CVPR 2025 Tutorial: Efficient Text-to-Image/Video Modeling

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Google Research

Different perspectives on *efficiency*

Different perspectives on *efficiency*

Compression

More compact latent spaces → more efficient generation

Different perspectives on *efficiency*

Compression

More compact latent spaces → more efficient generation

Structured representations

Latent representation design that enables efficient modeling

Different perspectives on *efficiency*

Compression

More compact latent spaces ⟶ more efficient generation

Structured representations

Latent representation design that enables efficient modeling

Data sparsity

Generative models designed for data-sparse settings

Agenda

Part I - Compression (15 min)

Factorized latent representations for video

Part II - Structured representations (15 min)

Multiscale image generation with autoregressive models

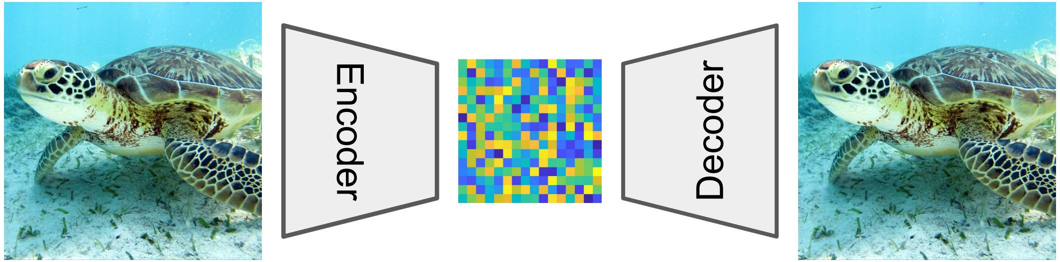
Part III - Data sparsity (< 10 min)

Diffusion models from a single 3D shape

Part I

Factorized latent representations for video

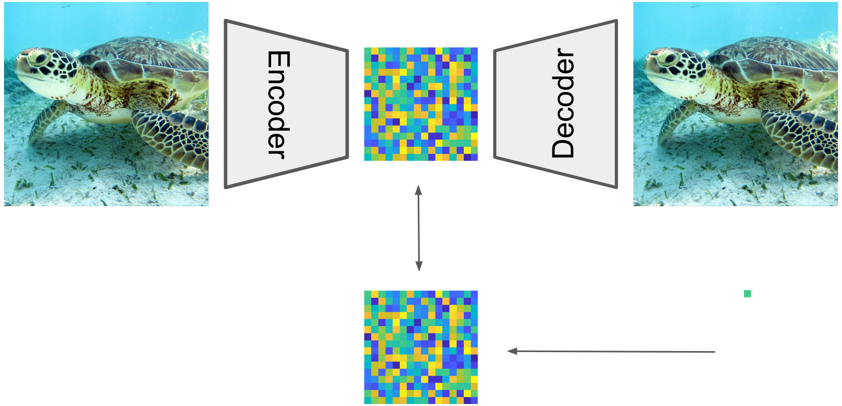
Latent generative models



- Reduce burden of generation in high dimension image/pixel space
- Reconstruction losses: pixel (MSE), perceptual (LPIPS), discriminator
- Latent representation is a heavily compressed, e.g. 512x512x3→64x64x4
- Individual tokens can be discrete (vector quantization) or continuous

van den Oord et al., *Neural Discrete Representation Learning*, 2017.
Razavi et al., *Generating Diverse High-Fidelity Images with VQ-VAE-2*, 2019.
Esser et al., *Taming Transformers for High-Resolution Image Synthesis*, 2020.
Rombach et al., *High-Resolution Image Synthesis with Latent Diffusion Models*, 2021.

Latent generative models



Autoregressive token decoding

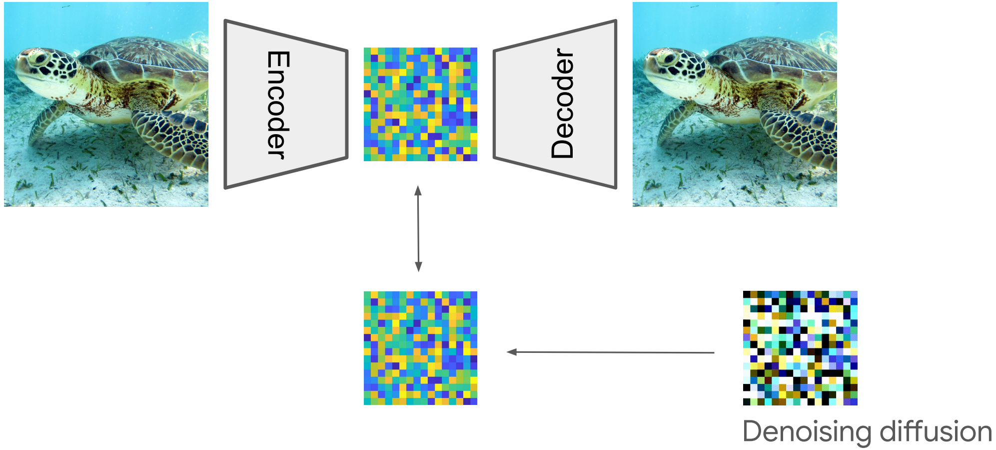
Stage 1: training autoencoder to learn latent feature space (image ⟶ visual tokens)

Stage 2: training a generative model for latent features

Autoregressive models (discrete tokens)

van den Oord et al., *Neural Discrete Representation Learning*, 2017.
Razavi et al., *Generating Diverse High-Fidelity Images with VQ-VAE-2*, 2019.
Esser et al., *Taming Transformers for High-Resolution Image Synthesis*, 2020.
Ramesh et al., *Zero-Shot Text-to-Image Generation*, 2021.
Yu et al., *Scaling Autoregressive Models for Content-Rich Text-to-Image Generation*, 2022.

Latent generative models



Stage 1: training autoencoder to learn latent feature space (image ⟶ visual tokens)

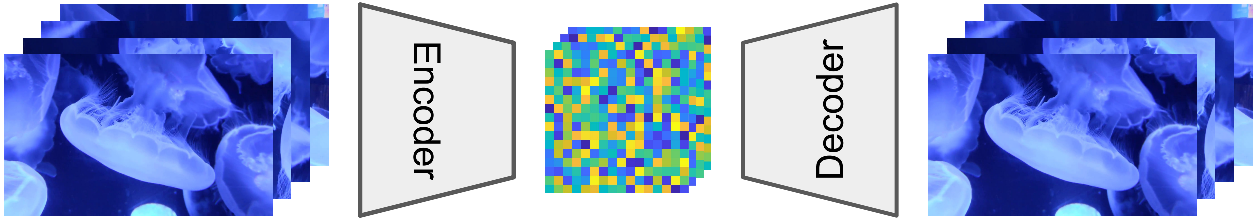
Stage 2: training a generative model for *latent features/tokens*

Autoregressive models (discrete tokens)

Diffusion models (continuous tokens)

Rombach et al., *High-Resolution Image Synthesis with Latent Diffusion Models*, 2021.
Peebles and Xie, *Scalable Diffusion Models with Transformers*, 2022.

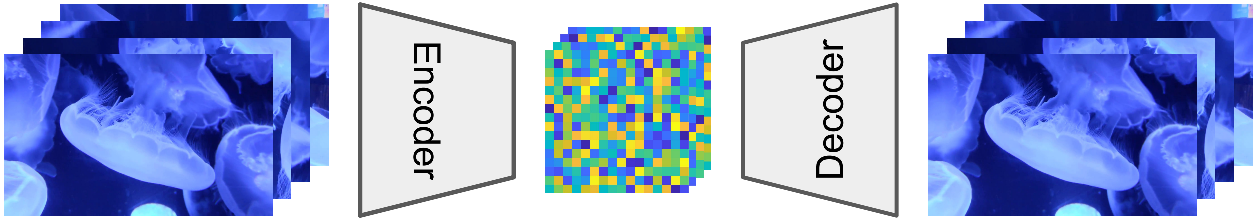
Video tokenization



Autoencoding spatiotemporal volumes

→ spatiotemporal latent features (H x W x T → H’ x W’ x T’, O(HWT) storage)

Video tokenization



Autoencoding spatiotemporal volumes

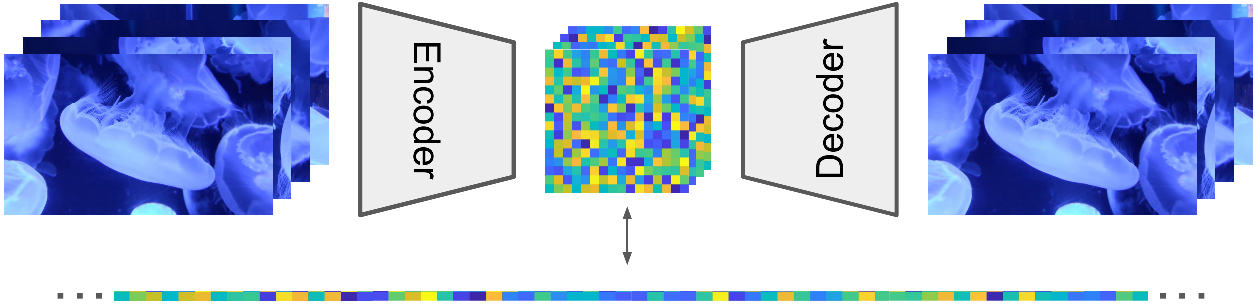
→ spatiotemporal latent features (H x W x T → H' x W' x T', O(HWT) storage)

Generative modeling w/spatiotemporal structure

3D U-Net (Video Diffusion Models, 2022)

Cicek et al., *3D U-Net: learning dense volumetric segmentation from sparse annotation*, 2016.
Ho et al., *Video Diffusion Models*, 2022.
Ho et al., *Imagen video: High definition video generation with diffusion models*, 2022.

Video tokenization



Autoencoding spatiotemporal volumes

→ spatiotemporal latent features (H x W x T → H' x W' x T', *O*(HWT) storage)

Generative modeling w/spatiotemporal structure

3D U-Net (Video Diffusion Models, 2022)

Sequence modeling (tokens unrolled into a 1D sequence)

Autoregressive transformers (TATS)

Masked transformers (Phenaki, Magvit, Magvit-v2)

Transformer diffusion (W.A.L.T.)

Ge et al., *Long Video Generation with Time-Agnostic VQGAN and Time-Sensitive Transformer*, 2022.
Villegas et al., *Phenaki: Variable length Video Generation From Open Domain Textual Descriptions*, 2022.
Yu et al., *MAGVIT: Masked Generative Video Transformer*, 2022.
Yu et al., *Language Model Beats Diffusion – Tokenizer is Key to Visual Generation*, 2023.
Gupta et al., *Photorealistic Video Generation with Diffusion Models*, 2024.

Video tokenization

For sequence models (masked transformer, autoregressive, diffusion transformer), efficiency is directly tied to the latent size

Can we further compress the latent space, without sacrificing reconstruction or generation quality?

Volumetric latent space – scales linearly with the input size

Plane-factorization (factorize volumetric data into orthogonal planes)

Size scales sublinearly with the input

Tri-plane factorization

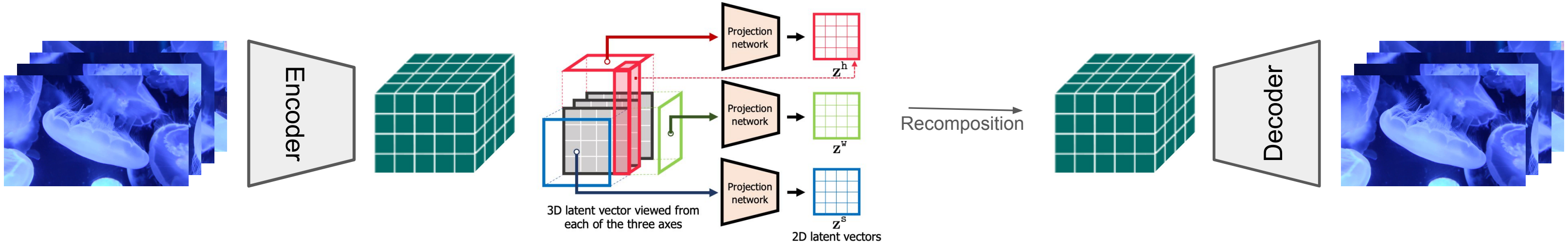


Image from Yu et al., Video Probabilistic Diffusion Models in Projected Latent Space, 2023.

Factorization

Triplane representations commonly used for 3D generation tasks

3D neural fields, 3D semantic scenes, 3D shapes

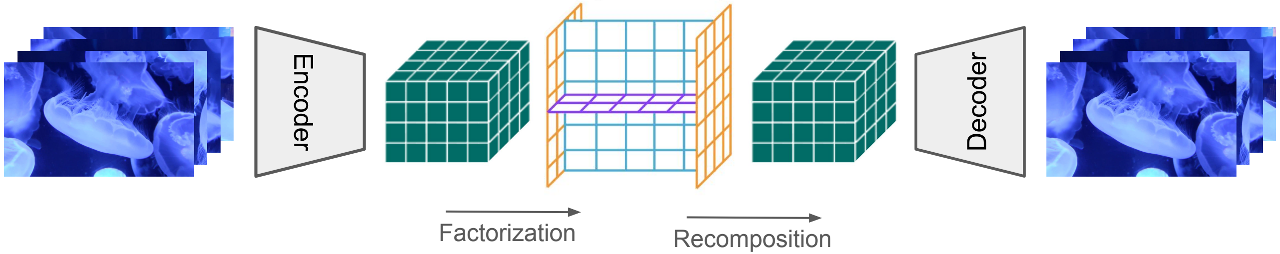
Recently applications to video tokenization: PVDM, HVDM, CMD

Benefit from 2D diffusion models for image generation

2D conv UNets for each plane w/cross attention, fine-tuning DiT

Wu et al., *Sin3dm: Learning a diffusion model from a single 3d textured shape*, 2023.
Shue et al., *3D neural field generation using triplane diffusion*, 2022.
Yu et al., *Video Probabilistic Diffusion Models in Projected Latent Space*, 2023.
Kim et al., *Hybrid Video Diffusion Models with 2D Triplane and 3D Wavelet Representation*, 2024.
Yu et al., Efficient video diffusion models via content-frame motion-latent decomposition, 2024.

Four-plane factorization



Triplane tokenization

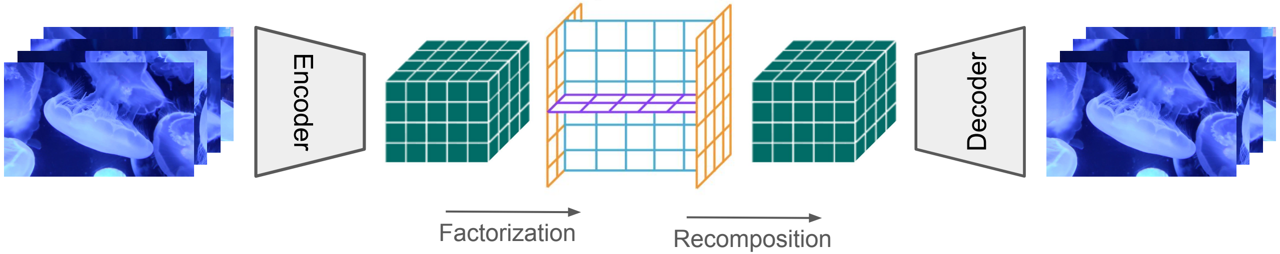
- Smaller latent sizes enable much faster generative model training and sampling
- Generation quality still lags behind volumetric latent generation
- Not easily adopted to all video generation tasks, e.g. frame extrapolation and interpolation

Four-plane factorization

- Two spatial planes (orange), two spatiotemporal planes (blue / purple)
- Structure allows flexibility for different image-conditioned video generation tasks
- Favorable efficiency vs quality tradeoff when introduced into volumetric architectures
    - 2x speedup in generative model training/sampling, comparable generation quality

Suhail et al., *Four-Plane Factorized Video Autoencoders*, 2024.

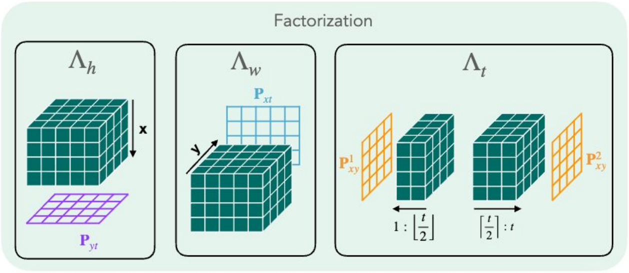
Four-plane factorization

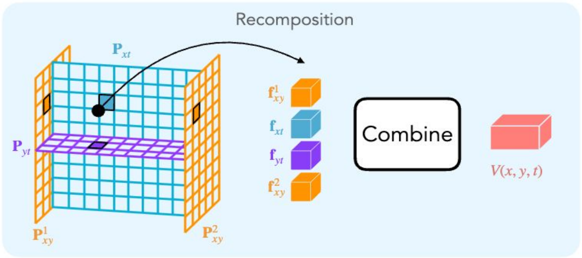


<u>Factorization</u>
The simplest operator (mean pooling) generalizes best, compared to learned linear projection, or transformer (PVDM)

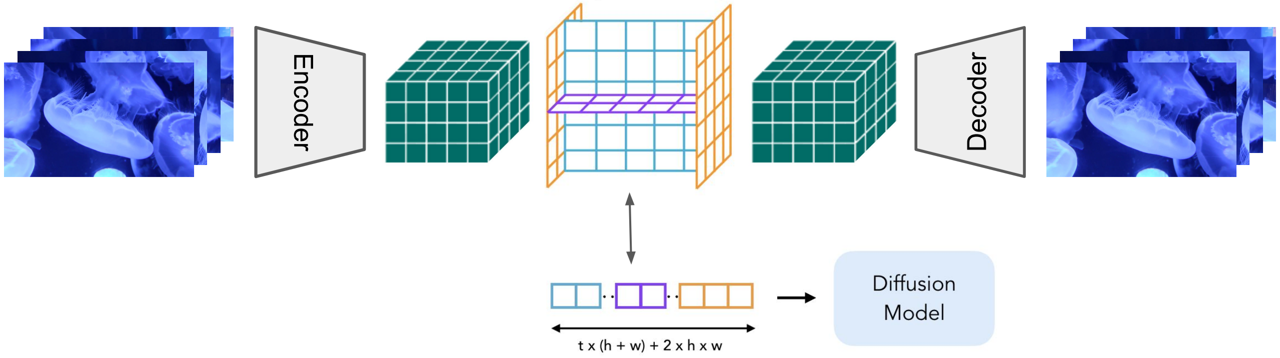
Spatial planes are obtained after splitting the volume into two non-overlapping segments along time

<u>Recomposition</u>
Features are combined through concatenation to reconstitute the volume





Four-plane factorization



Adopt the W.A.L.T. framework for analysis

- Encoder is Magvit-v2 causal 3D convolution architecture (also used by OpenSora, CogVideoX, ...)
- Continuous 8-dimensional tokens
- Generation is diffusion transformer model

W.A.L.T. + Four-plane tokenization

- Introduce volume factorization and recomposition steps at the latent bottleneck
- All other AE/Diffusion details mirror W.A.L.T.

Gupta et al., Photorealistic Video Generation with Diffusion Models, 2024.
Zheng et al., Open-Sora: Democratizing Efficient Video Production for All, 2024.
Yang et al., CogVideoX: Text-to-Video Diffusion Models with An Expert Transformer, 2024.

Reconstruction

Kinetics-600 dataset, 17 frame videos

Res.	Method	PSNR↑	SSIM↑	LPIPS↓	Seq.Len
128x128	Volumetric	27.64	0.85	0.049	1280
	4Plane	27.11	0.82	0.051	672
256x256	W.A.L.T.	26.27	0.79	0.089	1280
	Four-plane	25.67	0.77	0.104	672
	WF-VAE	27.86	0.83	0.064	1280
	Four-plane-WF-VAE	26.98	0.81	0.073	672

Number of frames	PSNR↑	SSIM↑	LPIPS↓
17	27.11	0.82	0.051
21	26.95	0.82	0.051
25	26.51	0.81	0.052

Four-plane reconstruction for longer videos

256x256 tokenizers - extra layer to the encoder and decoder
Comparable reconstruction metrics despite half the sequence length
WF-VAE is the AE architecture for OpenSoraPlan

Carreira et al., *A Short Note About Kinetics-600*, 2018.
Li et al., *WF-VAE: Enhancing Video VAE by Wavelet-Driven Energy Flow for Latent Video Diffusion Model*, 2024.
Lin et al., *Open-Sora Plan: Open-Source Large Video Generation Model*, 2024.

Generation

Tokenizer: Kinetics-600 dataset, 17 frame videos
Diffusion model trained on UCF-101

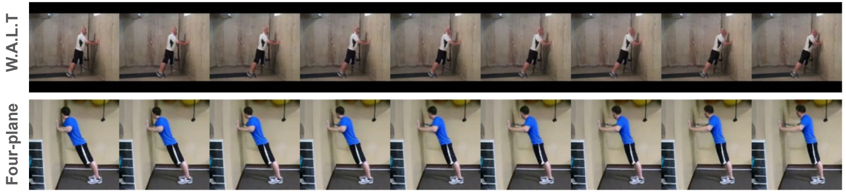
	Class Conditional Generation (FVD ↓)		Params	Steps
	UCF-101 (128x128)	UCF-101 (256x256)		
MAGVIT	76	-	306M	48
MAGVIT-v2	58	-	307M	24
WALT	39	84.68	214M	50
Four-plane	38	58.27	214M	50

	Class Conditional Generation (FVD ↓)		Params	Steps
	UCF-101 (128x128)	UCF-101 (256x256)		
PVDM	-	399.4	-	400
HVDM	-	303.1	63M	100
CMD	73	-	-	-
Tri-plane	52	-	214M	50
Four-plane	38	58.27	214M	50

Generation cost (TPU-v5e-2x2, four 17-frame 128x128 videos):
0.71s Four-plane, 1.59s W.A.L.T. (> 2x faster)

Yu et al., *MAGVIT: Masked Generative Video Transformer*, 2022.
Yu et al., *Language Model Beats Diffusion – Tokenizer is Key to Visual Generation*, 2023.
Yu et al., *Video Probabilistic Diffusion Models in Projected Latent Space*, 2023.
Kim et al., *Hybrid Video Diffusion Models with 2D Triplane and 3D Wavelet Representation*, 2024.
Yu et al., Efficient video diffusion models via content-frame motion-latent decomposition, 2024.

Class-conditional generation



(a) Pushup

(b) Surfing

Text-to-Video

300M internet videos

FVD (17 frame, 128x128): 18.22 for W.A.L.T., 20.24 for Four-plane

W.A.L.T. 128x128

Four-plane 128x128

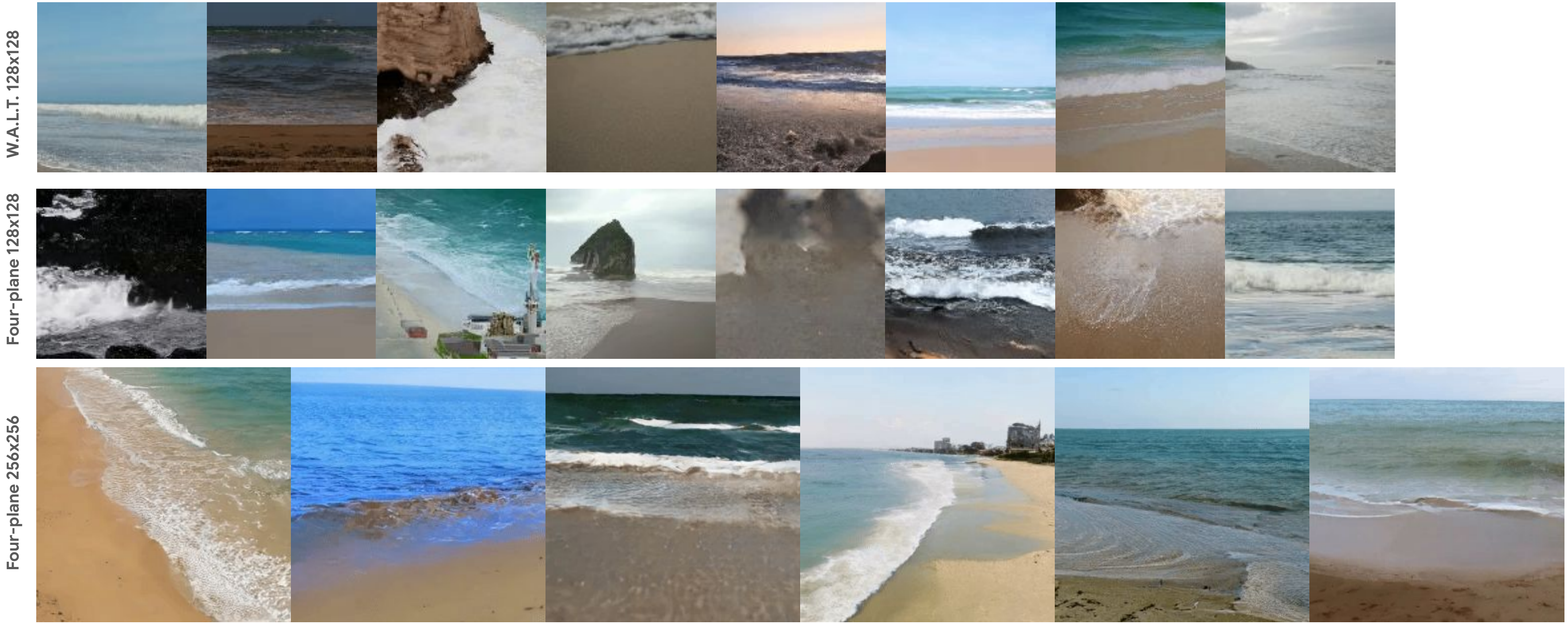
Four-plane 256x256

“Flying over the mountains with a river”

Text-to-Video

300M internet videos

FVD (17 frame, 128x128): 18.22 for W.A.L.T., 20.24 for Four-plane



"A wave reaching the beach"

Part II

Multiscale image generation with autoregressive models

Part III

Diffusion models from a single 3D shape