A. Introduction

In the main paper we have introduced RIVER- a new model and an efficient training procedure to perform video prediction based on Flow Matching and randomized past frame conditioning. This supplementary material provides details that could not be included in the main paper due to space limitations. In section B we describe in details the architecture of our model and how we trained it on different datasets. In section C we show the training curve of the model and in section D we conduct an analysis on the training time and memory consumption and compare with that of other methods. In section F we provide more samples generated with our model.

B. Architecture and Training Details

Autoencoder. In this section we provide the configurations of the VQGAN [9] for all the datasets used in the main paper (see Table 5). All models were trained using the code from the official taming transformers repository.¹

Vector Field Regressor. In this section we provide implementation details of the network that regresses the conditional time-dependent vector field \( v_t(x | x_{t-1}, x^c, \tau - c) \). As mentioned in the main paper, the network is implemented as a U-ViT [4]. The detailed architecture is provided in Figure 10 and is shared across all datasets. First, the inputs \( x, x_{t-1} \) and \( x^c \) are channel-wise concatenated and linearly projected to the inner dimension of the ViT blocks. Besides in and out projection layers, the network consists of 13 standard ViT blocks with 4 long skip connections between the first 4 and the last 4 blocks. At each skip connection the inputs are channel-wise concatenated and projected to the inner dimension of the ViT blocks. All ViT blocks apply layer normalization [1] before the multihead self-attention [23] (MHSA) layer and the MLP. The inner dimension of all ViT blocks is 768 and 8 heads are used in all MHSA layers.

All models are trained for 300K iterations with the AdamW [17] optimizer with the base learning rate equal to \( 10^{-4} \) and weight decay \( 5 \cdot 10^{-6} \). A learning rate linear warmup for 5K iterations is used along with a square root decay schedule. For the CLEVRER [28] dataset, random color jittering is additionally used to prevent overfitting. We observed that without it, the objects may change colors in the generated sequences (see Figure 12). In all experiments we used \( \sigma_{\text{min}} = 10^{-7} \).

Additionally, we would like to highlight once again that the excellent tradeoff of RIVER demonstrated in Figure 1 of the main paper is the motivation to use flow matching instead of diffusion. Flow matching exhibits faster convergence compared to diffusion models. Moreover, on BAIR we observed DDPM fail to converge (see Figure 11). Besides this, the same theoretical arguments used by the authors of flow matching in the case of images can be extended to the case of videos.

C. Training Curve

In Figure 9 we show the FVD [22] and PSNR of RIVER trained on CLEVRER [28] against the iteration time. As we can see, the training is stable and more iterations lead to better results.
Table 5. Configurations of VQGAN [9] for different datasets. Notice that on the CLEVRER [28] dataset we did not utilize an adversarial training.

|                  | BAIR64×64 [8] | BAIR256×256 [8] | KTH [20] | CLEVRER [28] |
|------------------|---------------|-----------------|---------|-------------|
| embed_dim        | 4             | 8               | 4       | 4           |
| n_embed          | 16384         | 16384           | 16384   | 8192        |
| double_z         | False         | False           | False   | False       |
| z_channels       | 4             | 8               | 4       | 4           |
| resolution       | 64            | 256             | 64      | 128         |
| in_channels      | 3             | 3               | 3       | 3           |
| out_ch           | 3             | 3               | 3       | 3           |
| ch               | 128           | 128             | 128     | 128         |
| ch_mult          | [1, 2, 2, 4]  | [1, 1, 2, 2, 4] | [1, 2, 2, 4] | [1, 2, 2, 4] |
| num_res_blocks   | 2             | 2               | 2       | 2           |
| attn_resolutions | [16]          | [16]            | [16]    | [16]        |
| dropout          | 0.0           | 0.0             | 0.0     | 0.0         |
| disc_conditional | False         | False           | False   | -           |
| disc_in_channels | 3             | 3               | 3       | -           |
| disc_start       | 20k           | 20k             | 20k     | -           |
| disc_weight      | 0.8           | 0.8             | 0.8     | -           |
| codebook_weight  | 1.0           | 1.0             | 1.0     | -           |

Figure 10. Architecture of the vector field regressor of RIVER. “ViT block” stands for a standard self-attention block used in ViT [7], that is an MHSA layer, followed by a 2-layer wide MLP, with a layer normalization before each block and a skip connection after each block. “Out projection” involves a linear layer, followed by a GELU [12] activation, layer normalization and a 3×3 convolutional layer.

D. Training Time and Memory Consumption

In Table 6, we compare the total training time and GPU (or TPU) memory requirements of different models trained on BAIR64×64 [8]. As we can see, RIVER is extremely efficient and can achieve a reasonable FVD [22] with significantly less compute than the other methods. For example, SAVP [16], which has the same FVD as RIVER, requires 4.6× more compute (measured by Mem×Time) and all the models that take less compute than RIVER have FVDs more than 250.

E. Sampling Speed

In this section we provide more comparisons in terms of the sampling speed with different models. We test the models on the BAIR 64×64 dataset, generating 16 frames and measuring the time the generation required. For evaluation we compare to some diffusion-based models with available code (RaMVd [13], MCVD [24]). In addition, we pick one RNN-based model (SRVP [11]) and one Transformer-based (LVT [19]), to cover different model architectures. The results are reported in Figure 13. Due to the sparse past frame conditioning, RIVER is able to generate videos with reasonable sampling time. However, if the focus is on the
| Method                | Memory (GB) | Time (Hours) | Mem×Time (GB×Hour) | FVD [22] |
|----------------------|-------------|--------------|---------------------|----------|
| RVD [27]             | 24          | -            | -                   | 1272     |
| MoCoGAN [21]         | 16          | 23           | 368                 | 503      |
| SVG-FP [6]           | 12          | 24           | 288                 | 315      |
| CDNA [10]            | 10          | 20           | 200                 | 297      |
| SV2P [2]             | 16          | 48           | 768                 | 263      |
| SRVP [11]            | 36          | 168          | 6048                | 181      |
| VideoFlow [14]       | 128         | 336          | 43008               | 131      |
| LVT [19]             | 128         | 48           | 6144                | 126      |
| SAVP [16]            | 32          | 144          | 4608                | 116      |
| DVD-GAN-FP [5]       | 2048        | 24           | 49152               | 110      |
| Video Transformer(S) [25] | 256       | 33           | 8448                | 106      |
| TriVD-GAN-FP [18]    | 1024        | 280          | 286720              | 103      |
| CCVS(Low res) [15]   | 128         | 40           | 5120                | 99       |
| MCVD(spatin) [24]    | 86          | 50           | 4300                | 97       |
| Video Transformer(L) [25] | 512       | 336          | 172032              | 94       |
| FitVid [3]           | 1024        | 288          | 294912              | 94       |
| MCVD(concat) [24]     | 77          | 78           | 6006                | 90       |
| NUWA [26]            | 2560        | 336          | 860160              | 87       |
| RaMViD [13]          | 320         | 72           | 23040               | 83       |
| RIVER                | 25          | 25           | 625                 | 106      |

Table 6. Compute comparisons. We report the memory and training times requirements of different models trained on BAIR64×64 [8]. The overall compute (Mem × Time) shows that RIVER delivers better FVD with much less compute.

F. Qualitative Results

Here we provide more visual examples of the sequences generated with RIVER. See Figures 15 and 17 for results on the BAIR [8] dataset, Figures 14 and 16 for results on the KTH [20] dataset and Figures 18 and 20 for video prediction and planning on the CLEVRER [28] dataset respectively. Besides this, we highlight the stochastic nature of the generation process with RIVER in Figure 19 and the impact of extreme (s > 0.5) warm-start sampling strength in Figure 21. For more qualitative results and visual comparisons with the prior work, please, visit our website https://araachie.github.io/river.

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Figure 12. A sequence generated with RIVER trained on the CLEVRER dataset without data augmentation. Notice how the color of the grey cylinder changes after its interaction with the cube. In order to prevent such behaviour, both the autoencoder and RIVER are trained with random color jittering as data augmentation. The first frame can be played as a video in Acrobat Reader.

Figure 13. FVD vs. inference speed, the time required to generate a 16 frames long 64×64 resolution video on a single Nvidia GeForce RTX 3090 GPU. The sizes of the markers are proportional to the standard deviation of measured times in 20 independent experiments.

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Figure 14. Video prediction on the KTH dataset. Odd rows show frames of the original video. Even rows show the video generated by RIVER when fed the context frames of the row above (GT). We observe that RIVER is able to generate sequences with diversity and realism. The images in the first column after the bold vertical line can be played as videos in Acrobat Reader.

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Figure 15. Video prediction on the BAIR dataset at $256 \times 256$ resolution. The model predicts the future frames conditioned on a single initial frame. The frames in the first column after the bold vertical line can be played as videos in Acrobat Reader.
Figure 16. Failure cases on the KTH dataset. A common failure mode is when a certain action gets confused with another one, which results in a motion that morphs into a different one. In all examples the model is asked to predict 25 future frames given the first 5. The images in the first column after the bold vertical line can be played as videos in Acrobat Reader.

Figure 17. Failure case on the BAIR dataset. A common failure mode emerges when generating longer sequences and is when the interaction causes objects to change their class, shape or even to disappear. The images in the first column after the bold vertical line can be played as videos in Acrobat Reader.
Figure 18. Video prediction on the CLEVRER dataset. In order to predict the future frames, the model conditions on the first 2 frames. Only the last context frame is shown. The model succeeds to predict the motion that was observed in the context frames. However, it cannot predict new objects as in the ground truth and introduces random new objects due to the stochasticity of the generation process. The images in the first column after the bold vertical line can be played as videos in Acrobat Reader.

Figure 19. Two sequences generated with RIVER trained on the CLEVRER dataset. The model was asked to predict 19 frames given 1. Note the very different fates of the blue cube in these two sequences. The images in the first column can be played as videos in Acrobat Reader.
Figure 20. Visual planning with RIVER on the CLEVRER dataset. Given the source and the target frames, RIVER generates intermediate frames, so that they form a plausible realistic sequence. The images in the first column can be played as videos in Acrobat Reader.

Figure 21. The effect of extreme ($s = 0.5$) warm-start sampling strength. The first frame in each row can be played as a video in Acrobat Reader.