the content in a distant future. Our experiment results demonstrate that the proposed hierarchical model can generate surprisingly long-term future, which are semantically accurate and capturing complex motions. We also show that the predicted frame quality is preserved through time, which enables *persistent* future prediction virtually near infinite horizon. [TODO:Move the bullet-itemized contribution to the text]

2 Method

Given the context frames $\mathbf{x}_{1:C} = \{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_C\}$, our goal is to synthesize the future frames $\mathbf{x}_{C+1:T} = \{\mathbf{x}_{C+1}, \mathbf{x}_{C+2}, ..., \mathbf{x}_T\}$ up to an arbitrary long-term future T. Let $\mathbf{s}_t \in \mathbb{R}^{W \times H \times N}$ denotes a dense label map of the frame $\mathbf{x}_t$ defined over N categories, which is inferred by the pre-trained semantic segmentation model[1]. Then given the context frames $\mathbf{x}_{1:C}$ and the label maps $\mathbf{s}_{1:C}$, our hierarchical framework synthesizes the future frames $\hat{\mathbf{x}}_{C+1:T}$ by following steps.

- The structure generator takes the context label maps as inputs, and produces a sequence of the future label maps by $\hat{\mathbf{s}}_{C+1:T} \sim G_{\text{struct}}(\mathbf{s}_{1:C}, \mathbf{z}_{1:T})$, where $\mathbf{z}_t$ denotes the latent variable encoding stochasticity of the structure.
- Given the context frames and the predicted structures, the image generator produces the RGB frames by $\hat{x}_{C+1:T} \sim G_{\text{image}}(\mathbf{x}_{1:C}, \{\mathbf{s}_{1:C}, \hat{\mathbf{s}}_{C+1:T}\})$.

Figure 1 illustrates the overall pipeline. Note that there are various factors beyond motion that cause spatio-temporal variations in the label maps, such as the emergence of new objects, partial observability, or even the dramatic changes of entire scene by the global camera motion (*e.g.*, panning). By learning to model these dynamics in the semantic labels with stochastic sequence estimator, and conditioning the video generation with the estimated labels, the proposed hierarchical model can synthesize the convincing frames into the very long-term future.

2.1 Sequential Dense Structure Generator

Our structure generator models the dynamics in the label maps by $p(\mathbf{s}_{\leq T}|\mathbf{z}_{\leq T}) = \prod_{t=1}^{T} p(\mathbf{s}_t|\mathbf{s}_{<t}, \mathbf{z}_{\leq t})$. We employ the sequence model based on VAE (Denton & Fergus, 2018) since (1) it provides a probabilistic framework to handle stochastic variations of the structure and (2) it can

[1]We employ the pre-trained network (Zhu et al., 2019) on *still images* to obtain segmentations in videos.

easily incorporate the discrete sequence (*i.e.,* label maps). Specifically, we optimize the following variational lower-bound of the sequence:

$$\sum_{t=1}^{T} \mathbb{E}_{q_\phi(\mathbf{z}_{\leq T}|\mathbf{s}_{\leq T})}[\log p_\theta(\mathbf{s}_t|\mathbf{z}_{\leq t}, \mathbf{s}_{<t})] - \beta D_{KL}(q_\phi(\mathbf{z}_t|\mathbf{s}_{\leq t})||p_\psi(\mathbf{z}_t|\mathbf{s}_{<t})). \tag{1}$$

where $q_\phi(\mathbf{z}_{\leq T}|\mathbf{s}_{\leq T})$ is the approximated posterior distribution and $p_\psi(\mathbf{z}_t|\mathbf{s}_{<t})$ is the prior distribution. At each step, it learns to represent and reconstruct each label map $\mathbf{s}_t$ through CNN-based encoder f^{enc} and decoder f^{dec}, respectively, while the temporal dependency of the label maps is modeled stochastically by the two LSTMs as follows:

$$\begin{aligned} \mu_\phi(t), \sigma_\phi(t) &= \text{LSTM}_\phi(\mathbf{h}_t) && \text{where} \quad \mathbf{h}_t = f^{\text{enc}}(\mathbf{s}_t), \\ \mathbf{z}_t &\sim \mathcal{N}(\mu_\phi(t), \sigma_\phi(t)), \\ \mathbf{g}_t &= \text{LSTM}_\theta(\mathbf{h}_{t-1}, \mathbf{z}_t) && \text{where} \quad \mathbf{h}_{t-1} = f^{\text{enc}}(\mathbf{s}_{t-1}), \\ \mathbf{s}_t &= f^{\text{dec}}(\mathbf{g}_t), \end{aligned} \tag{2}$$

where LSTM_θ and LSTM_ϕ respectively approximate the generative and the posterior distributions recurrently up to the time step t. Unlike Denton & Fergus (2018); Villegas et al. (2019) that exploits skip-connection from the last observed context frame during both training and testing time, we skip hidden representations of the encoder to the decoder at every time step during testing to handle long-term dynamics in structure.

During training, we apply the teacher-forcing by feeding ground-truth label maps and sampling the latent $\mathbf{z}_t$ from the posterior distribution $\mathcal{N}(\mu_\phi(t), \sigma_\phi(t)) = \text{LSTM}_\phi(f^{\text{enc}}(\mathbf{s}_t))$. During inference, we recursively generate label maps by (1) sampling $\mathbf{z}_t$ from the prior distribution $\mathcal{N}(\mu_\psi(t), \sigma_\psi(t)) = \text{LSTM}_\psi(f^{\text{enc}}(\hat{\mathbf{s}}_{t-1}))$, (2) producing the frame $\hat{\mathbf{s}}_t$ through decoder, and (3) discretizing the predicted label map by taking pixel-wise maximum. Such discretization provides additional merits for being more robust against error propagation than continuous structures such as 2D keypoints (Villegas et al., 2017b; Yan et al., 2018; Yang et al., 2018) or optical flow (Walker et al., 2017).

Extension to object boundary prediction When the pre-trained instance-wise segmentation model is available, we can optionally extend the structure generator to jointly predict the object boundary maps. Such structure can add a notion of object instance, and is useful to improve the image generator in sequences with many occluding objects. Let $\mathbf{e}_t \in \{0, 1\}^{W \times H}$ denotes the object boundary map at frame $\mathbf{x}_t$. Then we train the denoising autoencoder $\hat{\mathbf{e}}_t = G_{\text{edge}}(\mathbf{s}_t)$ that produces a boundary map given a label map for each frame[1]. We train G_{edge} using conditional GAN objective to maximize the joint probability between the label and boundary maps $p(\mathbf{s}_t, \mathbf{e}_t)$. The boundary and label maps are then combined as the output of the structure generator $\tilde{\mathbf{s}}_t = [\hat{\mathbf{s}}_t, \hat{\mathbf{e}}_t]$, and is used as an input to the image generator described below. See Appendix B.2 for implementation details.

2.2 Structure-Conditional Pixel Sequence Generator

Given a sequence of the structures and the context frames, the image generator learns to model conditional distribution of the RGB frames by $p(\mathbf{x}_{\leq T}|\mathbf{s}_{\leq T}) = \prod_{t=1}^{T} p(\mathbf{x}_t|\mathbf{x}_{<t}, \mathbf{s}_{\leq t})$. We formulate this task as a video-to-video translation problem, and employ the state-of-the-art conditional video generation model (Wang et al., 2018). Specifically, the video synthesis network F in Wang et al. (2018) consists of three main components; the generator H, occlusion mask predictor M, and optical flow estimator W, which are combined to generate each frame $\hat{\mathbf{x}}_t$ by the following operation:

$$\hat{\mathbf{x}}_t = F(\hat{\mathbf{x}}_{t-\tau:t-1}, \mathbf{s}_{t-\tau:t}) = (1 - \mathbf{m}_t) \odot \hat{\mathbf{w}}_{t-1} + \mathbf{m}_t \odot \mathbf{h}_t \tag{3}$$

where $\hat{\mathbf{w}}_{t-1} = W(\hat{\mathbf{x}}_{t-\tau:t-1}, \mathbf{s}_{t-\tau:t})$ is the warped previous frame $\hat{\mathbf{x}}_{t-1}$ using the estimated optical flow, $\mathbf{h}_t = H(\hat{\mathbf{x}}_{t-\tau:t-1}, \mathbf{s}_{t-\tau:t})$ is the hallucinated frame at t, and $\mathbf{m}_t = M(\hat{\mathbf{x}}_{t-\tau:t-1}, \mathbf{s}_{t-\tau:t})$ is the soft occlusion mask blending $\hat{\mathbf{w}}_{t-1}$ and $\mathbf{h}_t$. Unlike models synthesizing future frames by transforming the context frames $\mathbf{x}_C$ (Villegas et al., 2019; 2017b; Yan et al., 2018; Tulyakov et al., 2018), this model is appropriate to synthesize long-term future since it can handle both transformation of the existing objects (via $\hat{\mathbf{w}}_{t-1}$) and synthesis of the emerging objects (via $\mathbf{h}_t$).

[1]We do not feed the predicted boundary map as input to the structure generator, as it makes the structure generator prune to error propagation thus prevents extrapolation to long-term future.

To ensure both frame-level and video-level generation quality, the video synthesis network F is trained against a conditional image discriminator D_I and a conditional video discriminator D_V through adversarial learning by

$$\mathcal{L}_I(F, D_I) = \mathbb{E}_{\phi_I(\mathbf{x}_{\leq T}, \mathbf{s}_{\leq T})}[\log D_I(\mathbf{x}_i, \mathbf{s}_i)] + \mathbb{E}_{\phi_I(\hat{\mathbf{x}}_{\leq T}, \mathbf{s}_{\leq T})}[\log(1 - D_I(\hat{\mathbf{x}}_i, \mathbf{s}_i))], \tag{4}$$

$$\begin{aligned}\mathcal{L}_V(F, D_V) = &\mathbb{E}_{\phi_V(\mathbf{w}_{<T}, \mathbf{x}_{\leq T}, \mathbf{s}_{\leq T})}[\log D_V(\mathbf{x}_{i-1:i-\tau'}, \mathbf{w}_{i-2:i-\tau'})] + \\ &\mathbb{E}_{\phi_V(\mathbf{w}_{<T}, \hat{\mathbf{x}}_{\leq T}, \mathbf{s}_{\leq T})}[\log(1 - D_V(\hat{\mathbf{x}}_{i-1:i-\tau'}, \mathbf{w}_{i-2:i-\tau'}))],\end{aligned} \tag{5}$$

where $\mathcal{L}_I(F, D_I)$ and $\mathcal{L}_V(F, D_V)$ are frame-level and video-level adversarial losses, respectively. For efficient training, we follow (Wang et al., 2018) to adopt sampling operators $\phi_I(\mathbf{x}_{\leq T}, \mathbf{s}_{\leq T}) = (\mathbf{x}_i, \mathbf{s}_i)$ and $\phi_V(\mathbf{w}_{<T}, \mathbf{x}_{\leq T}, \mathbf{s}_{\leq T}) = (\mathbf{w}_{i-2:i-\tau'}, \mathbf{x}_{i-1:i-\tau'}, \mathbf{s}_{i-1:i-\tau'})$ for frame and video-level adversarial learning objectives, respectively, where i is an integer sampled from $\mathrm{U}(1, T)$ and $\mathrm{U}(\tau' + 1, T + 1)$ for frame sampling operator ϕ_I and video sampling operator ϕ_V, respectively. Then the final learning objective is formulated by

$$\min_F \max_{D_I, D_V} \mathcal{L}_I(F, D_I) + \mathcal{L}_V(F, D_V). \tag{6}$$

During training, the model is trained to estimate a frame sequence using the ground-truth structures, while we use the predicted structures by the structure generator during the testing.

3 Related Work

The task of predicting future video frames has been extensively studied over the past few years (Villegas et al., 2019; Denton & Fergus, 2018; Lee et al., 2018; Babaeizadeh et al., 2018; Vondrick et al., 2016; Finn et al., 2016; Clark et al., 2019; Castrejon et al., 2019). Early approaches focus on modeling simple and deterministic dynamics using regression loss (Srivastava et al., 2015; Ranzato et al., 2014) or predictive coding (Lotter et al., 2017). However, such deterministic models may not be appropriate for modeling stochastic variations in real-world videos. Recently, deep generative models have been employed to model dynamics in complex videos. Babaeizadeh et al. (2018) proposed a variational approach for modeling stochasticity in a sequence. Denton & Fergus (2018) incorporated more flexible frame-wise inference models. The prediction quality of the variational models has been further improved by employing rich structure in latent variables (Castrejon et al., 2019), maximally increasing the network parameters (Villegas et al., 2019), or incorporating adversarial loss (Vondrick et al., 2016; Clark et al., 2019; Tulyakov et al., 2018; Villegas et al., 2017a). Despite their success, these approaches still fail to generate long-term videos and the common artifacts were losing object structures, switching object categories, *etc.*. Our approach addresses these issues by explicitly predicting dynamics in a low-dimensional label map using a hierarchical model.

Hierarchical models studied in the past for video prediction were usually in specific video domains (Villegas et al., 2017b; Wichers et al., 2018; Liang et al., 2017; Yan et al., 2018; Walker et al., 2017; Minderer et al., 2019). Villegas et al. (2017b) employed LSTMs to predict human body joints and visual analogy making to create textures, which is extended by Wichers et al. (2018) and Minderer et al. (2019) to unsupervised approaches. Other approaches employed sequential VAE (Yan et al., 2018) or GAN (Yang et al., 2018) to predict the human body posture. However, these approaches are designed specifically for certain objects, and evaluated under simple videos containing only a single moving object. Also, they mostly utilized deterministic model to learn structure-level dynamics. These simplified assumptions on video content and dynamics limit their application to real-world videos. We propose to resolve these limitations by using dense semantic label maps as universal representation and stochastic sequential estimator for modeling video dynamics.

4 Experiments

In this section, we present our results on three challenging video datasets. Full videos are available at anonymous website: https://bit.ly/2EyDSem

4.1 Evaluation Metrics

Below we describe the evaluation metrics used in the experiment. Unless otherwise specified, we use 64×64 images for all quantitative evaluation for fair comparison to the existing works.

Short-term prediction We employ three conventional metrics in literature to evaluate the prediction performance on short-term videos (*i.e.,* less than 50 frames): VGG cosine similarity (CSIM) measuring the frame-wise perceptual similarity using VGG features, mean Intersection-over-Union

(mIoU) measuring the structure-level similarity using the label maps extracted by the pre-trained segmentation network (Zhu et al., 2019) and Fréchet Video Distance (FVD) (Unterthiner et al., 2018) measuring a Fréchet distance between the ground-truth videos and the generated ones in a video representation space. Detailed evaluation protocols are described in Appendix A.4.

Long-term prediction Compared to short-term prediction, evaluating prediction quality of arbitrary long-term video is challenging for a number of reasons. First, the ground-truth videos are seldom available at this scale, making it impossible to adopt metrics based on the frame-wise comparison (*e.g.,*, CSIM, mIoU). Second, the uncertainty of future prediction increases exponentially with time, making it intractable to employ density-based metrics (*e.g.,*, FVD) as it requires exponentially many samples. Since our goal is to demonstrate video prediction at the scale of hundreds to thousands of frames, we introduce a novel metric based on FVD, which enables evaluation of temporal and frame-level quality without ground-truth sequences and allows tractable evaluation through time. Specifically, we introduce a *shot-level* video-quality evaluation metric as

$$\text{ShotFVD}(t) = \sum_{t=1}^{T} \text{FVD}(\hat{X}_{t:t+\omega-1}, X_{\omega}) \tag{7}$$

which computes a FVD between the ground-truth shots $X_{\omega} = \{X_{\omega}^{1}, \cdots, X_{\omega}^{L}\}$ and the predictions $\hat{X}_{t:t+\omega-1} = \{\hat{X}_{t:t+\omega-1}^{1}, \cdots, \hat{X}_{t:t+\omega-1}^{M}\}$ in a sliding window manner, where L denotes the total number of overlapping shots in training video and M denotes the number of predicted shots. The shot-wise FVD then allows us to evaluate the quality of generated frames and their motions in a short interval defined by ω *through time*. We also compute Inception Score (Salimans et al., 2016) for frame-level quality evaluation, which does not require ground-truths thus appropriate for long-term evaluation. Please find Appendix A.4 for more details.

Human evaluation We conduct user study by Amazon Mechnical Turnk (AMT). To evaluate the prediction quality in different time scales, we presented videos predicted up to 5, 300, 450 frames by different methods and ask users to choose the best. Please find Appendix A.4 for more details.

4.2 Results on Human Dancing Sequences

We first present our results on human dancing videos collected from Web (Wang et al., 2018).

Baselines We compare our method with the two state-of-the-art video prediction models. SVG-extend (Villegas et al., 2019) is directly operating on RGB frames via stochastic estimator, and served as our baseline for non-hierarchical model. Following Villegas et al. (2019), we employ the largest model with maximum parameters for fair comparison. We employ Villegas et al. (2017b) as a hierarchical model designed specifically for long-term prediction of human motion using the pose (Newell et al., 2016). All models are trained to predict 40 future frames given 5 context frames.

Short-term prediction results We evaluate the short-term prediction performance by synthesizing 50 future frames given the 5 context frames and comparing them to ground-truths. Table 1 summarizes the quantitative evaluation results (see Figure **??** for qualitative results). Even in a short prediction interval, our method generates substantially higher quality samples than the compared methods in terms of modeling appearance (CSIM), structure (mIoU), and motion (FVD). We observe that it is because the dancing sequences contain rapid and complex variations in dynamics, making prediction task particularly challenging. We discuss more detailed analysis across methods in a long-term prediction task below.

Table 1: Quantitative comparisons of short-term prediction results.

Model	CSIM(↑)	mIoU(↑)	FVD(↓)
SVG-extend	0.6654	0.0519	2125.29
Villegas et al.	0.7637	0.1755	1987.55
Ours	**0.8164**	**0.3454**	**1398.98**

Long-term prediction results We evaluate 500 frame prediction results based on shot-wise (FVD) and frame-wise (Inception score). Figure 2 and 3 summarize the quantitative and qualitative comparisons, respectively. We notice that the SVG-extend fails to model complex dynamics in dancing, as both the Inception score and FVD are constantly getting worse through time. It is because the dancing motions involve fast transition and frequent self-occlusions, escalating catastrophic error propagation through time. On the other hand, as shown in the Inception score, (Villegas et al., 2017b) produces much reasonable future frames as it exploits human body joints for generation. However, the deterministic LSTM module is not strong enough to capture complex dancing motions, and ends up generating static postures in the long term that leads to very high FVD scores. In contrast, we observe that our method generates both realistic frames and convincing motions,

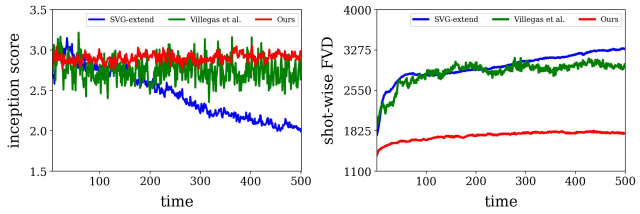

Figure 2: Quantitative comparisons of the long-term prediction on human dancing sequences.

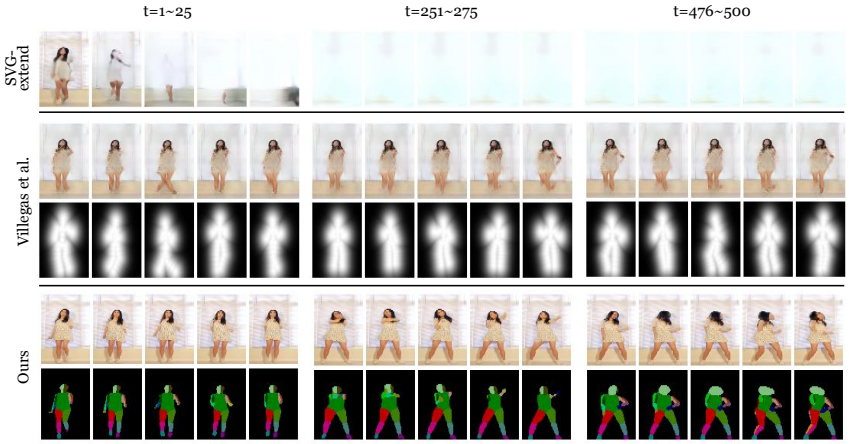

Figure 3: Qualitative comparisons of long-term video generation results across models on human dancing sequences. All models are conditioned on the same context frames.

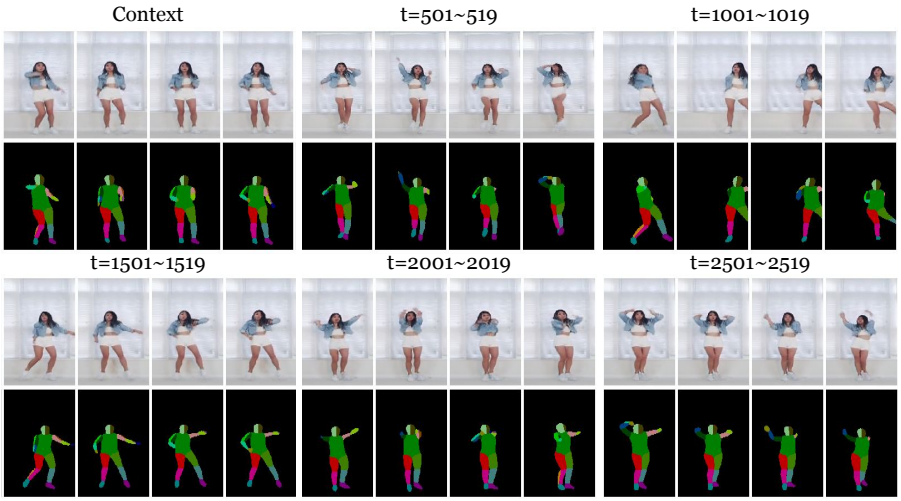

Figure 4: Long-term prediction results on a 128×128 human dancing sequence. We omit ground-truth frames since we extrapolate our model beyond the time horizon where the ground-truths exist.

leading to stable Inception and FVD scores in a long-term future. Also, contrary to Villegas et al. (2017b) that produces a deterministic future, our model can synthesize multiple futures based on the stochastic sequence estimator for structure. Figure A illustrates that the generated frames by our method are covering diverse and interesting motions. When our method is applied to predict 2500+ frames in 128×128 resolution (Figure 4), we observe that it generates future frames that are convincing and involve diverse dance motions without noticeable quality degradation through time.

4.3 Results on KITTI Benchmark

Baselines In addition to SVG-extend, we employ the future segmentation model (Bhattacharyya et al., 2019) (Bayes-WD-SL) predicting the dense label map of future as a strong baseline for hierar-

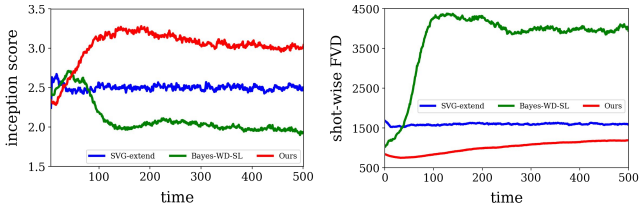

Figure 5: Quantitative comparisons of the long-term generation quality on KITTI Benchmark.

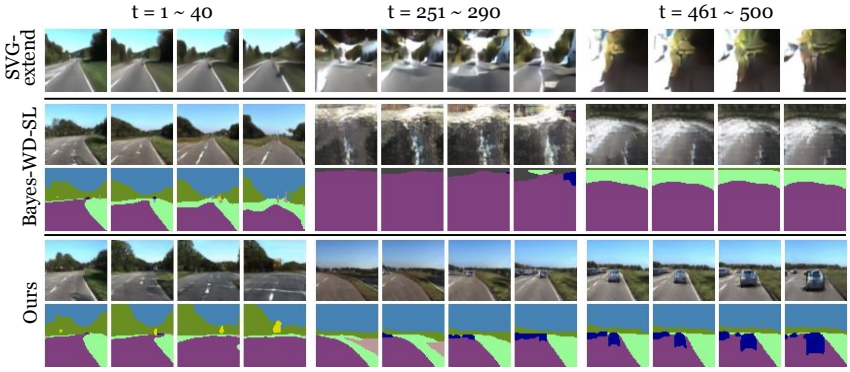

Figure 6: Qualitative comparisons of long-term video generation results across models. Although all models succeed in generating plausible frames in a short-term ($t = 1 \sim 40$), only our approach can generate persistent and convincing futures even in the end ($t = 251 \sim 500$).

chical model. Since it generates only the label maps, we employ the same image generator with ours to produce RGB frames from the predicted label maps. All models are trained to predict 15 future frames given 5 context frames. Please refer to the appendix for the detailed architecture settings.

Short-term prediction results We evaluate the short-term prediction performance by synthesizing 50 future frames given the 5 context frames and comparing them to ground-truths. Table 2 summarize the quantitative evaluation results (see Figure C for qualitative results). We observe that SVG-extend performs worse in terms of structural accuracy (mIoU) and motion (FVD), as it loses the object structure and generates arbitrary pixel dynamics. The Bayes-WD-SL performs better in terms of mIoU, as it conditions the frame prediction with the structure estimation. However, as shown high FVD score, it fails to model temporal variations in the structure, largely due to its feedforward architecture. In contrary, our method generates semantically accurate motions and structures, and substantially outperforms the others in all metrics.

Table 2: Quantitative comparisons of short-term prediction results.

Model	CSIM(↑)	mIoU(↑)	FVD(↓)
SVG-extend	0.6664	0.3529	1448.84
Bayes-WD-SL	0.6533	0.4225	956.05
Ours	**0.6789**	**0.5137**	**762.73**

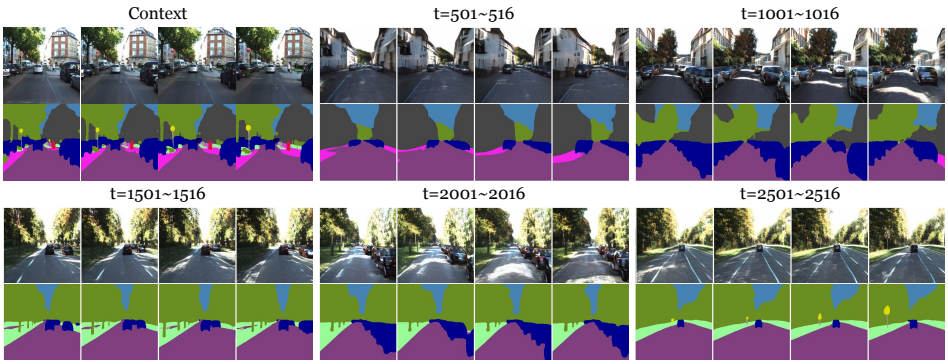

Figure 7: Long-term prediction results on a high-resolution KITTI sequence. Both the frames and the label maps are predicted by our method. Our method can generate high-resolution frames (256×256 pixels) into the long-term future without particular quality degradation.

Table 3: Comparison to future segmentation methods on Cityscapes dataset.

Model	person	rider	car	truck	bus	train	motorcycle	bicycle	mIoU GT
S2S (Luc et al., 2017)	0.37	0.18	0.70	0.43	0.55	0.26	0.27	0.38	0.39
F2F (Luc et al., 2018)	0.33	0.20	0.72	0.53	0.58	0.38	0.30	0.25	0.41
Ours	**0.41**	**0.28**	**0.77**	**0.75**	**0.73**	**0.49**	**0.40**	**0.45**	**0.54**

Long-term prediction results Figure 5 and Figure 6 summarize the quantitative and qualitative comparison results, respectively. In both measures, our method outperforms the other baselines with substantial margins, showing that our method synthesizes both reasonable motions and high-quality frames. We notice that SVG-extend simulates arbitrary pixel motions, resulting in relatively constant Inception and shot-wise FVD scores through time. However, these unstructured motions lead to rapid destruction in recognizable concepts in the synthesized frames (Figure 6). We also observe similar failure in future segmentation baseline (Bayes-WD-SL), which converges to monotonic label maps due to severe error propagation. Interestingly, we observe that the Inception Score of our method increases through time. It is because the long-term prediction by our method often leads to scenes with simple and typical structures, such as a highway, where the image generator can produce more high-quality frames than complicated scenes appearing early in the test videos. Note that such transition of the scene is still reasonable as it is frequently observed in the training data. Nonetheless, we observe that our method generates reasonable sequences through time, and the quality of the synthesized frames is maintained in a reasonable range even in a very distant future. Finally, Figure 7 illustrates the prediction results over 2500 future frames. We observe that the generated sequences are reasonable in both structure and motion, and capture interesting translations of the scenes through time (*e.g.,* from suburban to rural areas).

4.4 Results on Cityscapes dataset

To further evaluate the quality of structure prediction, we compare our structure generator with existing future segmentation methods that directly predict the segmentation map of the future frames.

Baselines We compare our method with S2S (Luc et al., 2017) and F2F (Luc et al., 2018), which are the state-of-the-arts in the future segmentation literature. S2S is a deterministic model based on fully-convolutional network that predicts future semantic label maps in a multi-scale and auto-regressive manner. F2F is an extension of S2S to future *instance* segmentation task by predicting the high-level feature maps of Mask R-CNN (He et al., 2017). Similar to KITTI, we use the label maps extracted by the pre-trained semantic segmentation network (Zhu et al., 2019) for the training.

Evaluation We follow the standard evaluation protocols in the literature (Luc et al., 2017; 2018) for quantitative and qualitative comparisons. For each validation sequence, each model is provided with 4 contexts, and produces up to 29th frame. Then, we compute mIoUs between ground-truths and predictions at 20th time-step. For fair comparisons with the future instance segmentation model (*i.e.,* F2F), we follow Luc et al. (2018) and measure mIoUs only for moving objects. For S2S and F2F, we use publicly available pre-trained models provided by the authors.

Results Table 3 presents the quantitative evaluation results (See Figure E for qualitative results). As it shows, the two baselines produce blurry predictions, resulting in inaccurate structures and multiple semantics in a single structure. These problems have been widely observed in the literature and attributed to the inability of deterministic models to handle stochasticity in data (Denton & Fergus, 2018). On the other hand, our method outperforms the two baselines in all classes as it can handle highly stochastic nature of complex driving scenes. Figure F illustrates the results of our full model including boundary map and image generator on 256×512 resolution videos. It shows that our method can generate convincing future even in extremely complex and high-resolution videos. See Appendix A.3.3 for more detailed discussion.

5 Conclusion

We proposed a hierarchical approach for persistent video prediction. We revisit the hierarchical model with stochastic estimation of dense label maps and integration of image generator robust against temporal misprediction in pixels and structures. Our experimental results show that a carefully designed hierarchical model can learn to synthesize a very long-term future with convincing structures and dynamics even in complex videos. By scaling up the video prediction to order-of-magnitude longer, we believe that our work can help the future research to focus on more challenging problems of learning a long-term dependency, eliminating explicit structure estimation, *etc.*

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APPENDIX

A ADDITIONAL EXPERIMENT RESULTS

This section provides additional experiment details and results that could not be accommodated in the main paper due to space restriction. Please find our anonymous website to assess full videos for qualitative analysis: https://bit.ly/2EyDSem.

A.1 HUMAN DANCING DATASET

A.1.1 DATASET

To evaluate if our model can learn complex and highly structured motion, we used videos of human dancing. We construct this dataset by crawling a set of videos from web containing a single person covering various dance moves. Following the pre-processings used in Wang et al. (2018), we crop the center of the video and resize it to square frames. We collect approximately 240 videos in total for training. For structure representation, we use the body parts segmentation obtained by DensePose (Alp Güler et al., 2018). We subsample each sequence by a factor of two.

A.1.2 IMPLEMENTATION DETAILS

SVG-extend (Villegas et al., 2019) We use the modified version of SVG (Denton & Fergus (2018)) by Villegas et al. (2019), which we refer to as SVG-extend throughout the paper. The two main differences between SVG and SVG-extend are two-fold: (1) SVG-extend adopts the shallower auto-encoder architecture than that of SVG. (2) SVG-extend replaces Fully-Connected-LSTM with Convolutional-LSTM Shi et al. (2015). These two modifications are to increase the capacity of the architecture.

Since the detailed architectural configuration of SVG-extend is not described in Villegas et al. (2019), we summarize our reproduced version of this framework in Table A, B, C, and D. On the 64×64 image resolution, we use the same architecture described in the tables, while, on 128×128 image resolution, we simply stack more convolutional blocks (non-linear convolutional layers followed by upsampling or downsampling layers) in the Encoder and Decoder networks so that the shape of $\mathbf{h}_t, \mathbf{z}_t, \mathbf{g}_t$ is kept to $\mathbb{R}^{128\times8\times8}$ agnostic to the image resolutions. For hyperparameters, we use $C = 5$; we set $\beta = 0.0005$; we use ADAM optimizer Kingma & Ba (2015) with the learning rate of 0.0001 and $(\beta_1, \beta_2) = (0.9, 0.999)$.

Villegas et al. (2017b)

A.1.3 QUALITATIVE RESULTS

Short-term prediction [TODO:add the qualitative results on short-term prediction and discussions here.]

Diversity of samples Figure A illustrates the multiple prediction results conditioned on the same context frames. We observe that our model produces diverse and plausible future frames, where such stochasticity mainly stems from the structure generator.

Long-term prediction results Figure B illustrates the prediction results on a very long-term future (over 2500 frames), which corresponds to the Figure 4 in the main paper. We observe that our method generates convincing frames without particular quality degradation and error propagation over a very long-term future. We also observe that the predicted frames contain interesting dance motions, such as the ones with horizontal translation ($t = 1000 - 1040$), dynamics on legs ($t = 500 - 540$) and arms ($t = 2000 - 2040$), *etc*.

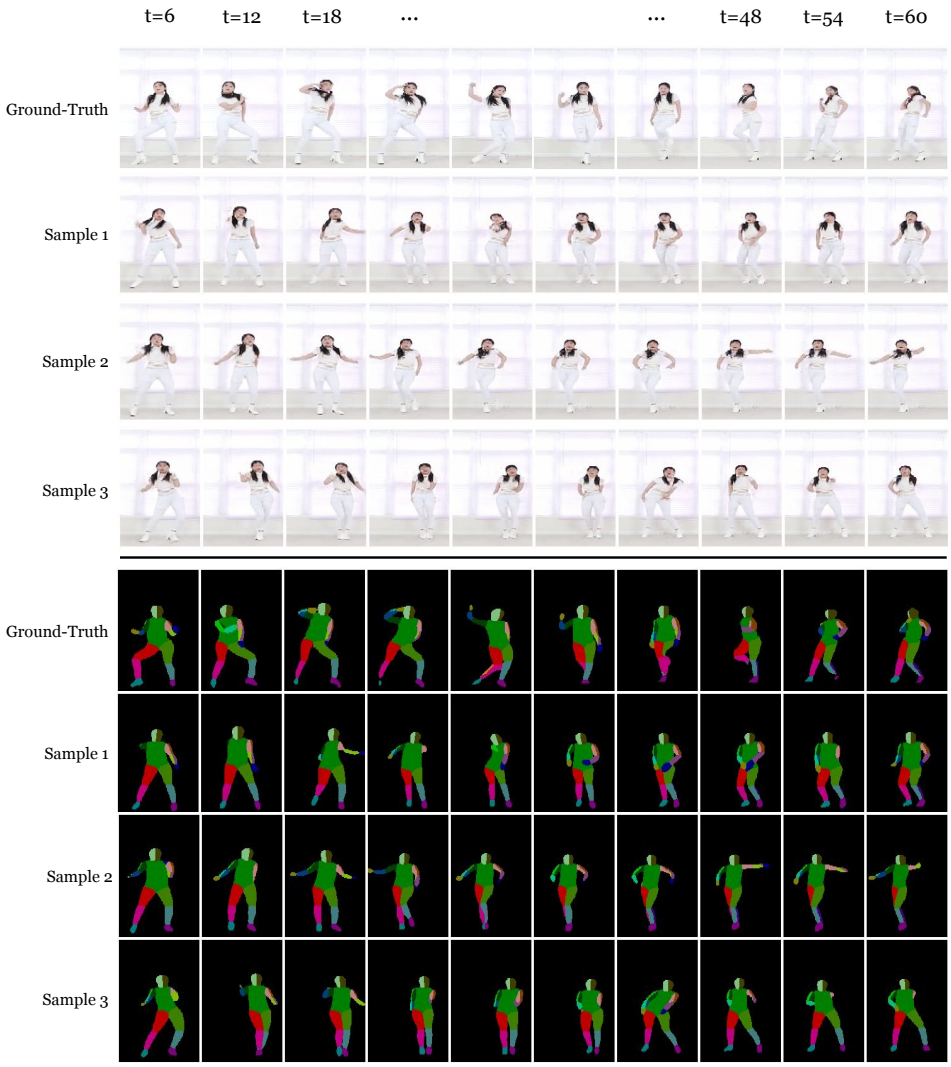

Figure A: Diverse video prediction results on a 128×128 dance sequence. All samples are conditioned on the same context frames.

Figure B: Long-term prediction results on a 128×128 human dancing sequence. Please find the anonymous website to assess the full video.

A.2 KITTI BENCHMARK

A.2.1 DATASET

An ability to cope with partial observability and high stochasticity is highly important in the video prediction task. To evaluate a model under this criterion, we adopt KITTI dataset (Geiger et al., 2013) consisting of driving scenes captured by a front-view camera in residential and rural areas. Since the segmentation labels are available for only a small subset of frames in this dataset (200 frames in total), we extract the labels using the semantic segmentation model (Zhu et al., 2019) pre-trained on still images (Cordts et al., 2016; Geiger et al., 2013) for both training (the entire sequences) and testing (only context frames). We follow the pre-processings and train/test splits used in Lotter et al. (2017), and subsample each sequence by a factor of two.

A.2.2 IMPLEMENTATION DETAILS

SVG-extend (Villegas et al., 2019) The architectural details described in A.1.2 still hold in this dataset.

Bayes-WD-SL (Bhattacharyya et al., 2019)

A.2.3 QUALITATIVE RESULTS

Short-term prediction Figure C illustrates the qualitative comparison for short-term prediction, which correspond to Table 2 in the main paper. As shown in Figure C, SVG performs very well at the very beginning of the prediction ($t = 1 \sim 40$), since it directly exploits the content from the last context frame via temporal skip-connection. However, its prediction quality degrades rapidly through time, as it loses the object structure and simulates arbitrary, unstructured pixel-wise motions in a long-term. The future segmentation baseline (Bayes-WD-SL) preserves much reasonable structure, since its generation is conditioned on the estimated label maps similar to ours. However, it fails to model structures in a *motion* and thus loses such structures at the end. These results demonstrate that both the unsupervised and hierarchical baselines fail to *extrapolate* to the long-term horizon than the one used during the training. Compared to these baselines, our method generates semantically more accurate motions and structures, and substantially outperforms the others especially in the latter prediction steps.

Diversity of samples [TODO:add the qualitative results and discussions here]

Long-term prediction results Figure D illustrates the long-term prediction results over 2500 frames in 25×256 resolution, which corresponds to the Figure 7 in the main paper. We observe that the generated sequences are reasonable in both structure and motion. Interestingly, unrolling the prediction over a very long-term leads to very interesting transitions of the scene, such as translation from suburban ($t < 1035$) to rural areas ($t > 1500$), which cannot be captured in a short-term period. We believe that these results illustrate well why the long-term prediction is important.

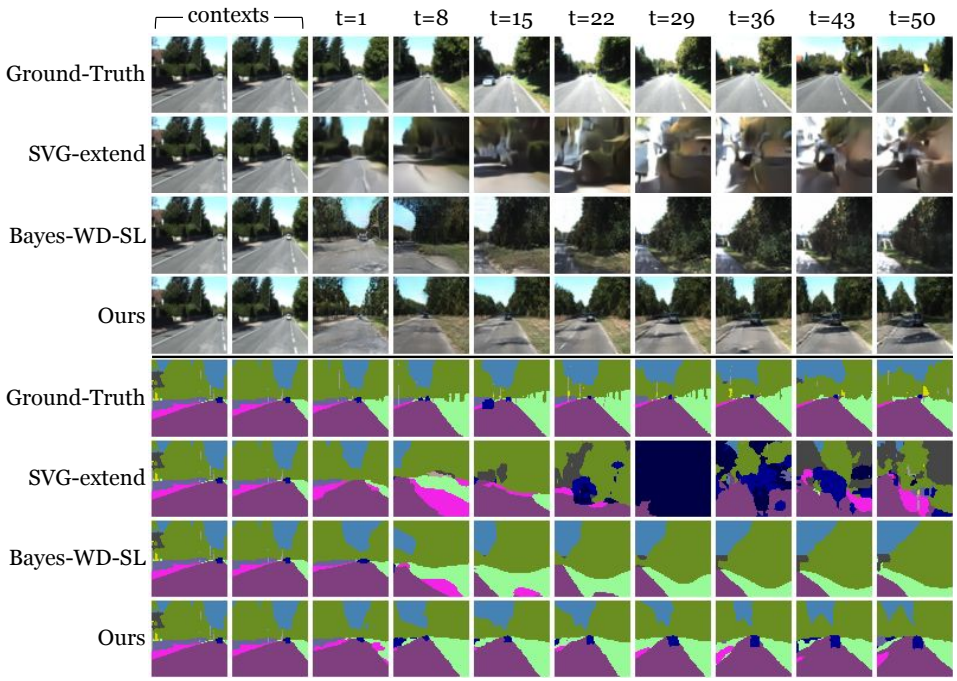

Figure C: Qualitative comparisons of frame-wise video prediction results across models: (top pane) given the same context frames, we sample 100 predictions for each model and show the their best predictions in terms of the cosine similarity metric. (bottom pane) for each best prediction, we show the semantic label maps predicted by pre-trained semantic segmentation network Zhu et al. (2019).

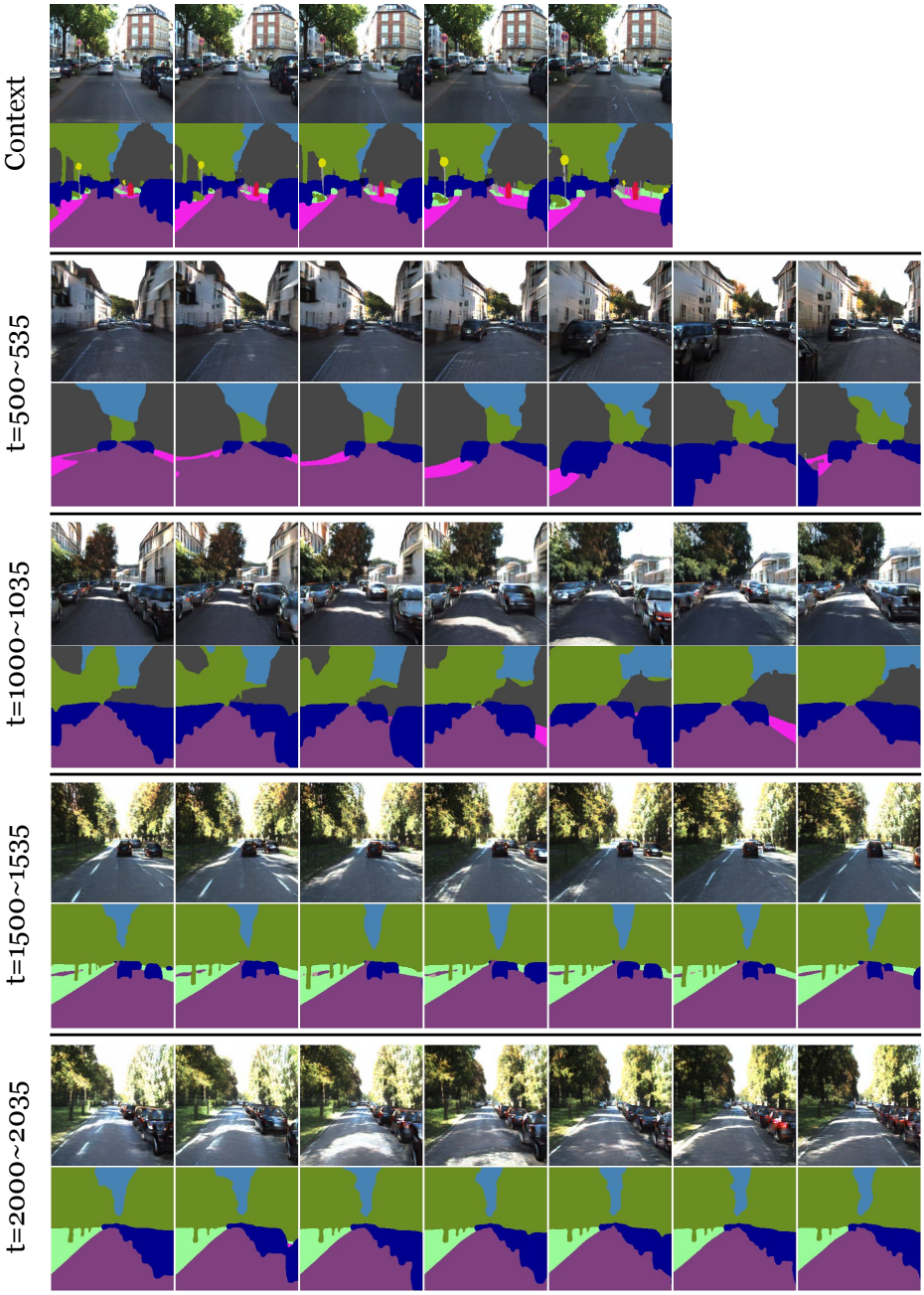

Figure D: Long-term prediction results on a high-resolution KITTI sequence. Both the frames and the label maps are predicted by our method. Our method can generate high-resolution frames (256×256 pixels) into the long-term future without particular quality degradation.

A.3 CITYSCAPES DATASET

A.3.1 DATASET

To evaluate the quality of forecasting dense labels by the structure generator, we employ the Cityscapes (Cordts et al., 2016), a widely-used benchmark in future segmentation tasks. The dataset consists of 2,975 training, 1,525 testing, and 500 validation sequences where each sequence is 30-frame-long and has ground-truth segmentation labels only in the 20th frame. Similar to KITTI dataset, we employ the pre-trained segmentation network (Zhu et al., 2019) to generate segmentation labels for training. Following (Luc et al., 2017; 2018), we subsample frames by a factor of three for each sequence and downsample the frames to 128×256 image resolution.

A.3.2 IMPLEMENTATION DETAILS

S2S (Luc et al., 2017)

F2F (Luc et al., 2018)

A.3.3 QUALITATIVE RESULTS

Qualitative comparison We present the qualitative comparisons of our method to existing future segmentation models, which corresponds to Table 3 in the main paper. As shown in the table, our method outperforms the two baselines in all classes, thanks to its ability to handle highly stochastic nature of complex driving scenes. We also compare qualitative samples of each model in Figure E. As shown in the figure, our model predicts convincing structures and their temporal dynamics are accurate. On the other hand, the two baselines produce blurry predictions, resulting in (1) inaccurate structures (S2S at all timestamps and F2F at 17-29th timestamps), and (2) multiple semantics in a single structure (S2S at all timestamps and F2F at 23-29th timestamps). These blurred prediction problems have been widely observed in the literature and attributed to the inability of deterministic models to handle stochasticity in data Denton & Fergus (2018).

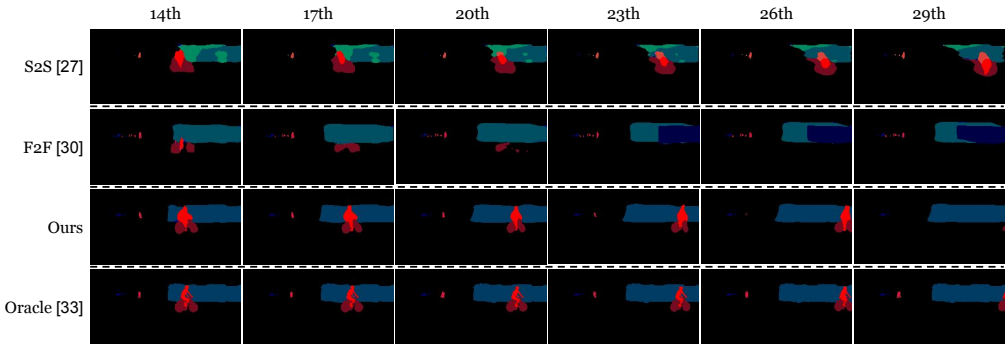

Figure E: Quantitative comparisons of future segmentation models. All models predict structures of moving objects (8 classes) up to 29th frame given 4 context frames (2, 5, 8, and 11th). The oracle is obtained by running the pre-trained segmentation model on the ground-truth frames. The results of compared methods (S2S and F2F) are based on the pre-trained models provided by the authors.

Long-term video prediction Figure F illustrates the qualitative results of video prediction results on Citsycapes dataset. As the Cityscapes contain many occluding objects, we employ the extended structure generator with instance boundary prediction to improve the frame prediction quality. We show in Figure F the predicted sequences up to 96 future frames conditioned on 4 context frames. As shown in the figure, our method can easily incorporate the additional structures (*i.e.,* instance boundary map), and can be generalized to much complex and high-resolution sequences to predict instance-wise structures into the long future without error propagations (*e.g.* blurred predictions in the structure space). On the other hand, we also observe some undesirable biases in the predicted motion dynamics in the structure space, such as static or cyclic motions of the structures (e.g.red dashed boxes in Figure F). We notice that it is because the training sequences in Cityscapes datasets are considerably short (*i.e.,*, 30 frames), which makes the structure generator to favor short-term

dependencies in the prediction (*e.g.*,, short-term skip connections). It leads to biases in the model and artifacts in long-term extrapolation, such as static motions in the distant objects (*e.g.*,, buildings and trees far away from the camera), fixed content (*e.g.*,, repeatedly generated objects), *etc.*, which are not observed in the other datasets with reasonably long training sequences.

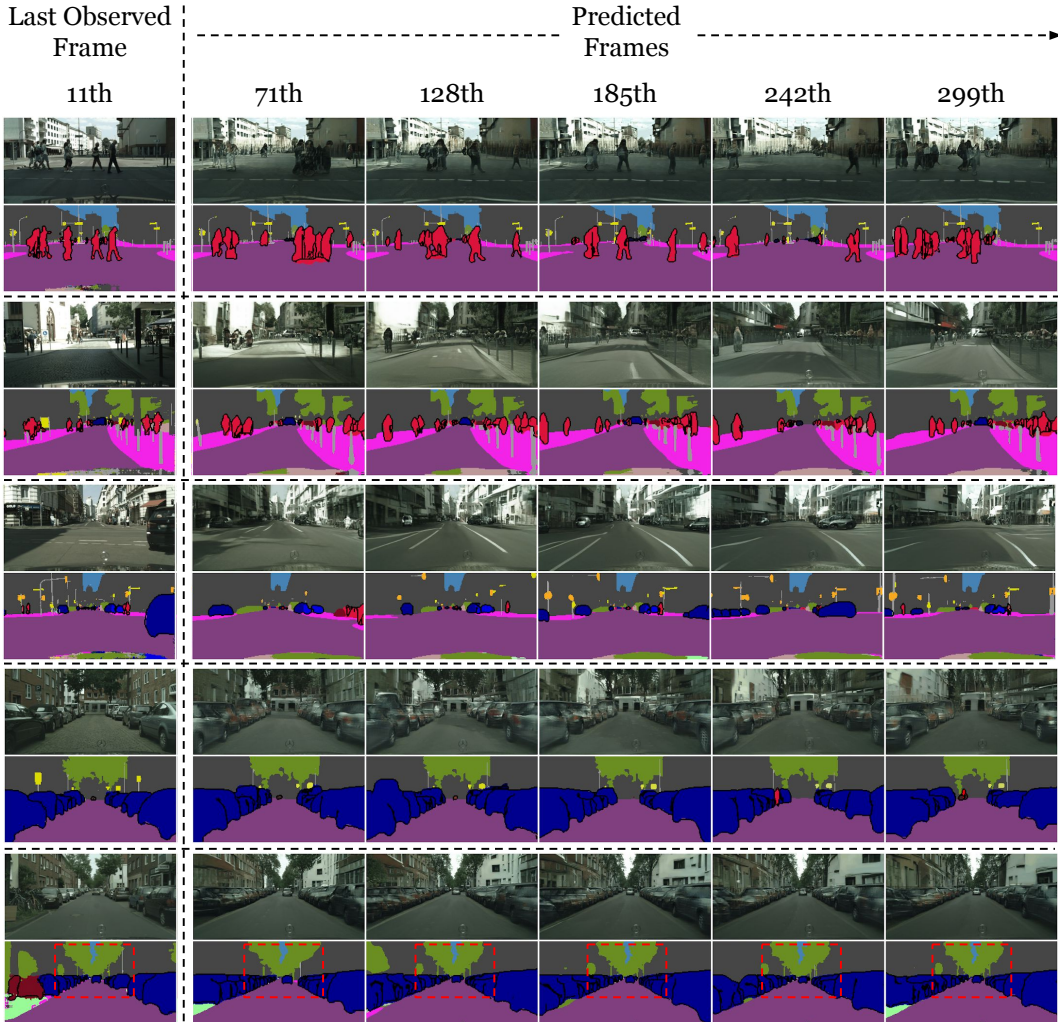

Figure F: Long-term prediction results on 256×512 Cityscapes dataset. We predict 96 future frames (14, 17, $\cdots$, 299th) given 4 context frames. Our structure generator is extended to produce additional instance boundary map for improved instance boundary demarcation in the image generator. Red dashed boxes indicate some biases in the prediction, such as static and cyclic motions in the predicted structures, which are attributed to the short training sequences in the Cityscapes dataset. Please refer to Section 4.4 for the description.

A.4 Evaluation protocols

Short-term prediction Following the previous works, we evaluate the short-term prediction quality by comparing the ground-truth and predicted frames in test videos. We employ three metrics: VGG cosine similarity (CSIM), mean Intersection-over-Union (mIoU), and Fréchet Video Distance (FVD) (Unterthiner et al., 2018). The first metric measures the frame-wise perceptual similarity using VGG features, while the second one measures the structure-level similarity using the label maps extracted by the pre-trained semantic segmentation network (Zhu et al., 2019). To handle stochasticity, we sample 100 predictions for each test clip and report the scores of the best scoring predictions. For the video-level evaluation, we adopt FVD that measures a Fréchet distance between

the ground-truth videos and the generated ones in a video representation space. We use a Inflated 3D Convnet (I3D) (Carreira & Zisserman, 2017) network pre-trained on Kinetics 400 dataset (Carreira & Zisserman, 2017) to obtain representations on videos, and use all 100 predictions to compute FVD against ground-truth sequences.

To evaluate the future segmentation results in Section 4.4,

Long-term prediction To evaluate the shot-wise FVD, we employ the For the models trained on KITTI dataset, we use a ResNet-18 (He et al., 2016) pre-trained on Places 365 (Zhou et al., 2017) to compute the Inception Score. For the models trained on the Human Dancing dataset, we use the Inception V3 (Szegedy et al., 2015) pre-trained on ImageNet (Russakovsky et al., 2015).

B MODEL ARCHITECTURE

In this section, we detail the architectures and hyperparameters used in our experiments.

B.1 SEQUENTIAL DENSE STRUCTURE GENERATOR

For this model, we use the modified version of SVG by *Villegas et al.* Villegas et al. (2019) which was originally proposed by *Denton et al.* Denton & Fergus (2018). The two main differences between the original and the modified version are two-fold: (1) *Villegas et al.* Villegas et al. (2019) use the shallower auto-encoder architecture than *Denton et al.* Denton & Fergus (2018). (2) *Villegas et al.* Villegas et al. (2019) use the Convolutional-LSTM Shi et al. (2015) while *Denton et al.* Denton & Fergus (2018) uses the Fully-Connected-LSTM. These modifications are to increase the capacity of the architecture.

Since the detailed architectural configuration of SVG is not described in Villegas et al. (2019), we summarize our reproduced version of this framework in Table A, B, C, and D. For all experiments on the 64×64 image resolution, we use the same architecture described in the tables. For much higher resolutions (*e.g.* 128×128 and 256×256), we simply stack more convolutional blocks (non-linear convolutional layers followed by upsampling or downsampling layers) in the Encoder and Decoder networks so that the shape of $\mathbf{h}_t, \mathbf{z}_t, \mathbf{g}_t$ is kept to $\mathbb{R}^{128\times8\times8}$ agnostic to the image resolution. For hyperparameters, we use $C = 5$ for KITTI and Human Dancing, and use $C = 4$ for Cityscapes; we set $\beta = 0.0005$; we use ADAM optimizer Kingma & Ba (2015) with the learning rate of 0.0001 and $(\beta_1, \beta_2) = (0.9, 0.999)$. We refer to and modify the publicly available code[1] from *Denton et al.* Denton & Fergus (2018) to reproduce *Villegas et al.* Villegas et al. (2019).

B.2 BOUNARY MAP PREDICTION

When the pre-trained instance-wise segmentation model is available, we can optionally extend the structure generator to jointly predict the object boundary maps. Such structure can add a notion of object instance, and is useful to improve the image generator in sequences with many occluding objects. Let $\mathbf{e}_t \in \{0, 1\}^{W\times H}$ denotes the object boundary map at frame $\mathbf{x}_t$. Then we train the denoising autoencoder G_{edge} to produce edge map of each frames by

$$\hat{\mathbf{e}}_t = G_{\text{edge}}(\mathbf{s}_t). \tag{8}$$

We employed the encoder-decoder network () as the conditional generator, and train it based on adversarial loss by

$$\mathcal{L}_{adv} = \mathbb{E}_{\mathbf{e},\mathbf{s}}[\log D(\mathbf{e}, \mathbf{s})] + \mathbb{E}_{\mathbf{s}}[\log(1 - D(\mathbf{e}, G_{\text{edge}}(\mathbf{s})))] \tag{9}$$

where D is the discriminator. Note that the edge generator in Eq. equation 8 is applied to each frames independently; we observe that adding the predicted boundary map as an input to the structure generator makes the model to be prune to error propagation. The boundary and label maps are then combined as the output of the structure generator $\tilde{\mathbf{s}}_t = [\hat{\mathbf{s}}_t, \hat{\mathbf{e}}_t]$.

[1] https://github.com/edenton/svg

B.3 STRUCTURE-CONDITIONAL PIXEL SEQUENCE GENERATOR

We use Vid2Vid [39] for our structure-conditional pixel sequence generator. For Vid2Vid on KITTI dataset of 64×64 resolution, we reduce the number of downsampling layers in the generator and the scale parameter of the patch discriminator to 1. We use $\tau = 5$ for KITTI and Human Dancing and use $\tau = 4$ for Cityscapes. We use $\tau' = 3$ for all experiments. If not specified otherwise, we do not modify any hyperparameters and simply follow the default settings for the training. We use the publicly available code[2].

Table A: Encoder Architecture.

Input: $\mathbf{s}_t \in \mathbb{R}^{N \times 64 \times 64}$
3×3 Conv 64, ReLU
3×3 Conv 64, ReLU $\rightarrow \mathbf{h}_t^1$
2×2 MaxPool
3×3 Conv 128, ReLU
3×3 Conv 128, ReLU $\rightarrow \mathbf{h}_t^2$
2×2 MaxPool
3×3 Conv 256, ReLU
3×3 Conv 256, ReLU
3×3 Conv 256, ReLU $\rightarrow \mathbf{h}_t^3$
2×2 MaxPool
3×3 Conv 128, ReLU $\rightarrow \mathbf{h}_t$

Table B: Posterior/Prior LSTM Architecture.

Input: $\mathbf{h}_t \in \mathbb{R}^{128 \times 8 \times 8}$
3×3 ConvLSTM 256, 3×3 Conv 256, ReLU $\rightarrow \mu(t), \sigma(t), \mathbf{z}_t \sim \mathcal{N}(\mu(t), \sigma(t)) \in \mathbb{R}^{128 \times 8 \times 8}$

Table C: Predictor LSTM Architecture.

Input: $[\mathbf{h}_t, \mathbf{z}_t] \in \mathbb{R}^{(128+128) \times 8 \times 8}$
3×3 ConvLSTM 256, ReLU
3×3 ConvLSTM 256, ReLU
3×3 Conv 128, ReLU $\rightarrow \mathbf{g}_t \in \mathbb{R}^{128 \times 8 \times 8}$

[2]https://github.com/NVIDIA/vid2vid

Table D: Decoder Architecture.

Input: $\mathbf{g}_t \in \mathbb{R}^{128\times8\times8}$
2×2 NN Upsample $\rightarrow \mathbf{g}_t^3$
Concatenate($\mathbf{g}_t^3, \mathbf{h}_t^3$)
3×3 Conv 256, ReLU
3×3 Conv 256, ReLU
3×3 Conv 128, ReLU
2×2 NN Upsample $\rightarrow \mathbf{g}_t^2$
Concatenate($\mathbf{g}_t^2, \mathbf{h}_t^2$)
3×3 Conv 128, ReLU
3×3 Conv 64, ReLU
2×2 NN Upsample $\rightarrow \mathbf{g}_t^1$
Concatenate($\mathbf{g}_t^1, \mathbf{h}_t^1$)
3×3 Conv 64, ReLU
3×3 Conv 3, LogSoftmax $\rightarrow \hat{\mathbf{s}}_t$