AiDD

2024 AI+研发数字峰会

AI+ Development Digital summit

AI驱动研发变革 促进企业降本增效

北京站 08/16-17

基于物理条件约束的可信视觉生成大模型

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演讲嘉宾

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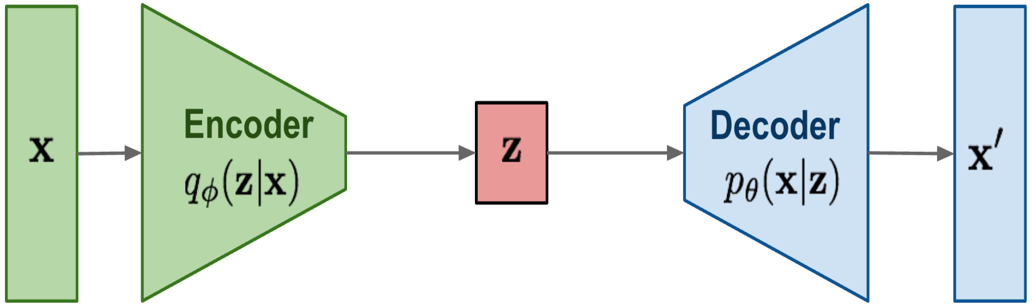
复旦大学人工智能创新与产业研究院研究员，长聘正教授，博士生导师。朱思语本科毕业于浙江大学，博士毕业于香港科技大学。在博士阶段，作为联合创始人创立了3D视觉公司Altizure，并后来被苹果公司收购。2017年至2023年，在阿里云人工智能实验室担任总监。2023年起，任职于复旦大学人工智能创新与产业研究院，担任研究员和博士生导师。朱思语的主要研究方向包括视频和三维生成式模型，涉及基于视觉的三维和视频的重建、生成、理解、方针和模拟。他发表了60余篇高水平会议和期刊论文，包括CVPR、ICCV、ICLR和TPAMI等计算机视觉和机器学习领域，包括Hallo, Champ, AnimateAnything等有一定行业影响力的视频生成大模型。在40余个计算机视觉国际比赛和榜单上取得第一名。

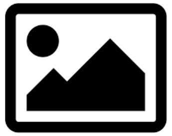
Visual generative model

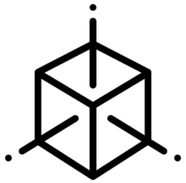
Input

VAE: maximize variational lower bound



Output

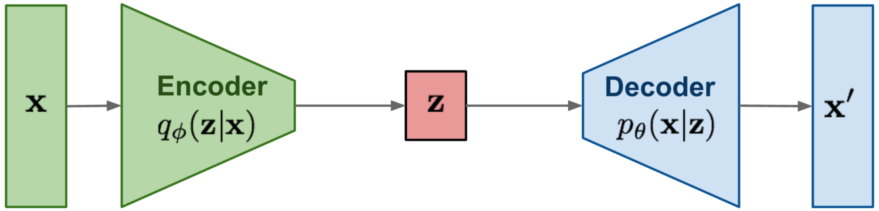




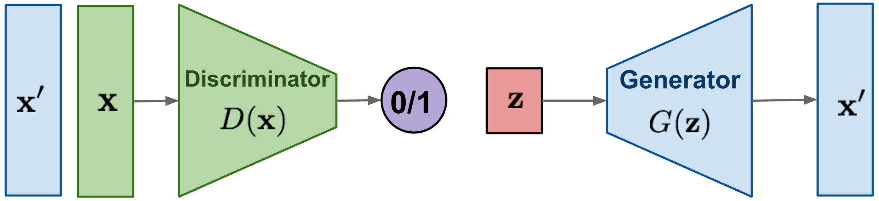
Video generative methods

- The field of video generation has seen rapid development, reaching several milestones...

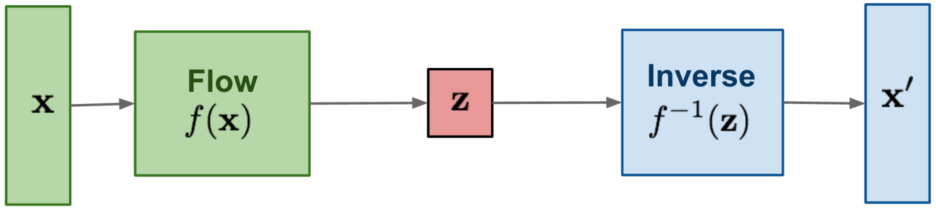
VAE: maximize variational lower bound



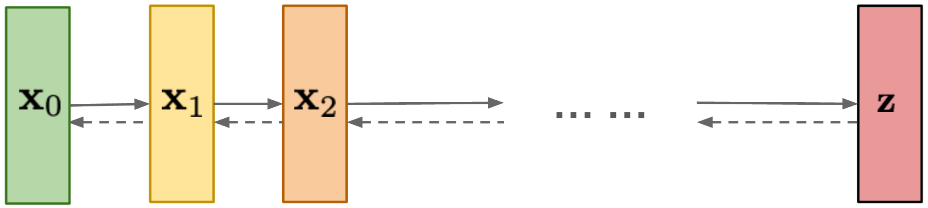
GAN: Adversarial training



Flow-based models: Invertible transform of distributions

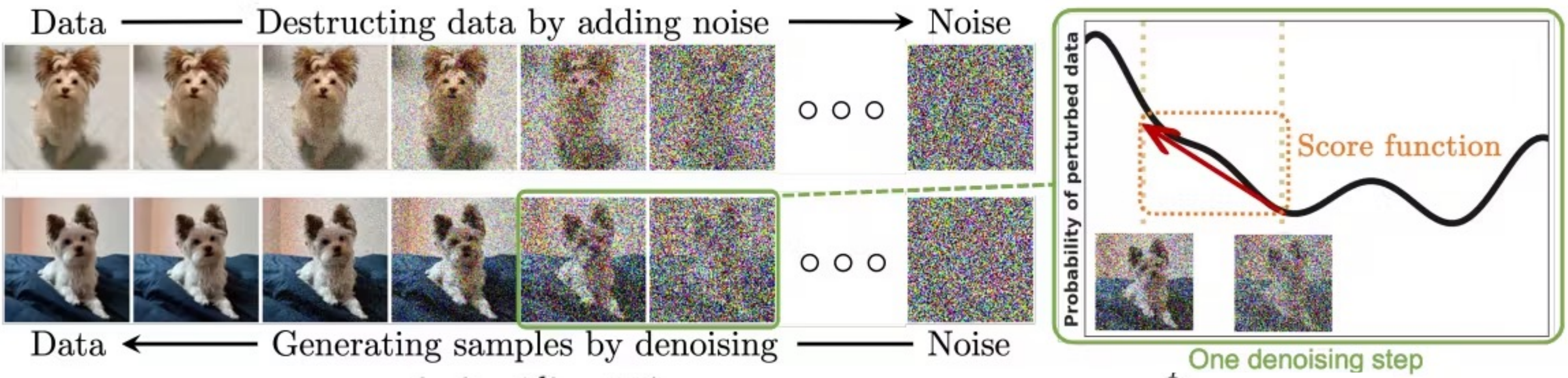


Diffusion models: Gradually add Gaussian noise and then reverse



Diffusion for visual generation (1)

- Denoising Diffusion Probabilistic Models (DDPMs)



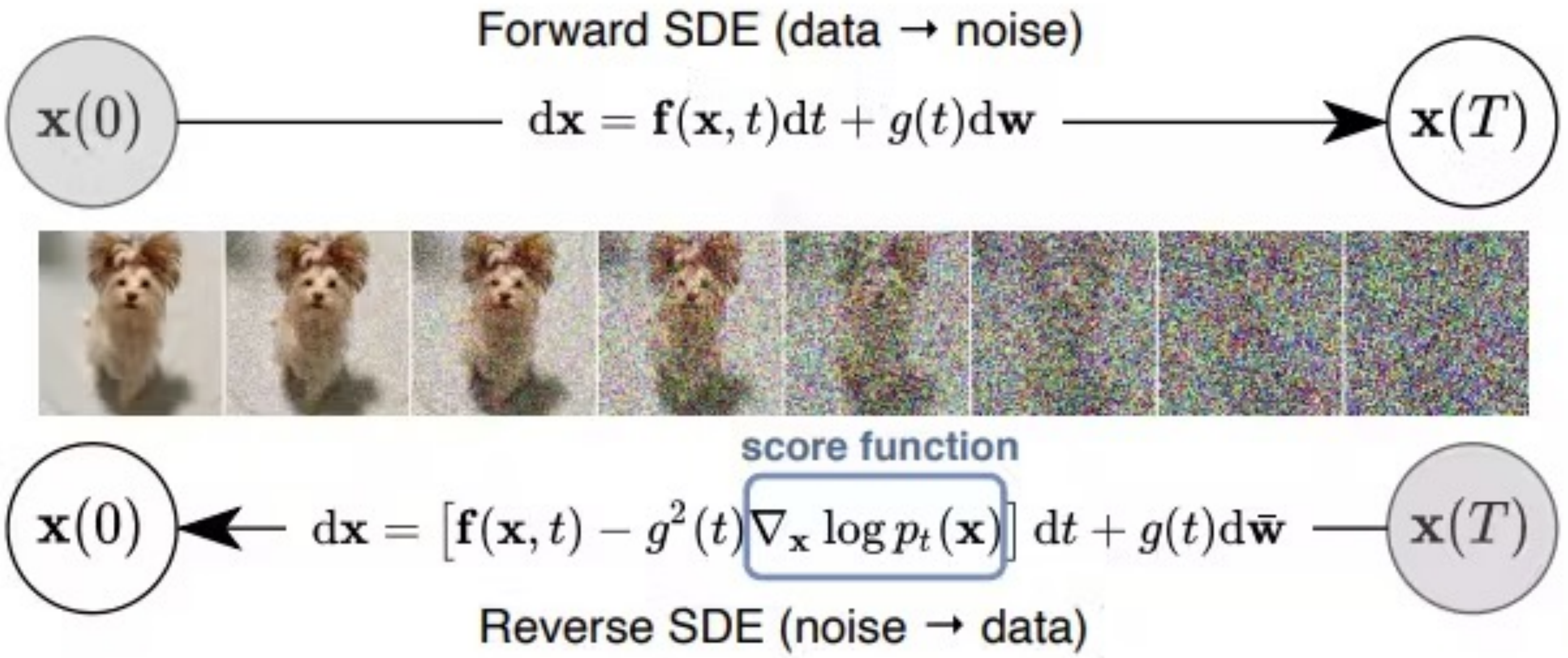
$$p(\mathbf{x}_T) = \mathcal{N}(\mathbf{x}_T; \mathbf{0}, \mathbf{I})$$

$$p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \underbrace{\mu_\theta(\mathbf{x}_t, t)}_{\substack{\text{Trainable network} \\ \text{(U-net, Denoising Autoencoder)}}}, \sigma_t^2\mathbf{I})$$

$$\Rightarrow \quad p_\theta(\mathbf{x}_{0:T}) = p(\mathbf{x}_T)\prod_{t=1}^{T} p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)$$

Diffusion for visual generation (2)

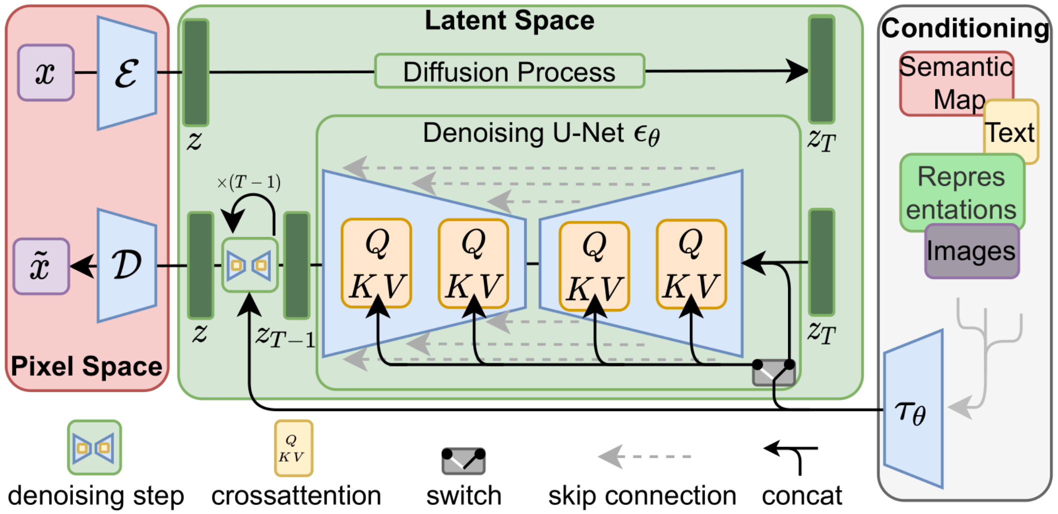
- Stochastic Differential Equations (Score SDEs)

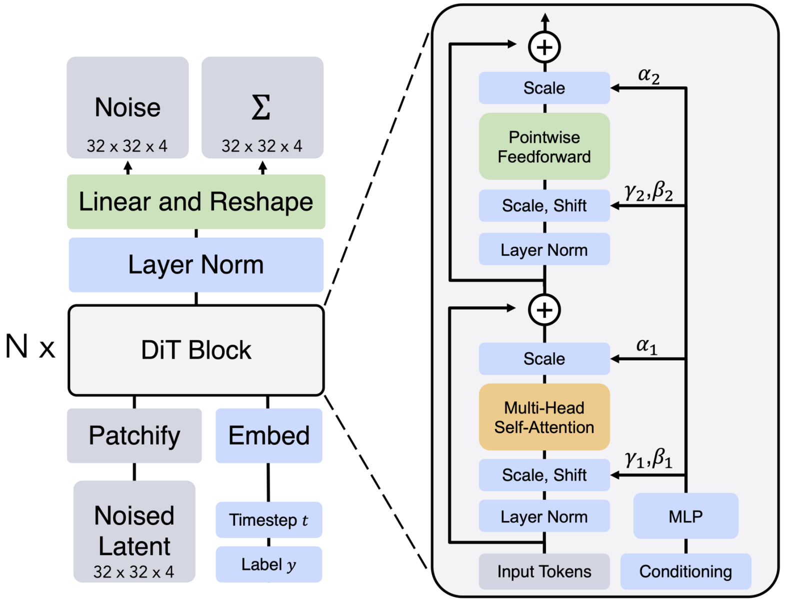


Key Elements of visual Diffusion Models

- Pixel diffusion (original input)
- Latent space diffusion

- Unet
- Transformer





Latent Diffusion Transformer

DiT Block with adaLN-Zero

Sora, breakthrough

- **<u>Consistency</u>**: consistency in 3D rendering, long-range coherence, and object permanence.
- **<u>High fidelity</u>**.
- **<u>Surprising length</u>**: extended video length capability (Sora: 1 minute vs. previous systems: seconds).
- **<u>Flexible resolution</u>**: generation of videos across various durations, aspect ratios, and resolutions.

Sora, key technologies

- The **DiT** framework by Meta (2022.12) is designed for video processing.
- Google's **MAGViT** (2022.12) focuses on Video Tokenization.
- Google DeepMind introduced **NaViT** (2023.07) to support various resolutions and aspect ratios.
- OpenAI's **DALL-E 3** (2023.09) enhances Video Caption generation for improved conditioned video creation.

Modeling the physical world

- We know that it is very complicated real physical model.

probabilistic

- bayesian inference;
- probabilistic graphical models.

deterministic

- mathematical equations;
- physics based simulation;
- control theory.

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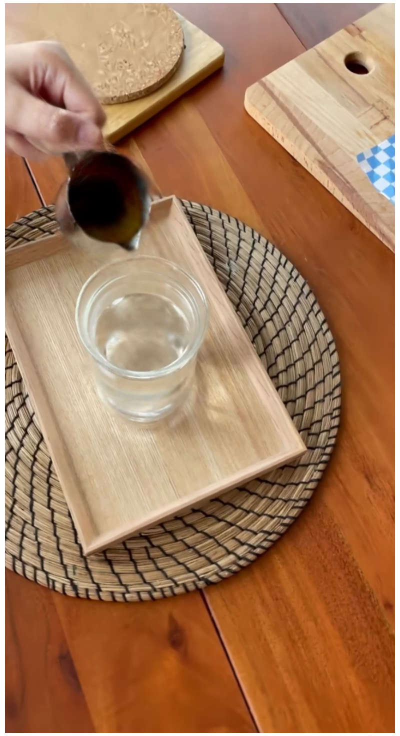
Key elements of a physical world

- Given a Sora demo (the walking woman in the Tokyo street), the key elements of a physical world, in the graphical way...

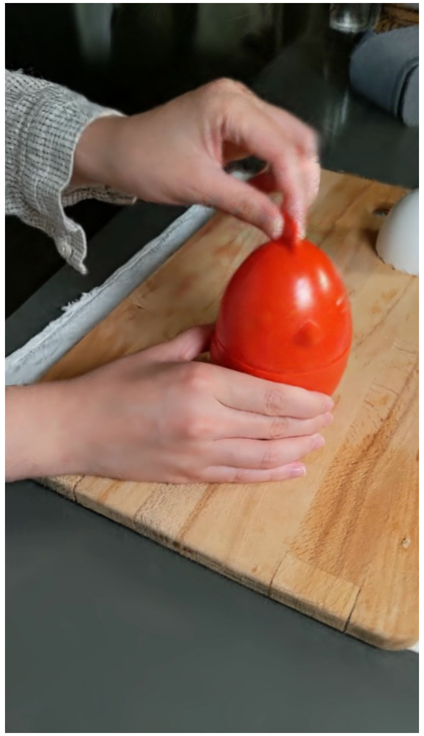
- Appearance
- Geometry
- Lighting
- Motion & Animation
- Audio

Modeling the physical world

- [CVPR] Gaussian-Flow: 4D Reconstruction with Dynamic 3D Gaussian Particle



Espresso



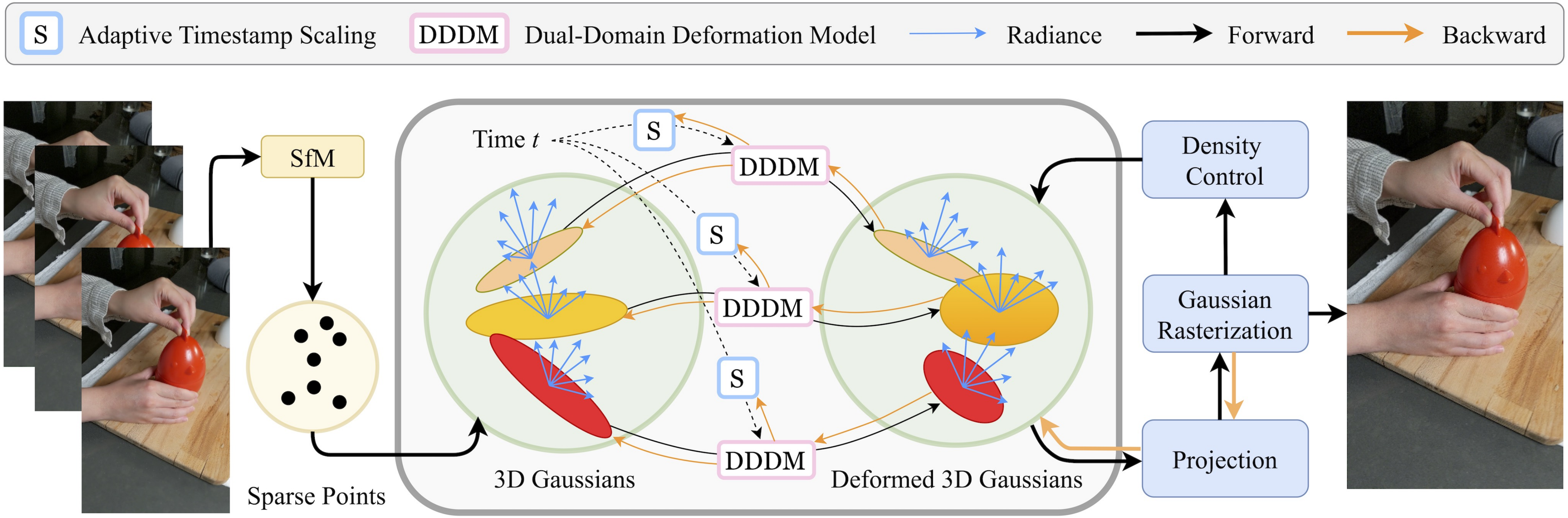
Chick-Chicken

Split-Cookie

Flame-Steak

Modeling the physical world

- [CVPR] Gaussian-Flow: 4D Reconstruction with Dynamic 3D Gaussian Particle



It is hard to model the physical world

- In fact, the world is hard to model in a **probablistic** way.
- Sora resource consumption...
  - 1 billions of images;
  - 1 millions of hours of video data;
  - 10 trillions tokens after tokenizing images and videos
  - Training with ~5,000 A100s in parallel.

It is hard to model the physical world

- Sora failure case in geometry and appearance.

It is hard to model the physical world

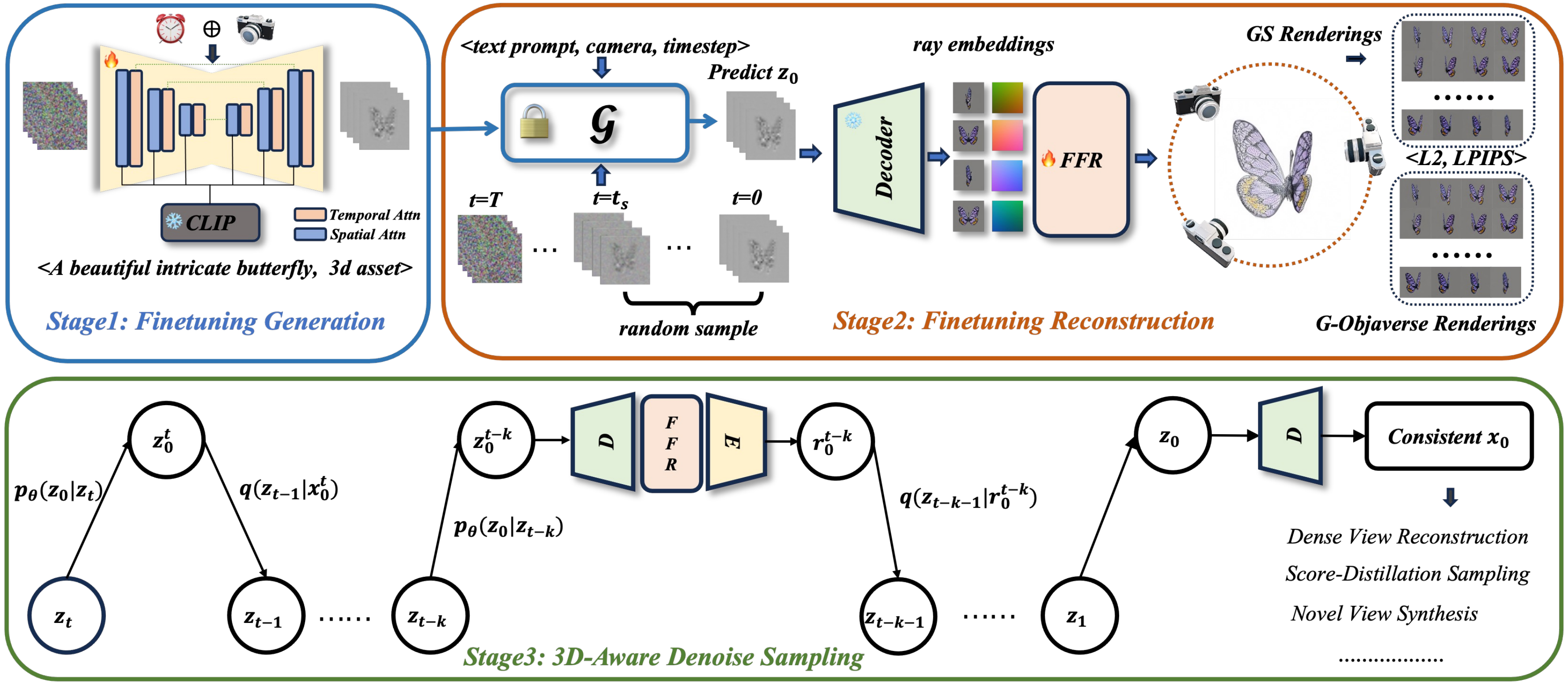
- Sora failure case in lighting.

It is hard to model the physical world

- Sora failure case in motion and animation.

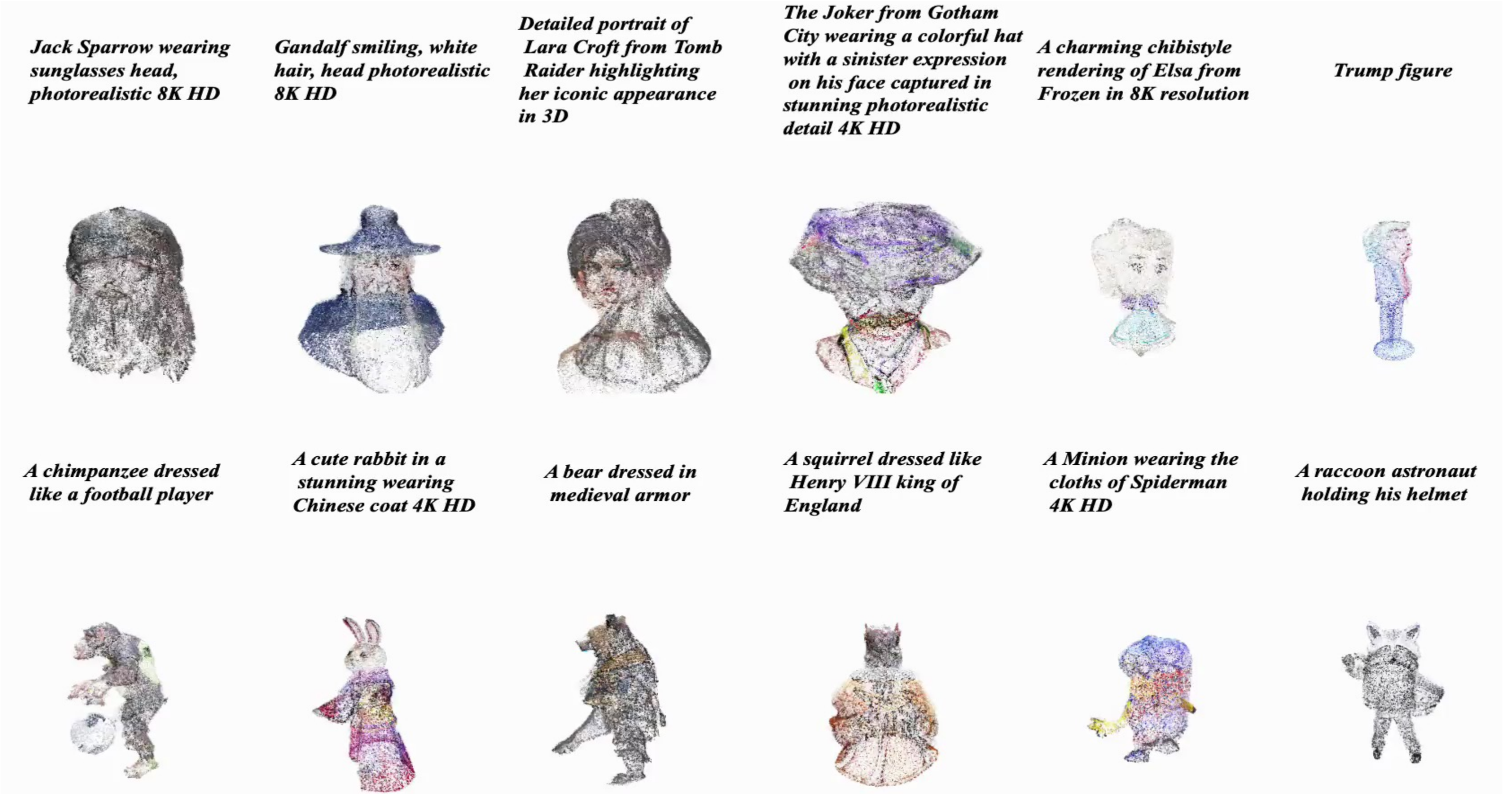
It is hard to model the physical world

- VideoMV: Consistent Multi-View Generation Based on Large Video Generative Model
- Geometric enhancement is still needed for multi-view images.



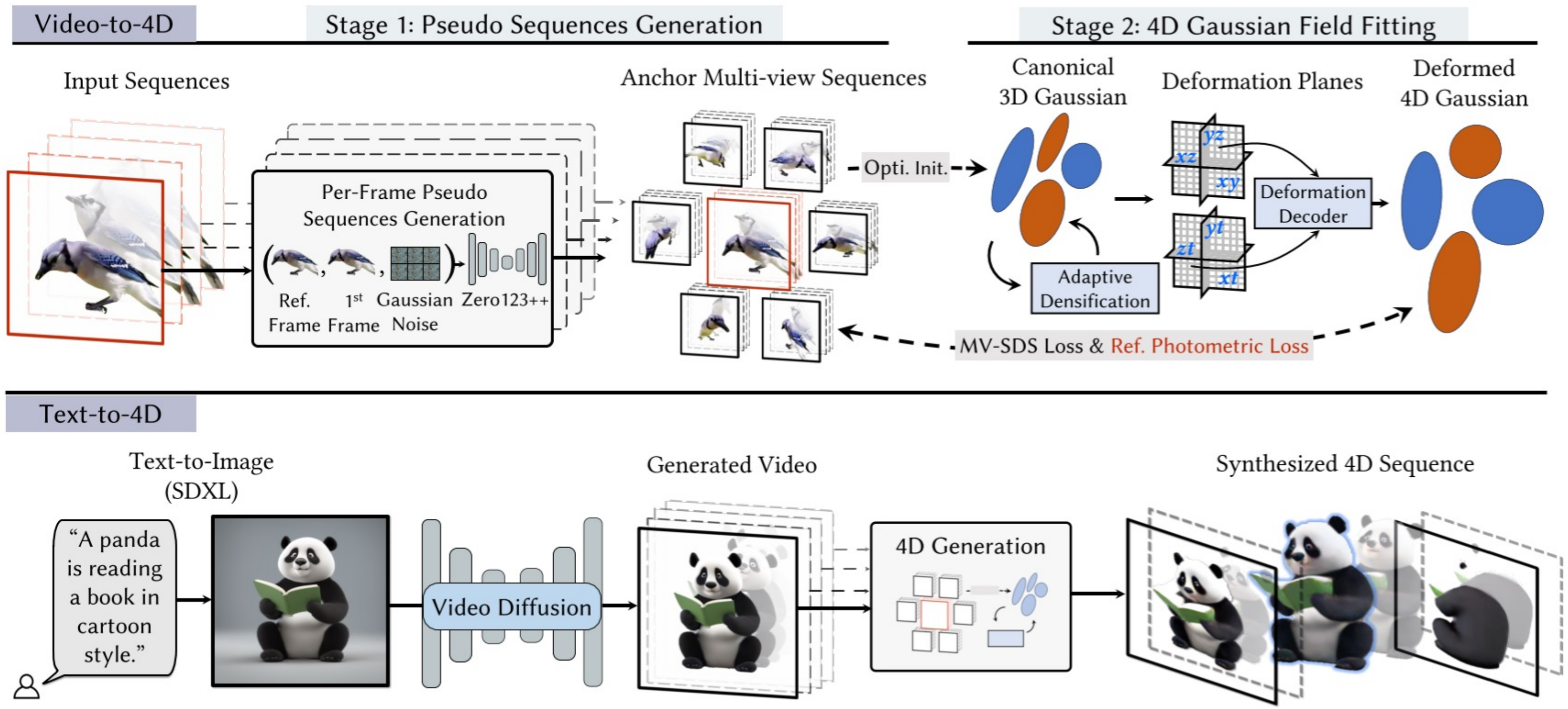
It is hard to model the physical world

- VideoMV: Consistent Multi-View Generation Based on Large Video Generative Model
- From a **static** aspects, SVD is able to model multi-view images.



It is hard to model the physical world

- Stag4D: Spatial-Temporal Anchored Generative 4D Gaussians
- From a temporal aspects...



It is hard to model the physical world

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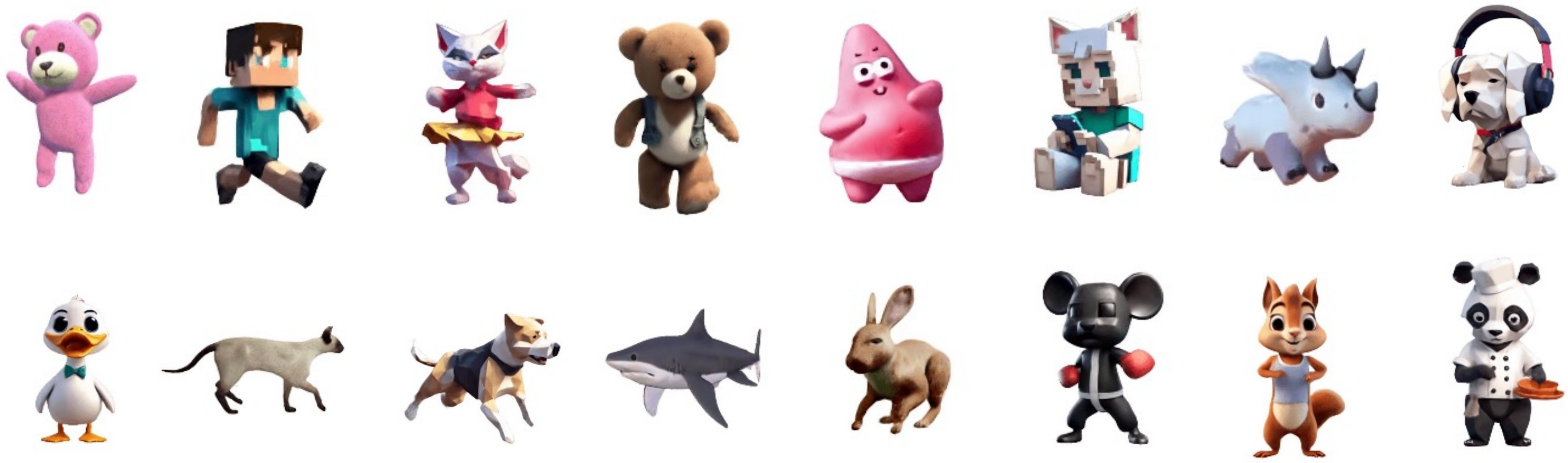
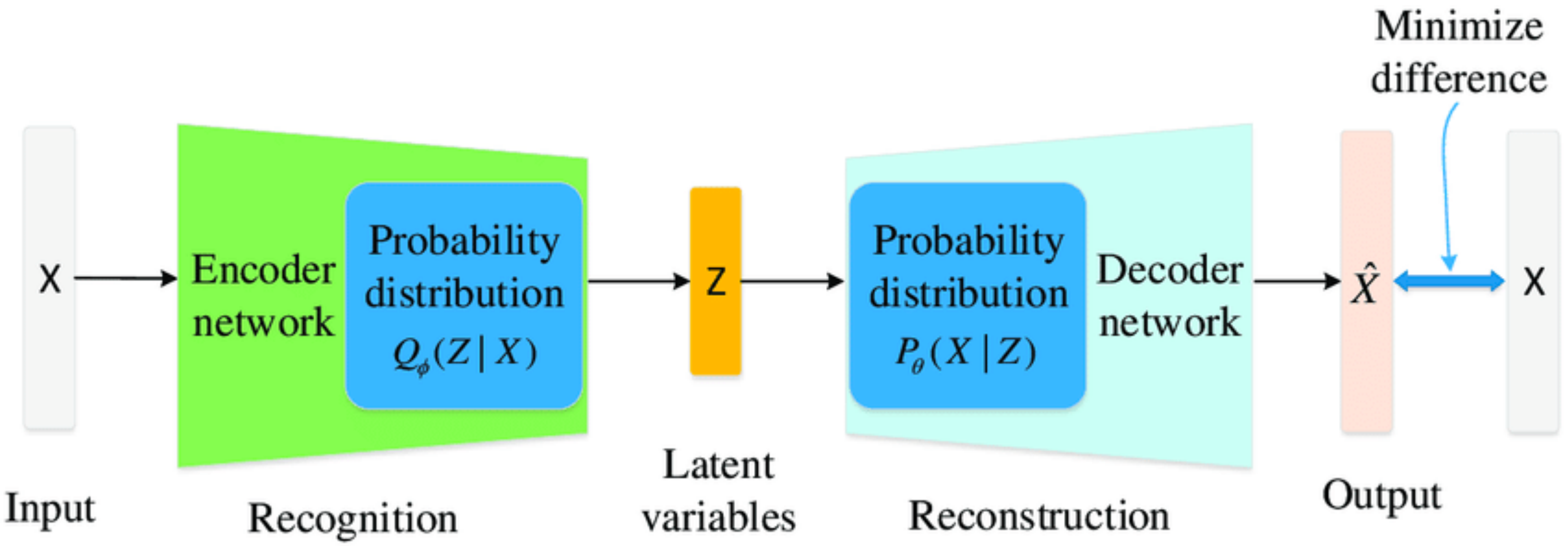


⏩ It is hard to model the physical world

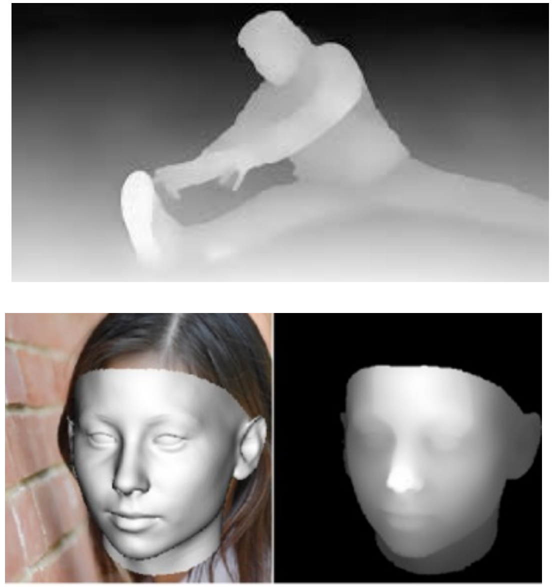
- Ilya Sutskever: compression is generalization.
- The best lossless compression for a dataset is the best generalization for data outside the dataset.



Apply the deterministic conditions

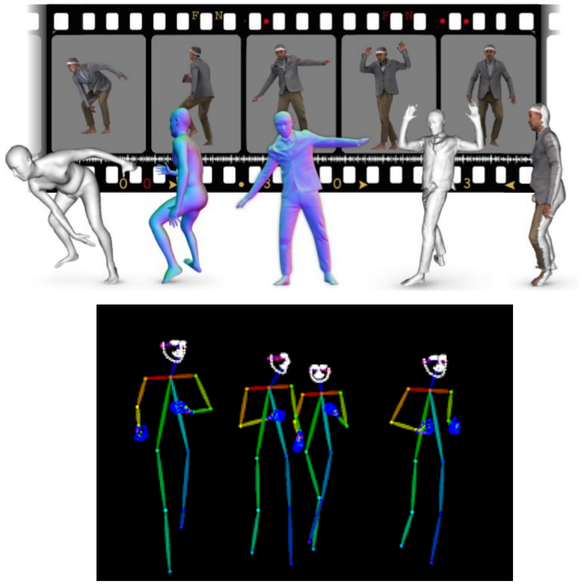
- Different representations of deterministic conditions in the physical world.
- Much less data and parameters!

Geometry



Lighting

Motion & Animation



Apply the deterministic conditions

- There are two ways to inject deterministic information.

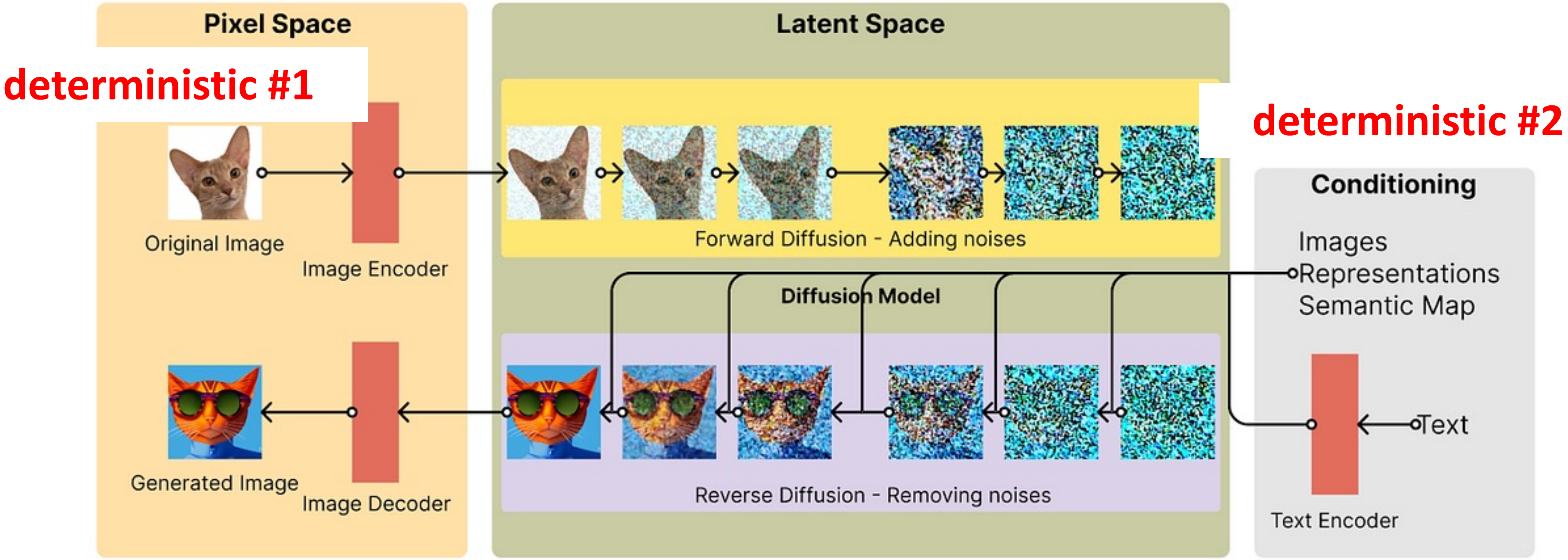
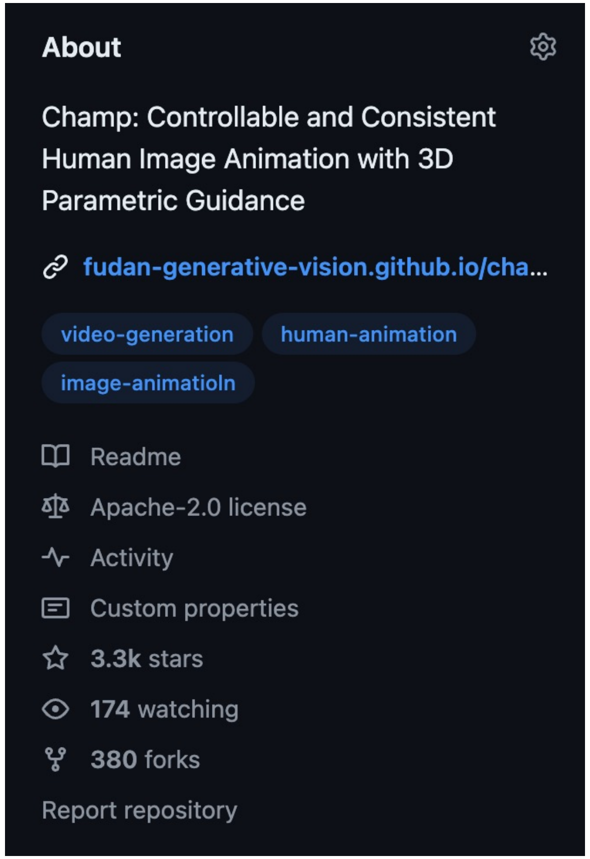


Image Human Animation

- Champ: Controllable and Consistent Human Image Animation with 3D Parametric Guidance



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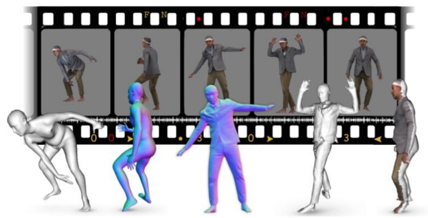
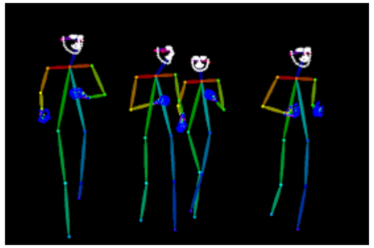




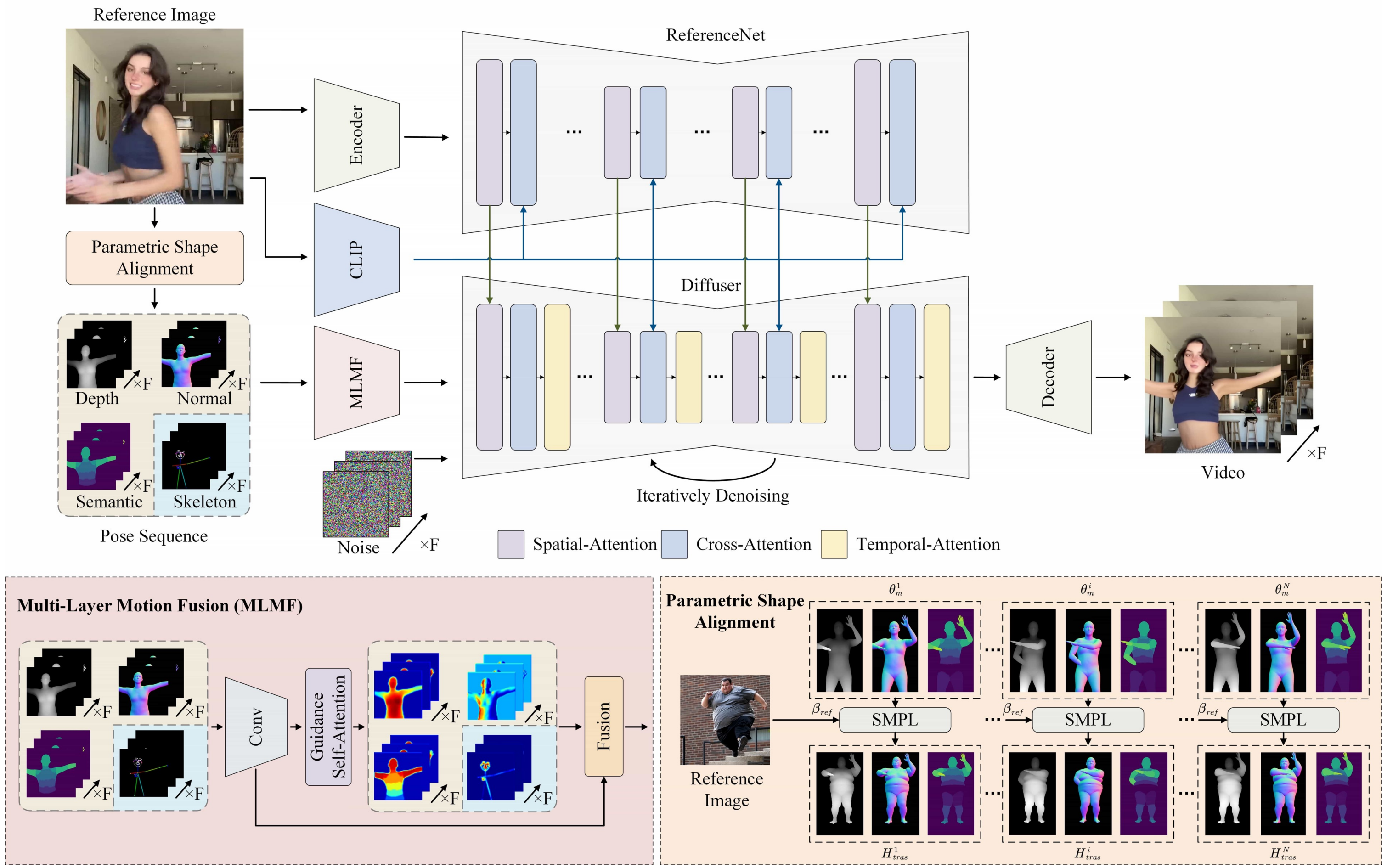


Image Human Animation

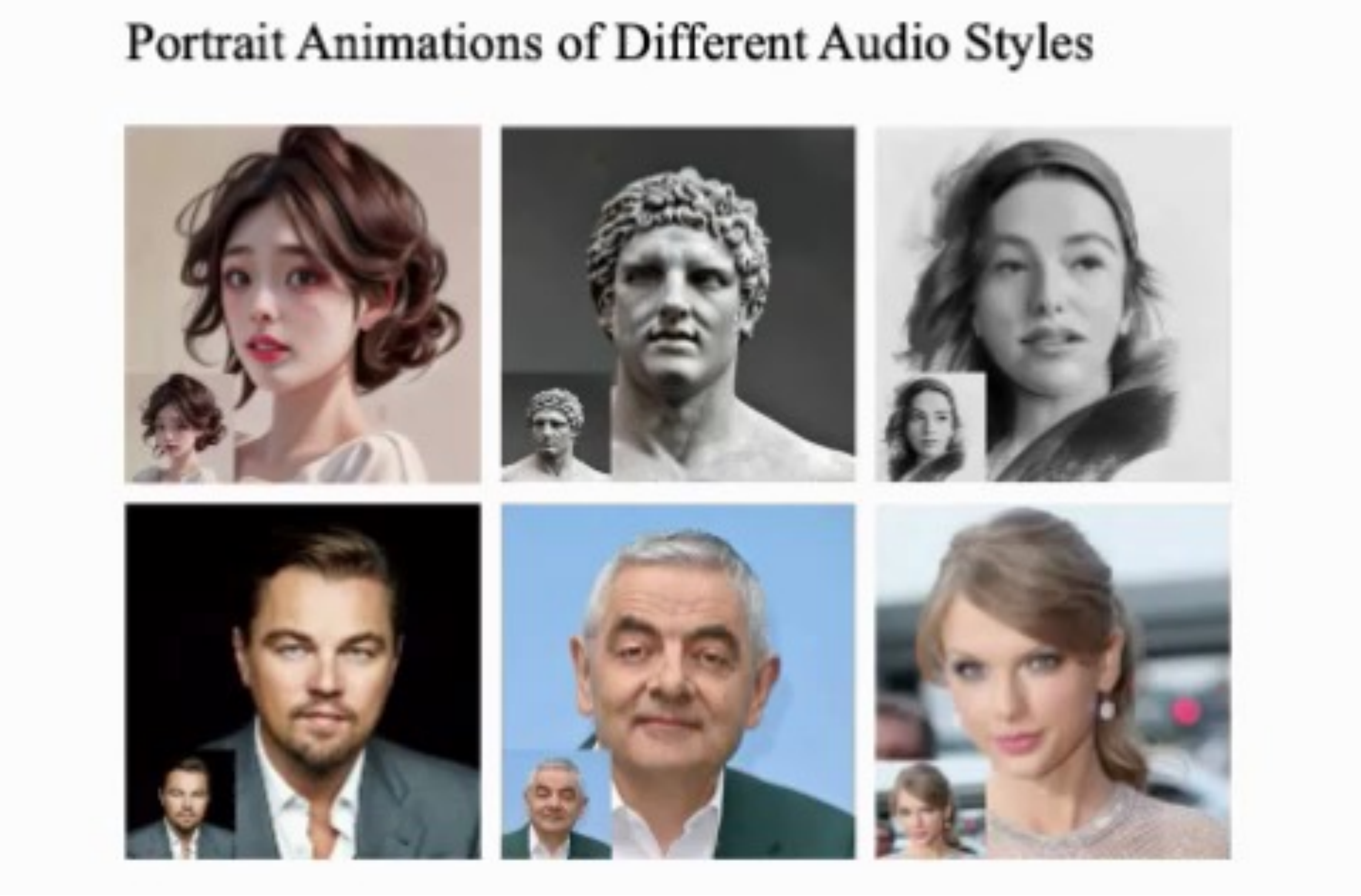
- Champ: Controllable and Consistent Human Image Animation with 3D Parametric Guidance

Method	L1 ↓	PSNR ↑	SSIM ↑	LPIPS ↓	FID-VID ↓	FVD ↓
MRAA	3.21E-04	29.39	0.672	0.296	54.47	284.82
DisCo	3.78E-04	29.03	0.668	0.292	59.90	292.80
MagicAnimate	3.13E-04	29.16	0.714	0.239	21.75	179.07
Animate Anyone	-	29.56	0.718	0.285	-	171.9
Ours	3.02E-04	29.84	0.773	0.235	26.14	170.20
Ours*	**2.94E-04**	**29.91**	**0.802**	**0.234**	**21.07**	**160.82**

Table 1: Quantitative comparisons on Tiktok dataset. * indicates that the proposed approach is fine-tuned on the Tiktok training data-set.

Image Portrait Animation

- Hallo: Hierarchical Audio-Driven Visual Synthesis for Portrait Image Animation



About

Hallo: Hierarchical Audio-Driven Visual Synthesis for Portrait Image Animation

fudan-generative-vision.github.io/hallo/

image-animation face-animation video-animation

- Readme
- MIT license
- Activity
- Custom properties
- 8.1k stars
- 535 watching
- 1.1k forks

Report repository

Image Portrait Animation

- Hallo: Hierarchical Audio-Driven Visual Synthesis for Portrait Image Animation

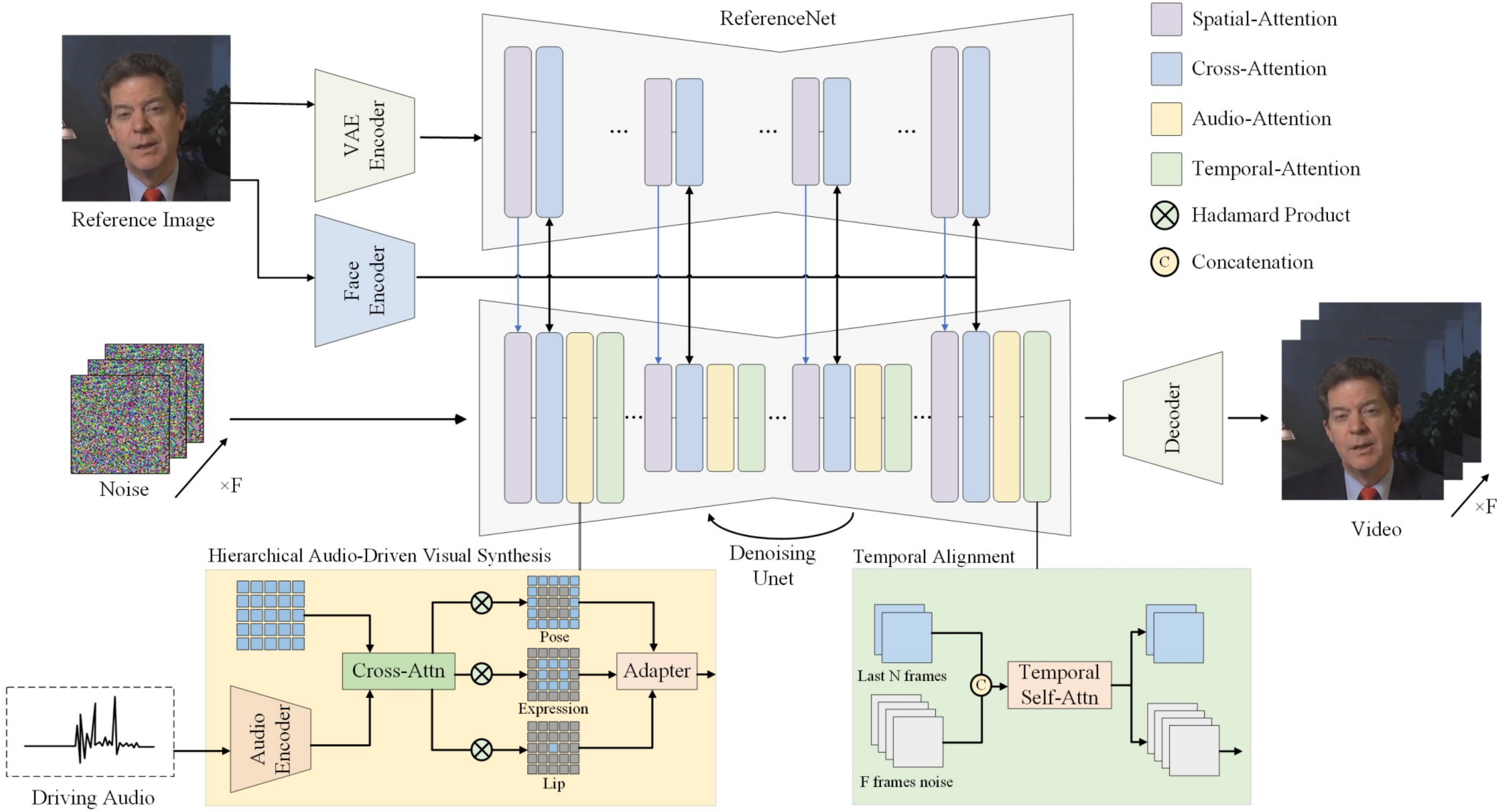


Image Portrait Animation

- Hallo: Hierarchical Audio-Driven Visual Synthesis for Portrait Image Animation

Method	FID↓	FVD↓	Sync-C↑	Sync-D↓	E-FID↓
SadTalker [49]	22.340	203.860	7.885	7.545	9.776
Audio2Head [38]	37.776	239.860	**8.024**	**7.145**	17.103
DreamTalk [20]	78.147	790.660	6.376	8.364	15.696
AniPortrait [42]	26.561	234.666	4.015	10.548	13.754
Ours	**20.545**	**173.497**	7.750	7.659	**7.951**
Real video	-	-	8.700	6.597	-

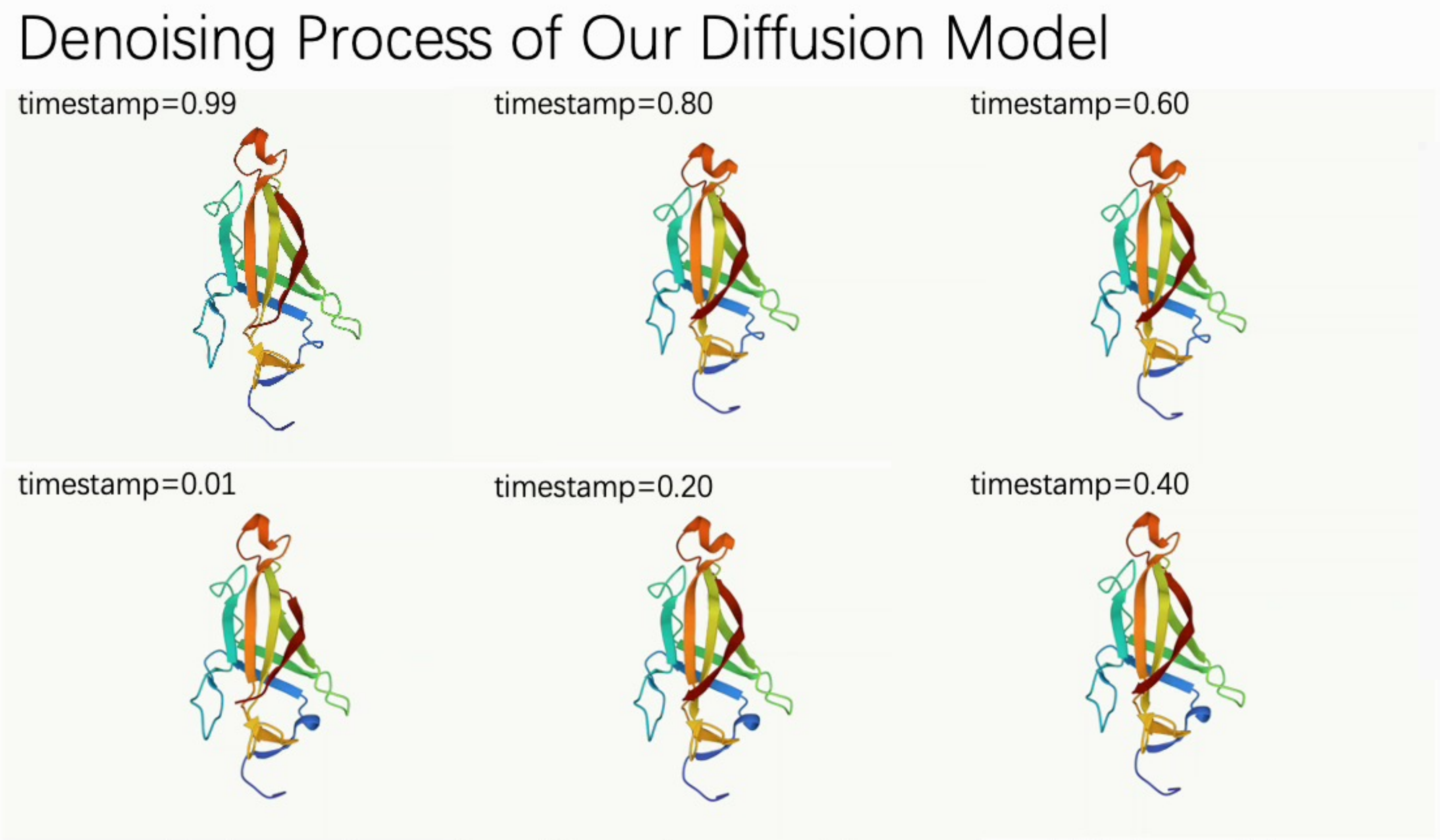
Table 1: The quantitative comparisons with the existed portrait image animation approaches on the HTDF data-set. Our proposed method excels in generating high-quality, temporally coherent talking head animations with superior lip synchronization performance.

Lip	Face	Pose	FID↓	FVD↓	SynC↑	SynD↓	E-FID↓
			20.581	193.062	6.499	8.691	9.133
✓			20.164	184.550	5.952	9.347	8.113
✓	✓		20.42	171.312	7.502	8.036	8.287
✓	✓	✓	20.545	173.497	7.750	7.659	7.951

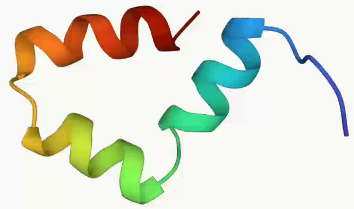
Table 5: Ablation study of hierarchical audio-visual (lip, face and pose) cross attention.

Dynamic Protein Structure Prediction

- 4D Diffusion for Dynamic Protein Structure Prediction with Reference Guided Temporal Alignment



The intermediate results at different time steps of the score-based diffusion model



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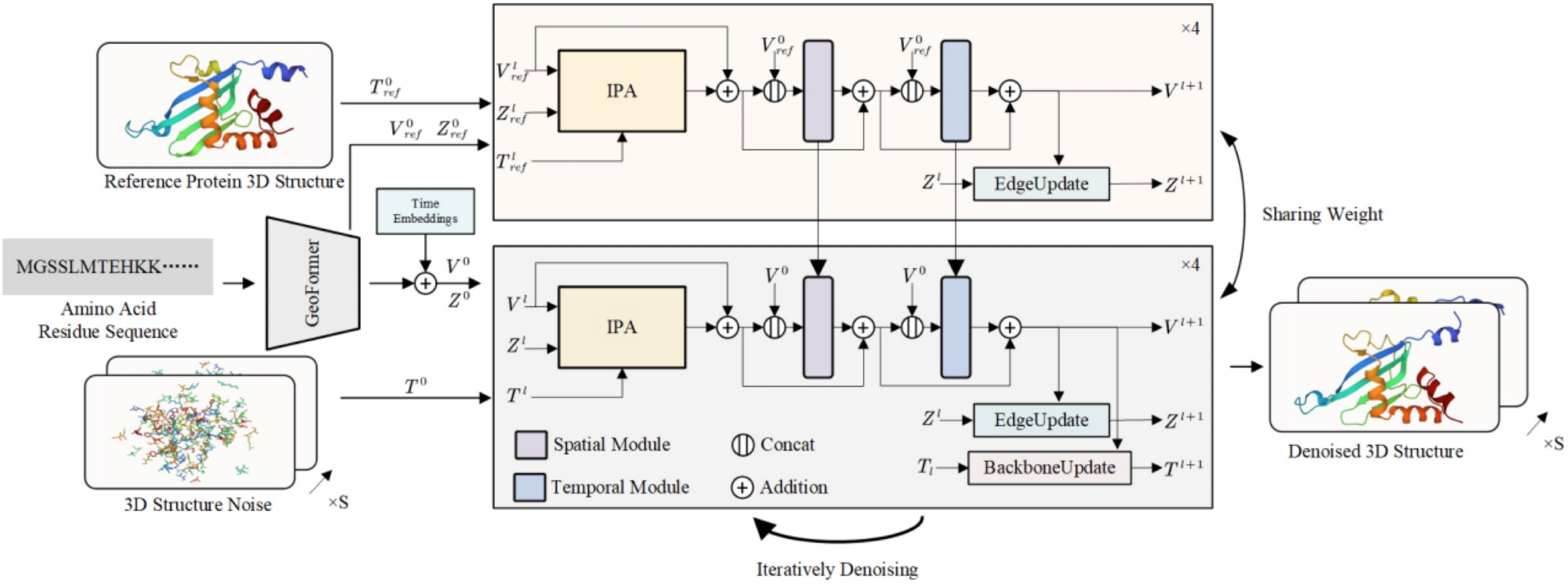
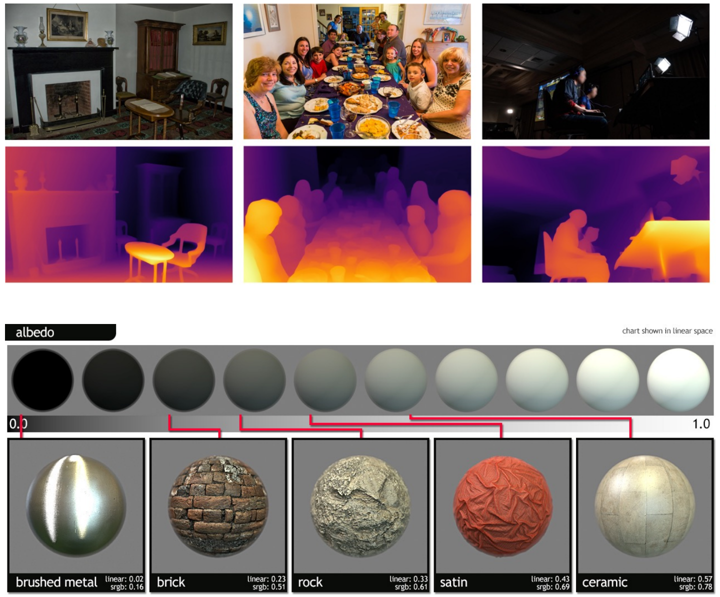


Future work

- Apply deterministic conditions to probabilistic diffusion.
- Less data and paramters!

Geometry

Lighting



Motion & Animation

THANKS