

Lumiere: A Space-Time Diffusion Model for Video Generation

Authors: Bar-Tal et al.

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Outline

- Motivation
- Method
- Evaluations
- Applications
- Societal Impact
- Limitations
- Conclusion

Motivation

- ▶ Restricted capability of existing models
 - ▶ Sensitive to error
 - ▶ Suffers from memory and computing constraints
 - ▶ Obtaining large-scale data is cumbersome
 - ▶ Training large-scale T2V is challenging

Motivation

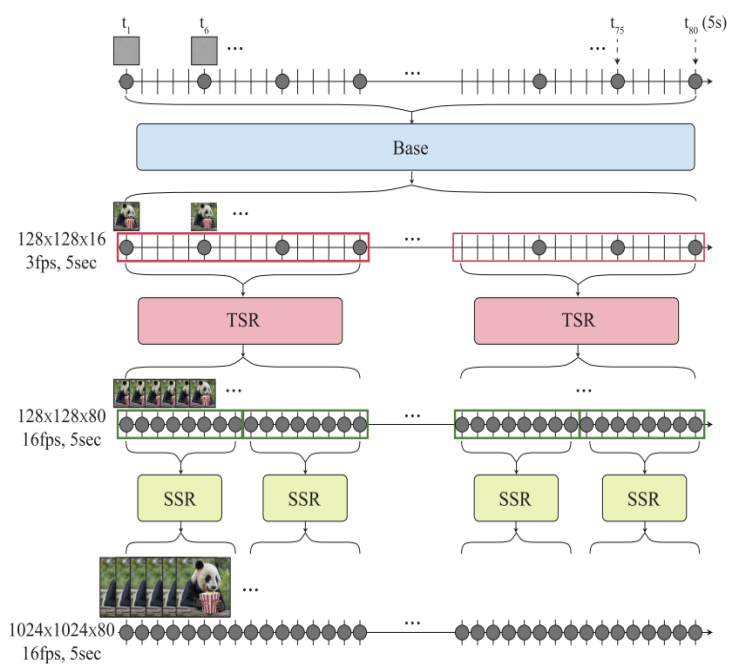
- ▶ Employing temporal cascades is hindersome
 - ▶ Generates aggressively sub-sampled set of keyframes
 - ▶ TSR modules are constrained to fixed, small temporal context
 - ▶ Cascaded training suffers from domain gap

Method - Lumiere

- ▶ Utilizes Diffusion Probabilistic Models
 - ▶ Through denoising steps, trained to approximate data distribution
 - ▶ Starting from noise, a clean sample is drawn from the targeted distribution
- ▶ Incorporates additional guiding signals

Method - Pipeline

(a) Common Approach with TSR model(s)

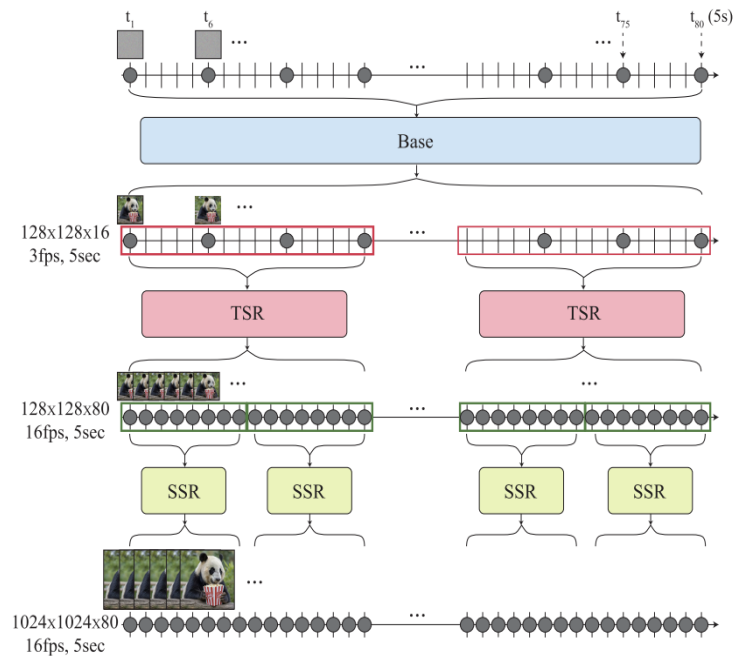


Common T2V Framework:

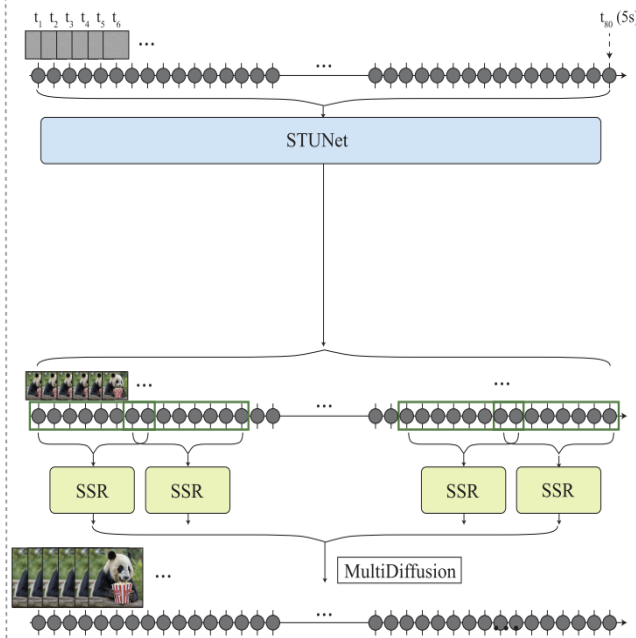
- Base Model
- Temporal Super-resolution Model (TSR)
- Spatial Super-resolution Model (SSR)

Method - Pipeline

(a) Common Approach with TSR model(s)



(b) Our Approach

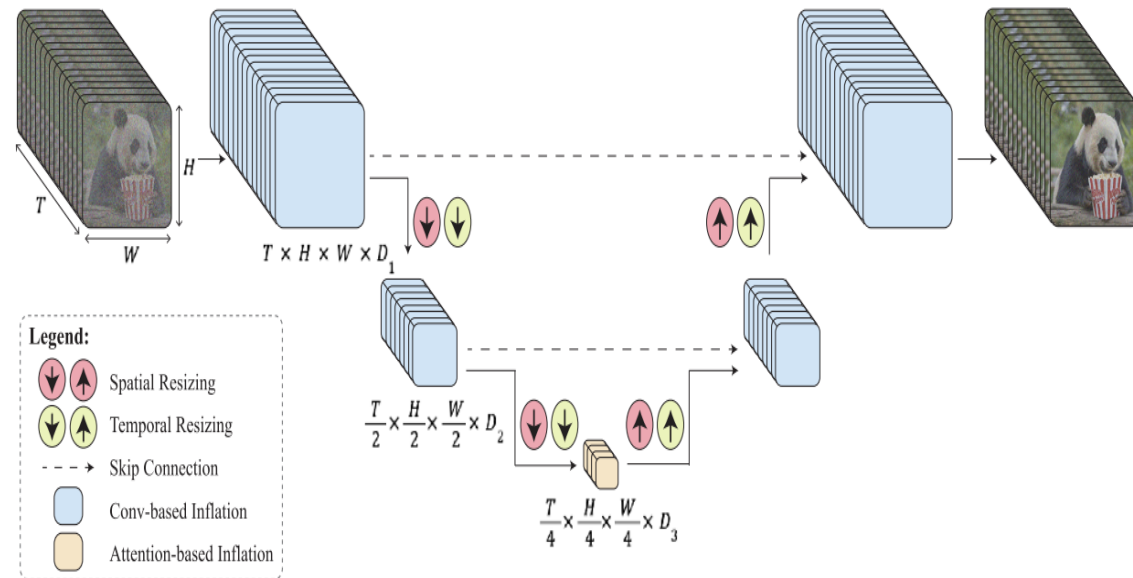


Lumiere Framework:

- Base Model
- Spatial Super-resolution Model (SSR)
- Multidiffusion

Method - STUnet

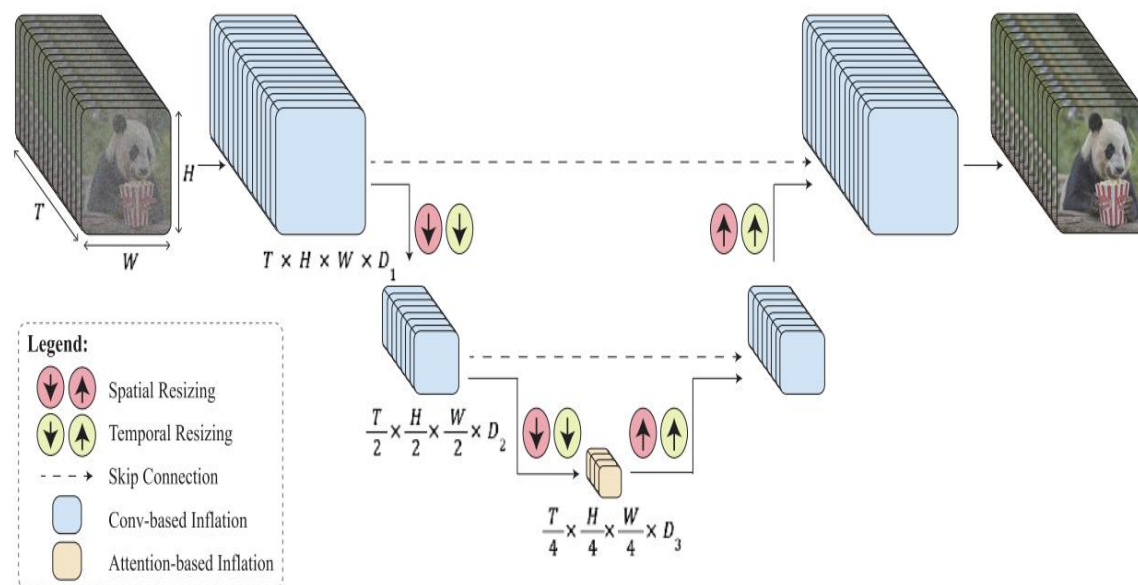
(a) Space-Time UNet (STUnet)



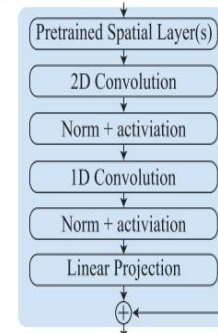
Employs traditional U-Net Model

Method - STUnet

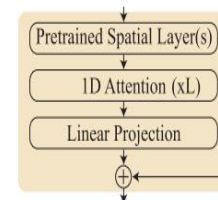
(a) Space-Time UNet (STUnet)



(b) Convolution-based Inflation Block

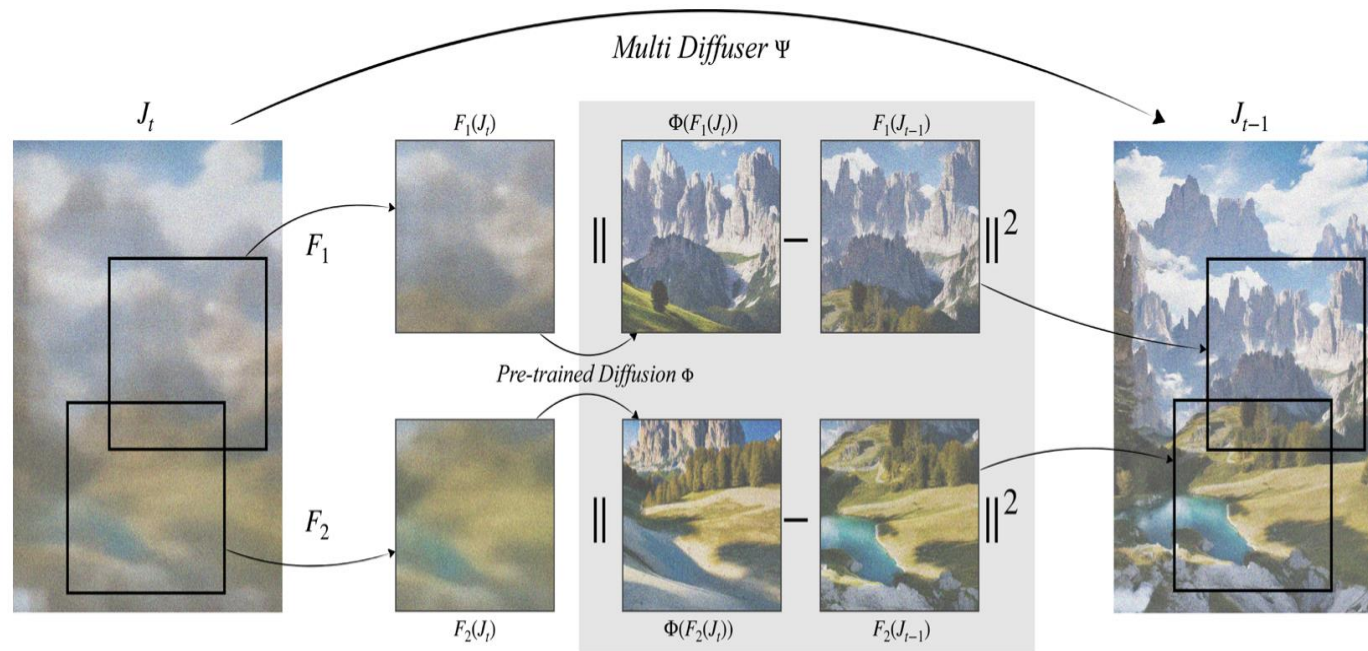


(c) Attention-based Inflation Block



- Interleave temporal blocks to T2I Architecture
- Trains only new parameters
- Performs identity Initialization
- Low computational Overhead

Method - Multidiffusion



Multidiffusion Framework:

- New generation process from a pre-trained model
- Fuses inconsistent directions into one global denoising step

SSR with Multidiffusion

- ▶ An inflated SSR network can only operate on short videos
- ▶ Employ multidiffusion for smooth temporal transition
- ▶ Multidiffusion prevents temporal artifacts
 - ▶ Resolved by linearly combining video segments

SSR with Multidiffusion

Mathematically:

- ▶ At each generation step:
 - ▶ split noisy input video $J \in \mathbb{R}^{H \times W \times T \times 3}$ into $1 \dots N$ overlapping segments
 - ▶ Where $J_i \in \mathbb{R}^{H \times W \times T' \times 3}$ is the i^{th} segment
 - ▶ Temporal duration: $T' < T$
- ▶ To reconcile per-segment SSR predictions:

$$\arg \min_{J'} \sum_{i=1}^n \|J' - \Phi(J_i)\|^2.$$

Evaluation Setup

- ▶ Train T2V model on 30M videos with text prompts
 - ▶ Videos are 80 frames long at 16 fps
 - ▶ 109 text prompts
 - ▶ Base model dimension: 128 x 128 frames
 - ▶ SSR dimension: 1024 x 1024 frames

Zero-shot on UCF-101

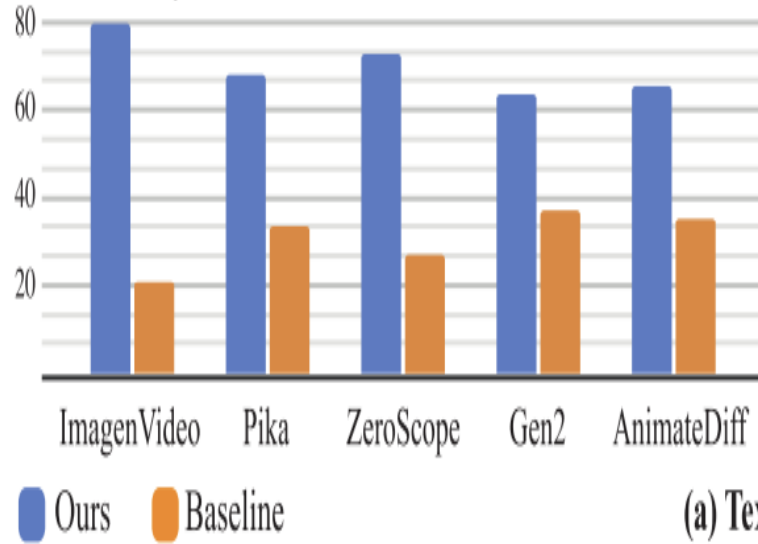
Method	FVD ↓	IS ↑
MagicVideo (Zhou et al., 2022)	655.00	-
Emu Video (Girdhar et al., 2023)	606.20	42.70
Video LDM (Blattmann et al., 2023b)	550.61	33.45
Show-1 (Zhang et al., 2023a)	394.46	35.42
Make-A-Video (Singer et al., 2022)	367.23	33.00
PYoCo (Ge et al., 2023)	355.19	47.76
SVD (Blattmann et al., 2023a)	242.02	-
Lumiere (Ours)	332.49	37.54

User Study

- ▶ Two-alternative Forced Choice protocol Adopted
 - ▶ Randomly ordered pairs of videos are provided
 - ▶ 400 user judgments obtained
 - ▶ 109 prompts were utilized
 - ▶ Fixed random seed
 - ▶ Spatial and Temporal alignment

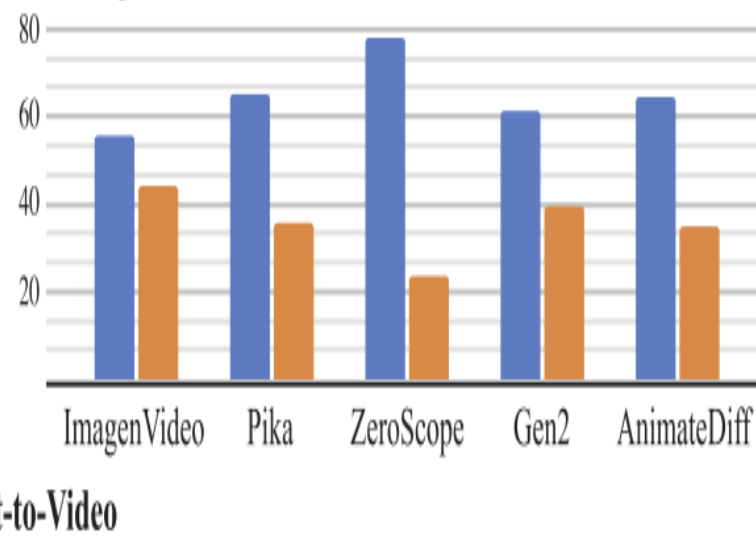
User Study

Video Quality

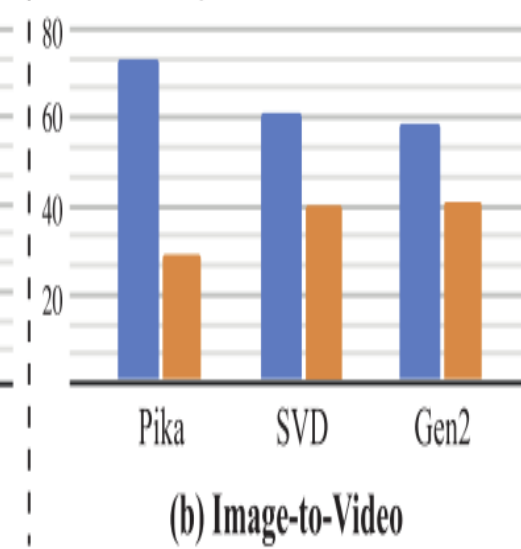


(a) Text-to-Video

Text Alignment



Video Quality



(b) Image-to-Video

User Study

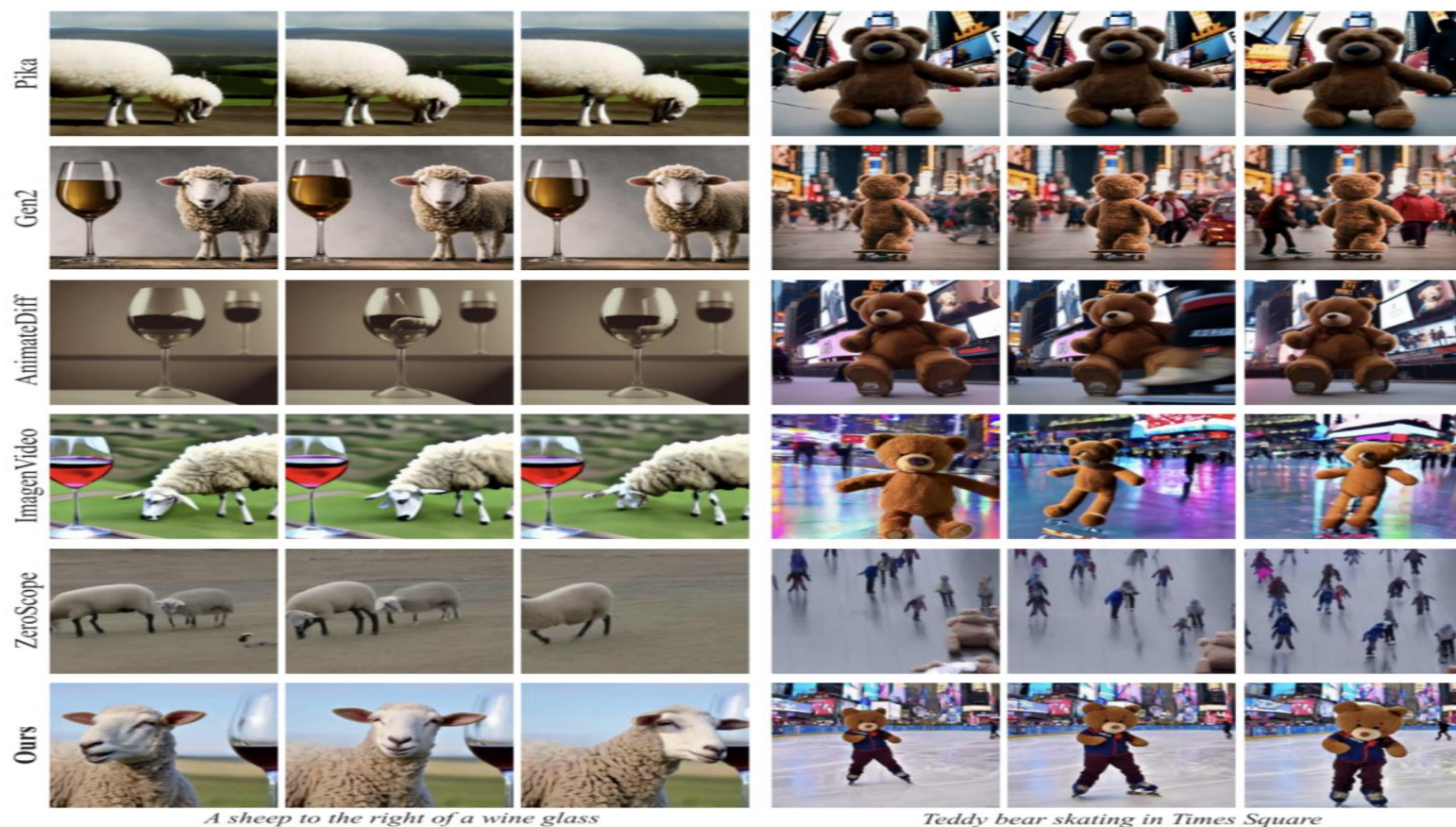
Left video



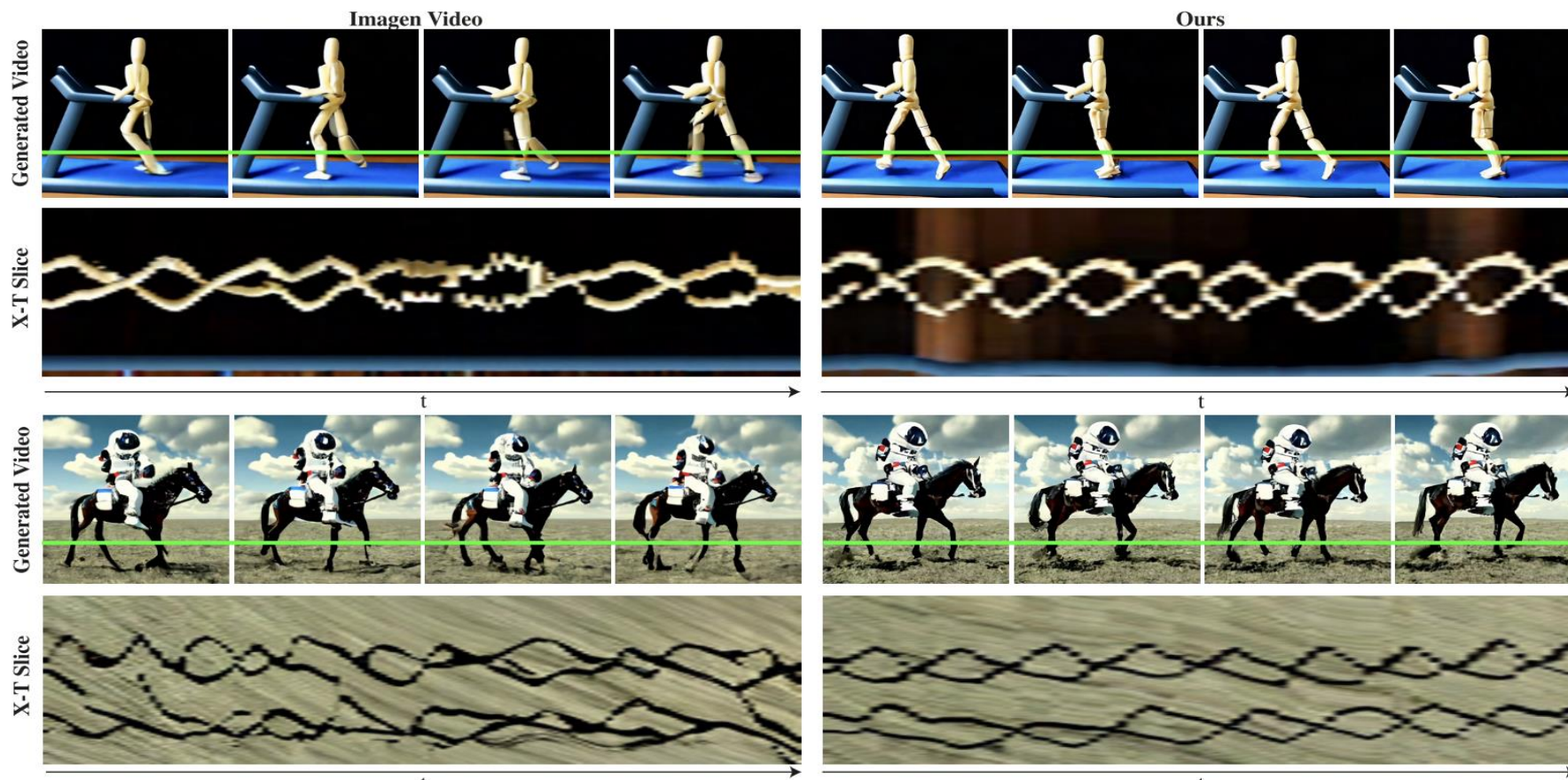
Right video



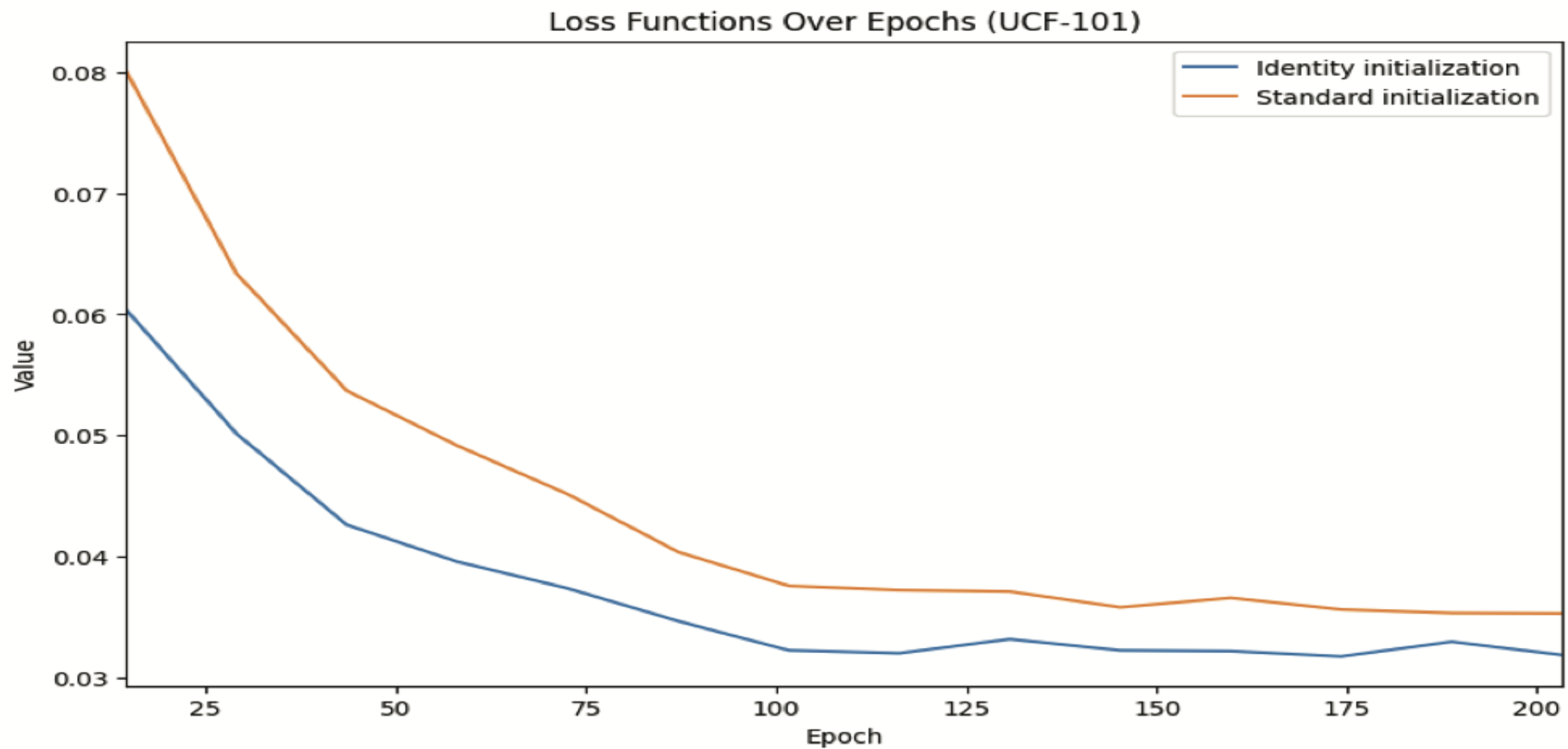
Qualitative Evaluation



Temporal Consistency



Ablation - Initialization



Visualize Initialization Schemes

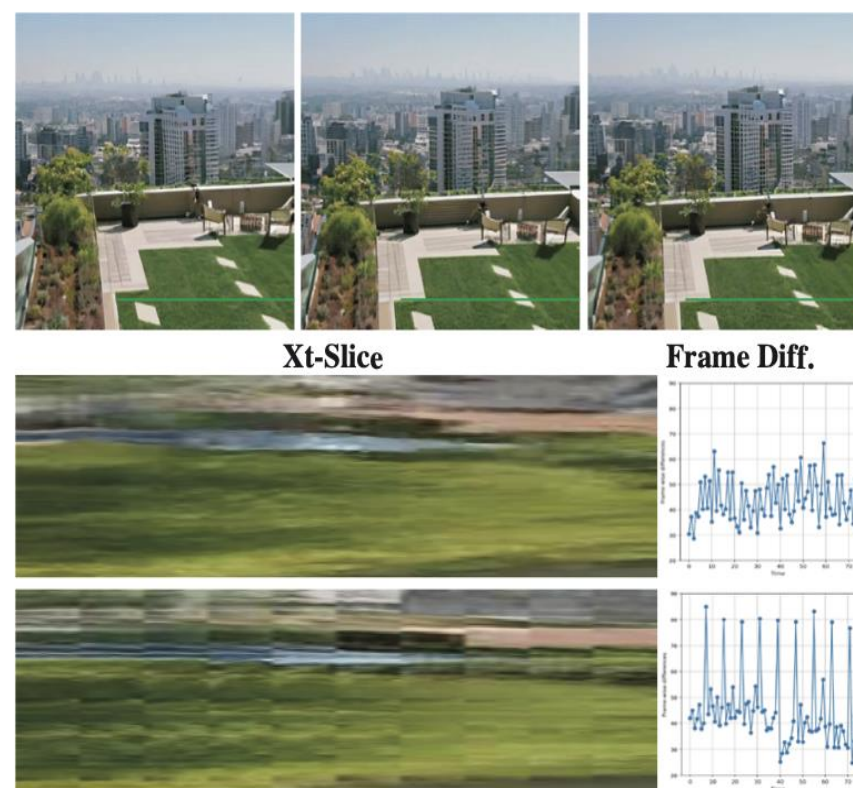
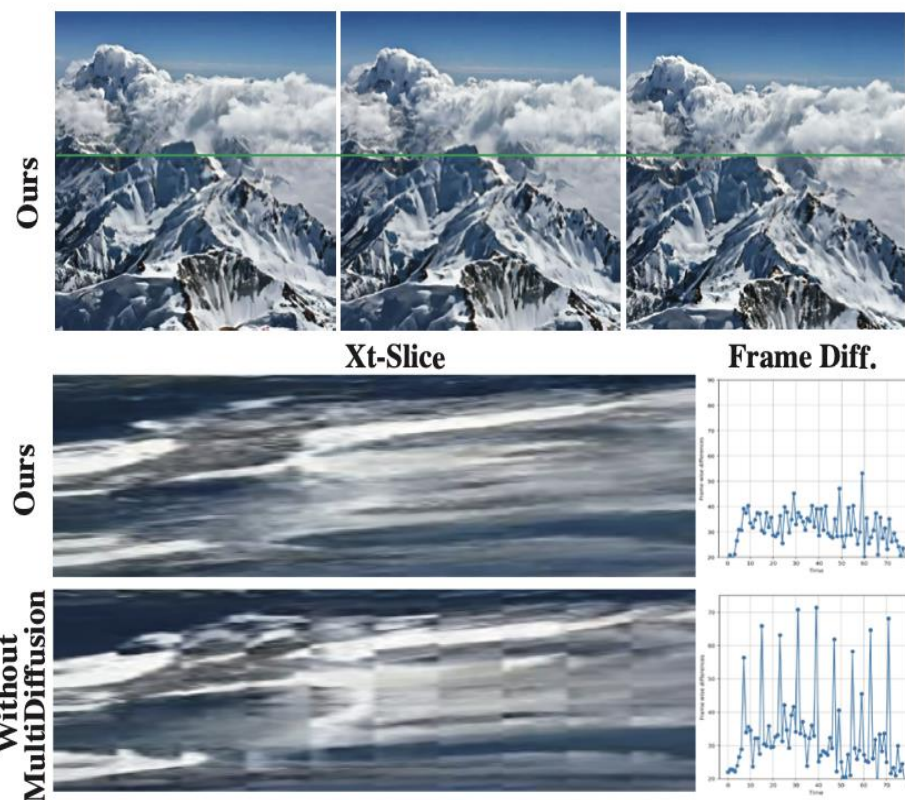
Standard



Identity



Ablation - Multidiffusion



Applications – Video Editing



Original Video



Generated Video

Application – Stylized Generation

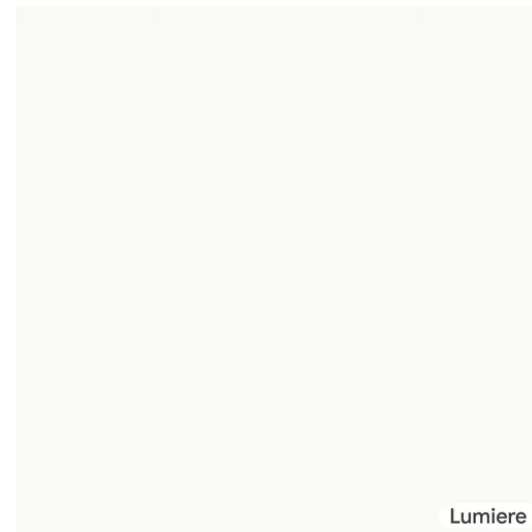
- ▶ Pre-trained T2I weights remain fixed
- ▶ Newly added temporal layers are trained
- ▶ Linear interpolation between fixed and fine-tuned T2I weights
 - ▶ $W_{interpolate} = \alpha \cdot W_{style} + (1 - \alpha) \cdot W_{orig}$
 - ▶ Where $\alpha \in [0.5, 1]$

Application – Stylized Generation

Vector art styles



Reference Image



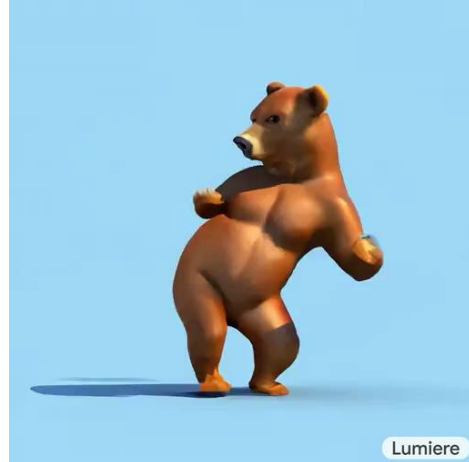
Output

Application – Stylized Generation

Realistic styles



Reference Image



Output

Application – Conditional Generation

- ▶ Model conditioned on additional input signals
 - ▶ Noisy video $J \in \mathbb{R}^{H \times W \times T \times 3}$
 - ▶ Text prompt
 - ▶ Masked conditioning video $C \in \mathbb{R}^{H \times W \times T \times 3}$
 - ▶ Binary Mask $M \in \mathbb{R}^{H \times W \times T \times 1}$
- ▶ Concatenated Tensor $\langle J, C, M \rangle = \mathbb{R}^{T \times H \times W \times 7}$

Application – Image to Video



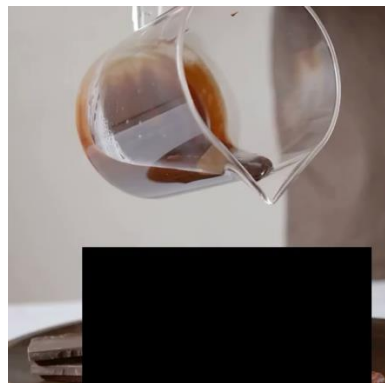
Application - Inpainting



Video + Mask



Output



Application - Cinemagraphs



Source Image + Mask



Output



Societal Impact

- ▶ Risk of misuse
 - ▶ Tools for detecting biases and malicious use cases
 - ▶ To ensure safe and fair use

Limitations

- ▶ The model cannot generate videos
 - ▶ Multiple shots
 - ▶ Transition between scenes
- ▶ The model operates in pixel space

Conclusion

- ▶ Presents a novel T2V framework
 - ▶ Built on a pre-trained T2I model
 - ▶ Introduces space-time U-Net Architecture
 - ▶ Utilizes Multidiffusion framework
- ▶ Demonstrates state-of-the-art generation results
- ▶ Showcases applicability to various downstream tasks



Thank you