From Multimodal Generative Models to Dynamic World Modeling

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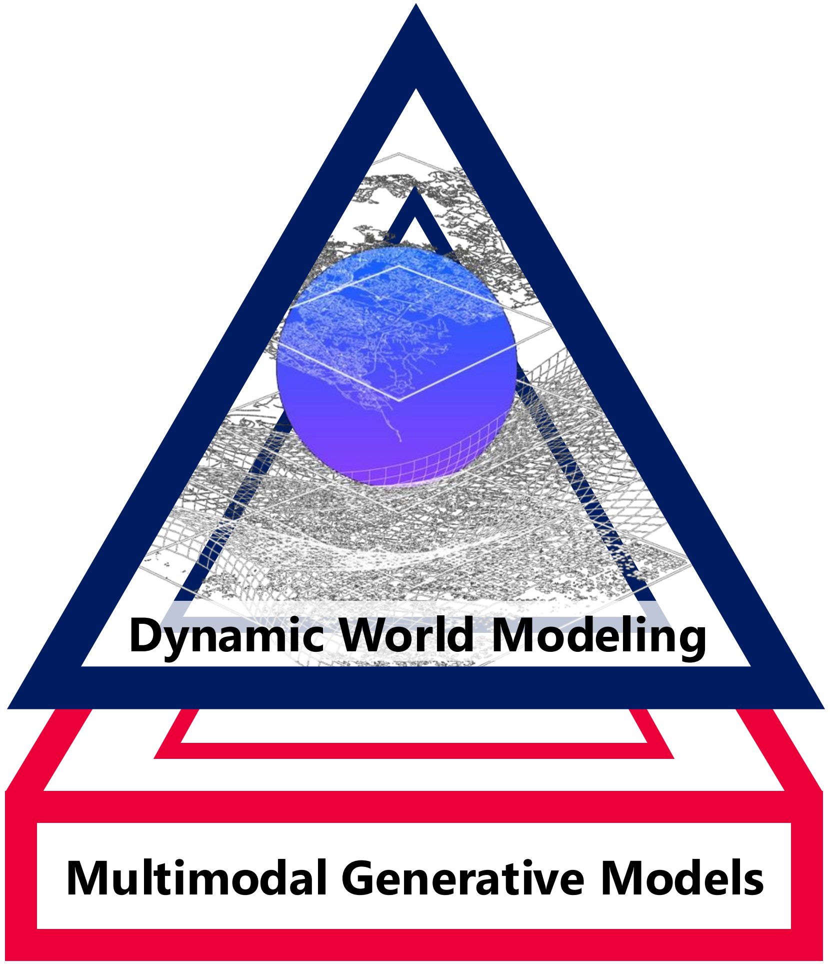
https://liuziwei7.github.io

Be Physical

How to Model Material and Illumination

Be Dynamic

How to Model Dynamic Scenes



Be Social

How to Model Social Interactions

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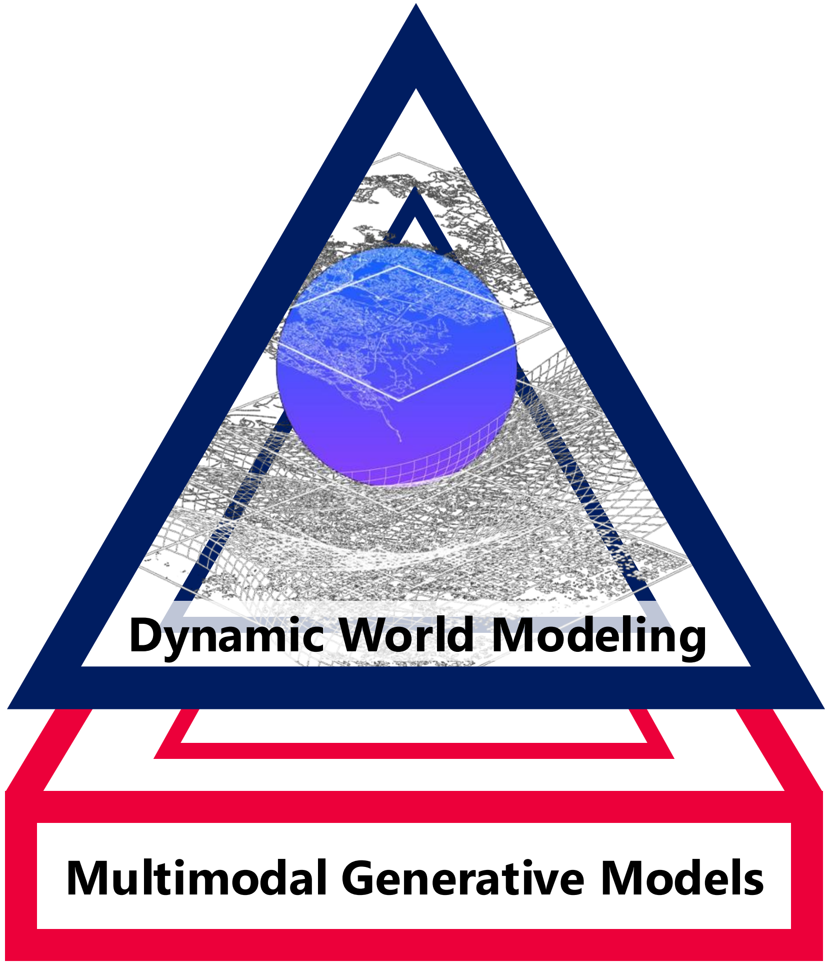


Be Social

How to Model Social Interactions

Be Physical: 3DTopia-XL

3DTopia/ 3DTopia-XL

3DTopia-XL: High-Quality 3D PBR Asset Generation via Primitive Diffusion

Zhaoxi Chen, Jiaxiang Tang, Yuhao Dong, Ziang Cao, Fangzhou Hong, Yushi Lan, Tengfei Wang, Haozhe Xie, Tong Wu, Shunsuke Saito, Liang Pan, Dahua Lin, Ziwei Liu

CVPR 2025 Highlight

Challenges

- High-resolution Generative 3D Representation
  - **Parameter-efficient**
    - Surface-only
    - As compact as possible
  - **Scalable Tokenization**
    - Rapid tensorization from input
    - Reversible conversion to GLB mesh
  - **Differentiable Rendering**
- Modelling of Physical Light Transport
  - Well-defined Geometry
  - PBR (Physically Based Rendering) Materials

Previous SOTA   Our Goal

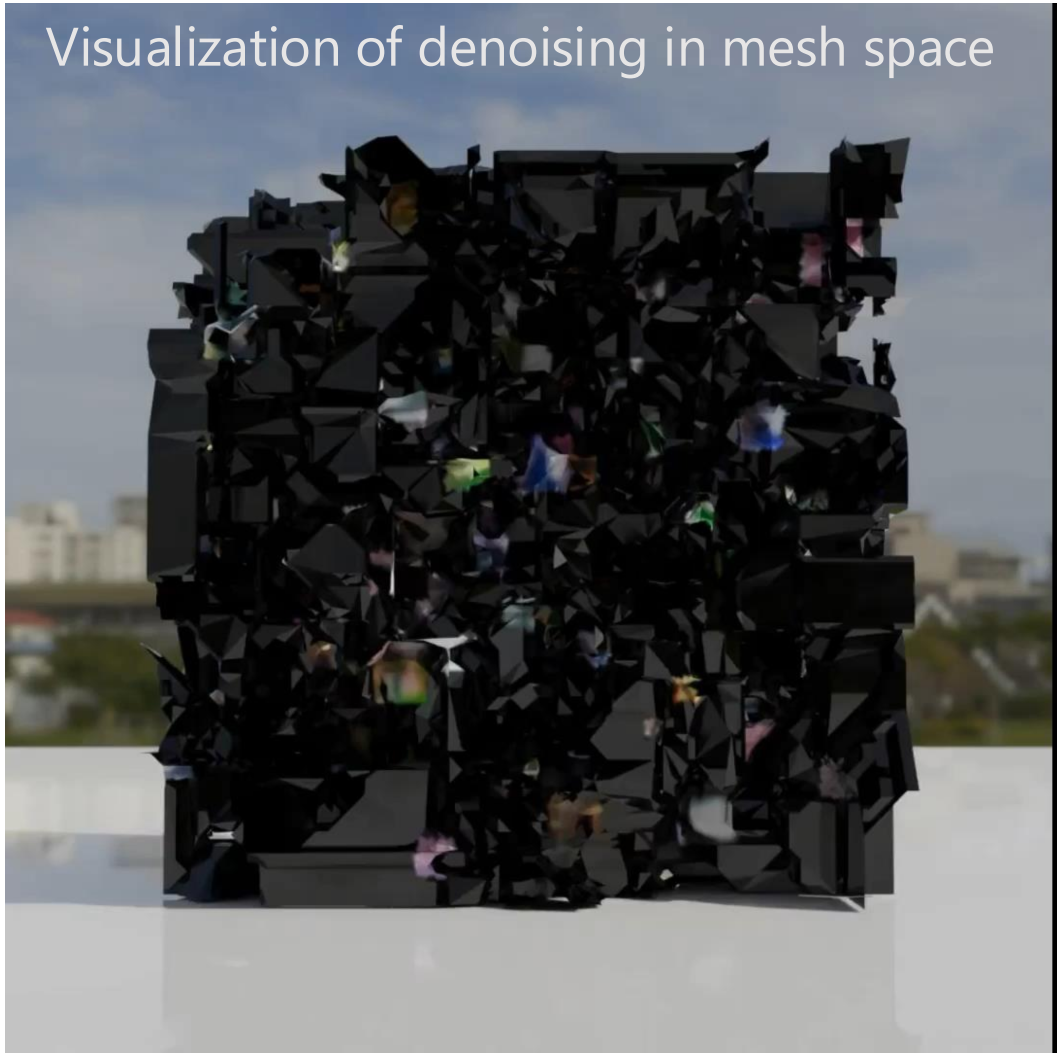
3DTopia-XL: A Native 3D Diffusion Model for PBR Asset

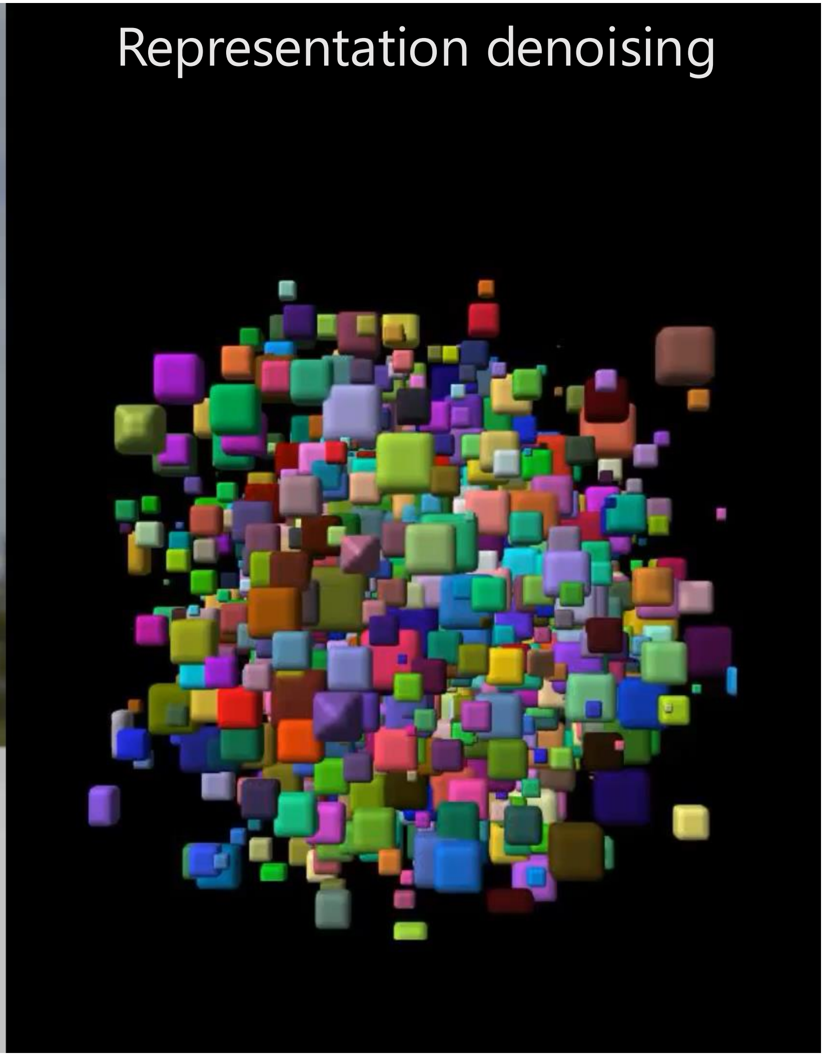
"A cute unicorn"

A Single Image / Texts

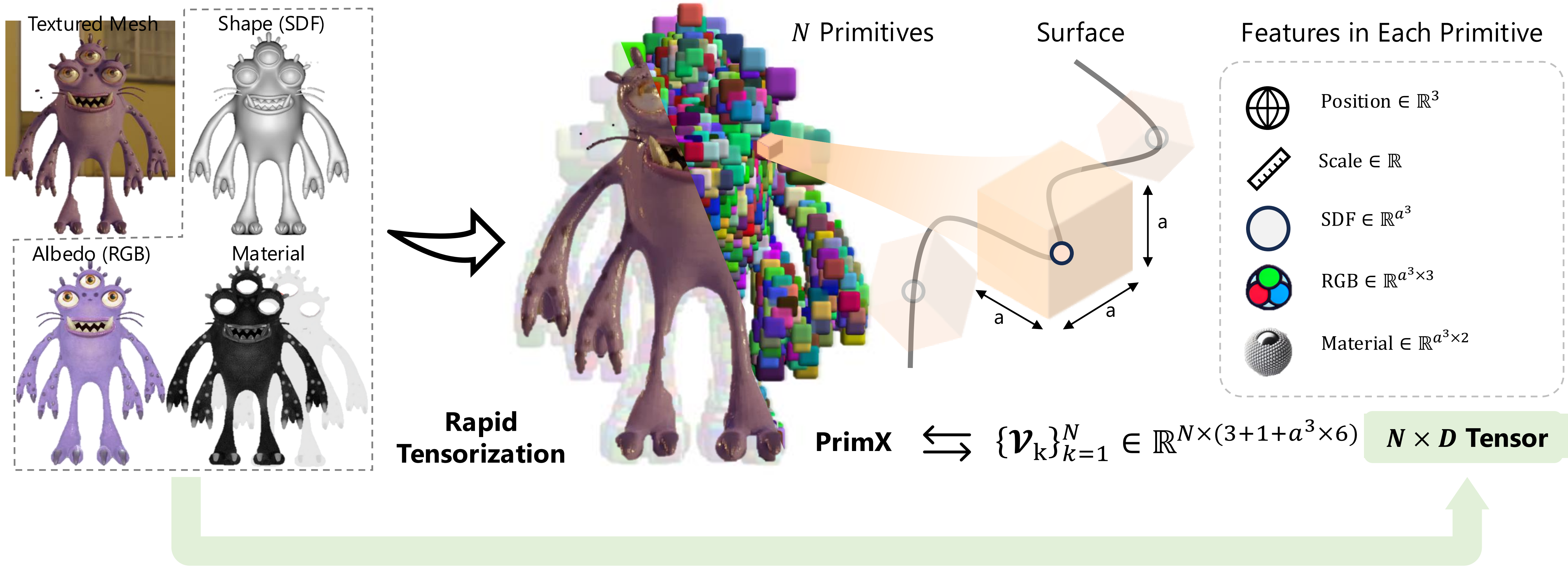
High-quality 3D Asset Ready for Blender

Key Idea: Primitive Diffusion



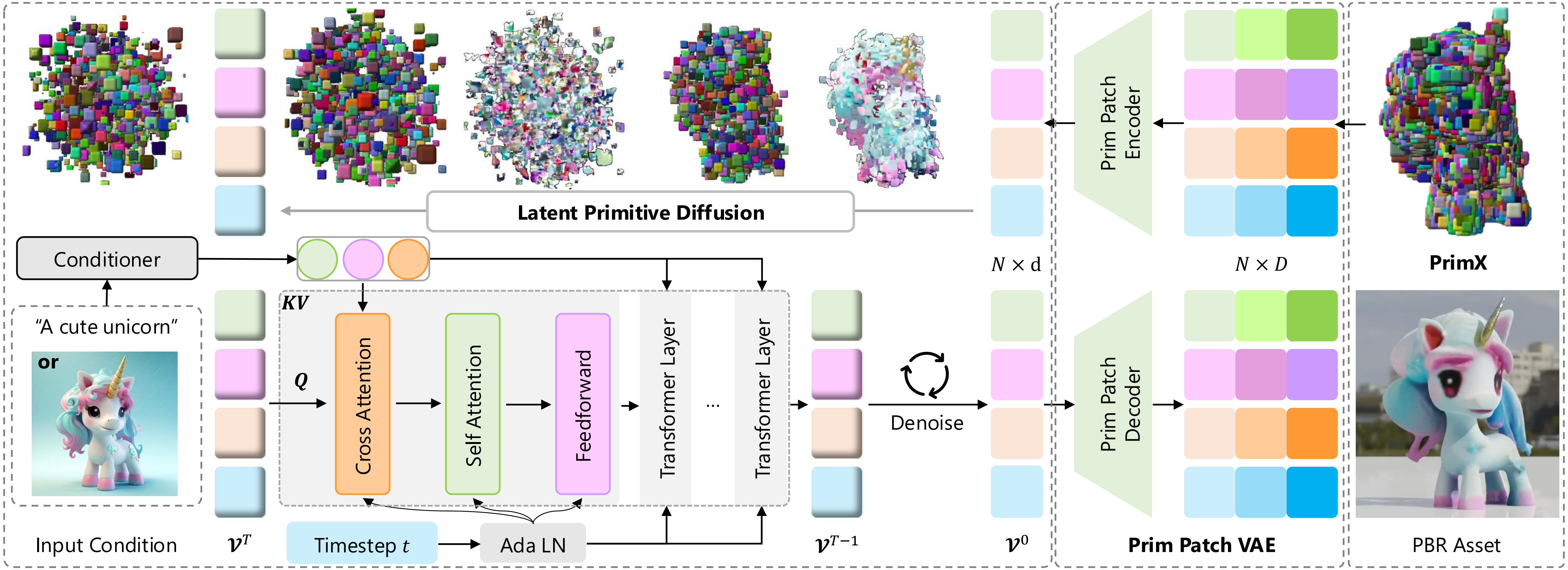


Stage I: Geometry, Texture, Materials into N×D Primitives

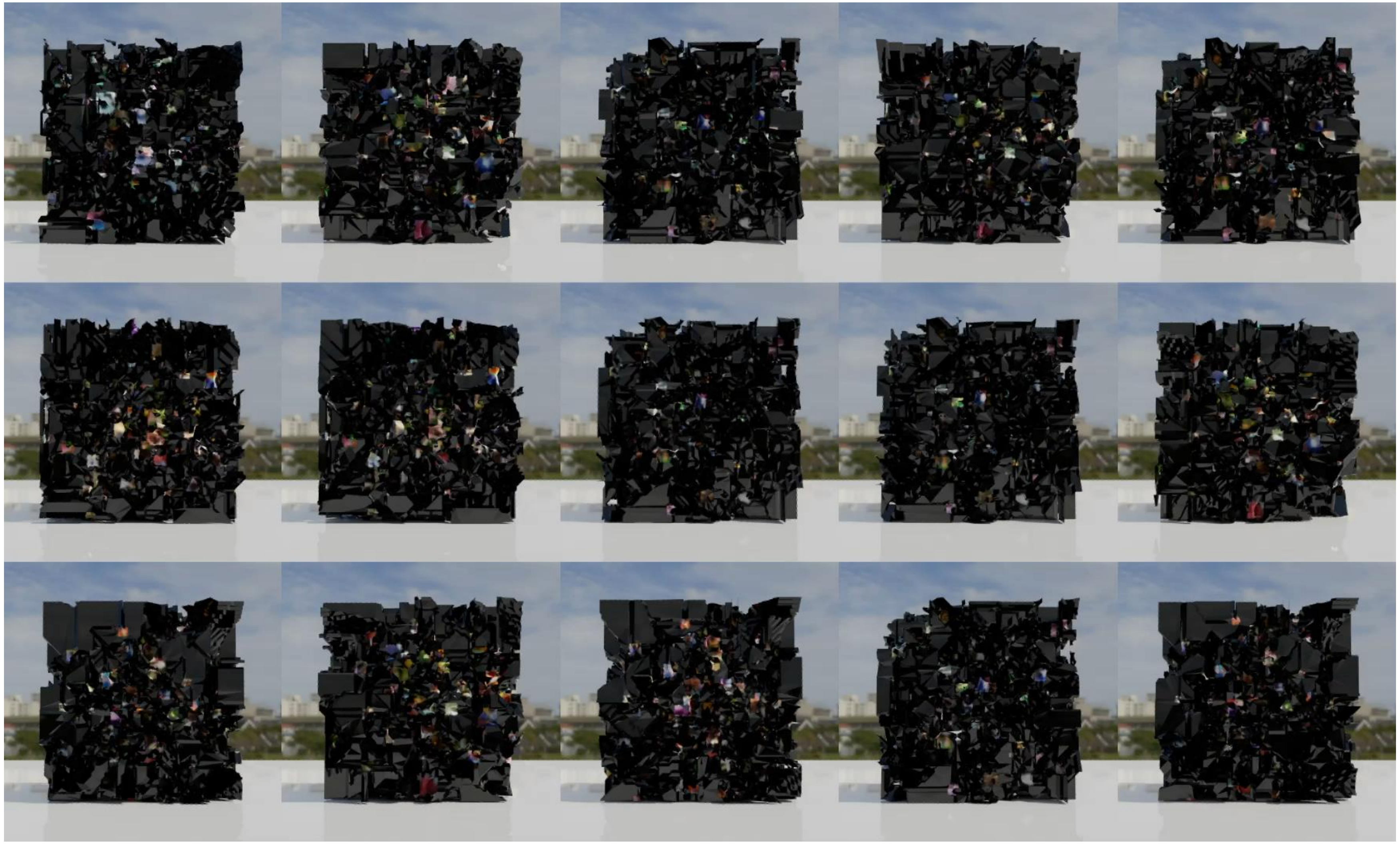


Tensorize a Textured Mesh into N×D Primitives

Stage II: Latent Primitive Diffusion



Gallery: Denoising in 5 Seconds



Gallery: Ready for Graphics Engines

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Be Physical: Neural LightRig

ZexinHe/Neural-LightRig

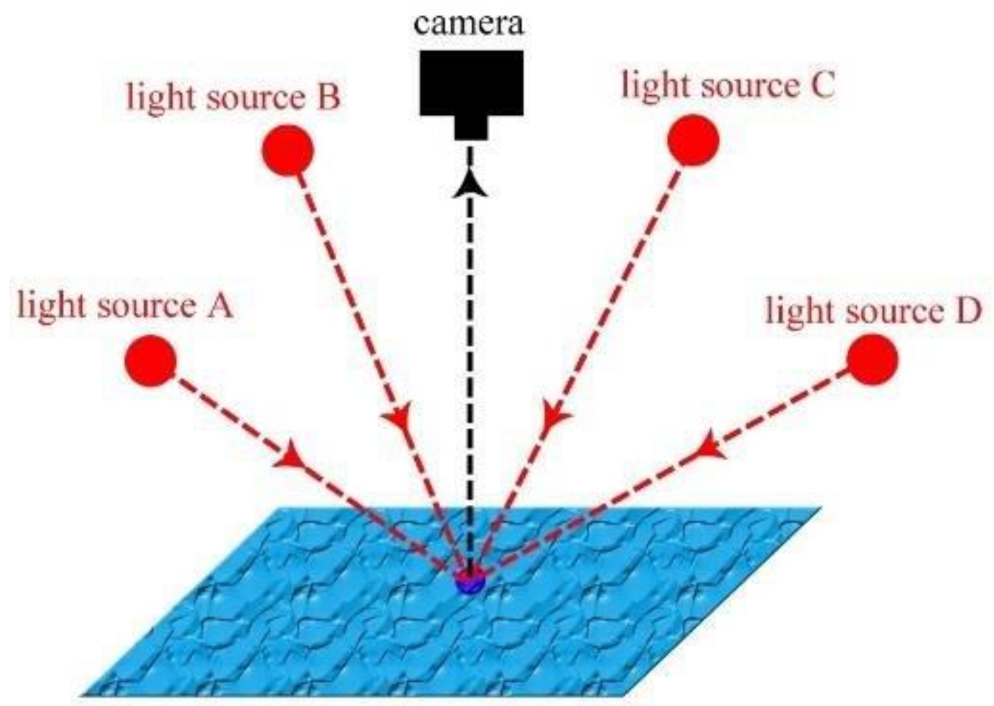
Neural LightRig: Unlocking Accurate Object Normal and Material Estimation with Multi-Light Diffusion

Zexin He, Tengfei Wang, Xin Huang, Xingang Pan, Ziwei Liu

CVPR 2025

A Long-Standing Challenge – Inverse Rendering

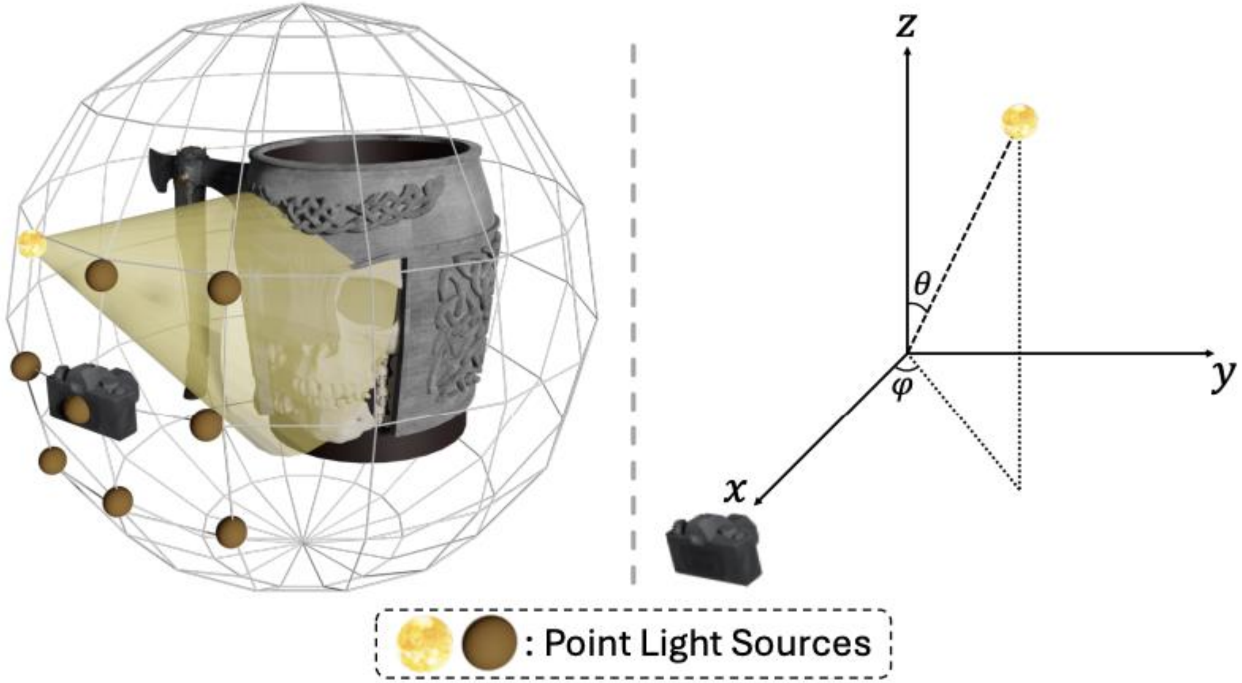
- Estimating geometry & materials from a single image is **ill-posed** and **under-constraint**
- Complex interaction among geometry, materials, and environmental lighting
- Traditional methods need photometric stereo setups[1] – **impractical** for in-the-wild images



[1] Robert J. Woodham. *Photometric method for determining surface orientation from multiple images*. 1989.
[2] Image source: https://www.researchgate.net/profile/Lyndon-Smith-4/publication/325473321/figure/fig1/AS:666789923020804@1535986514936/The-principle-of-photometric-stereo-which-employs-a-single-camera-to-capture-multiple_W640.jpg.

Insights

- Diffusion models can generate consistent multi-view images[1]
- Relighting diffusion models can synthesize images under various lighting conditions[2]
- Relit images reveal different aspects of geometry & material – **reducing ambiguity**



[1] Ruoxi Shi, *et al. Zero123++: A single image to consistent multi-view diffusion base model.* 2023.
[2] Lvmin Zhang, *et al. Scaling In-the-Wild Training for Diffusion-based Illumination Harmonization and Editing by Imposing Consistent Light Transport.* 2025.

Methodology

- Multi-Light Diffusion
  - Fine-tuning a pre-trained image diffusion model to generate consistent relit images
  - These multi-light images enrich information and reduce the inherent uncertainty
- Large G-Buffer Reconstruction
  - Feed-forward regression U-Net to estimate geometry and PBR materials

Quantitative Evaluations

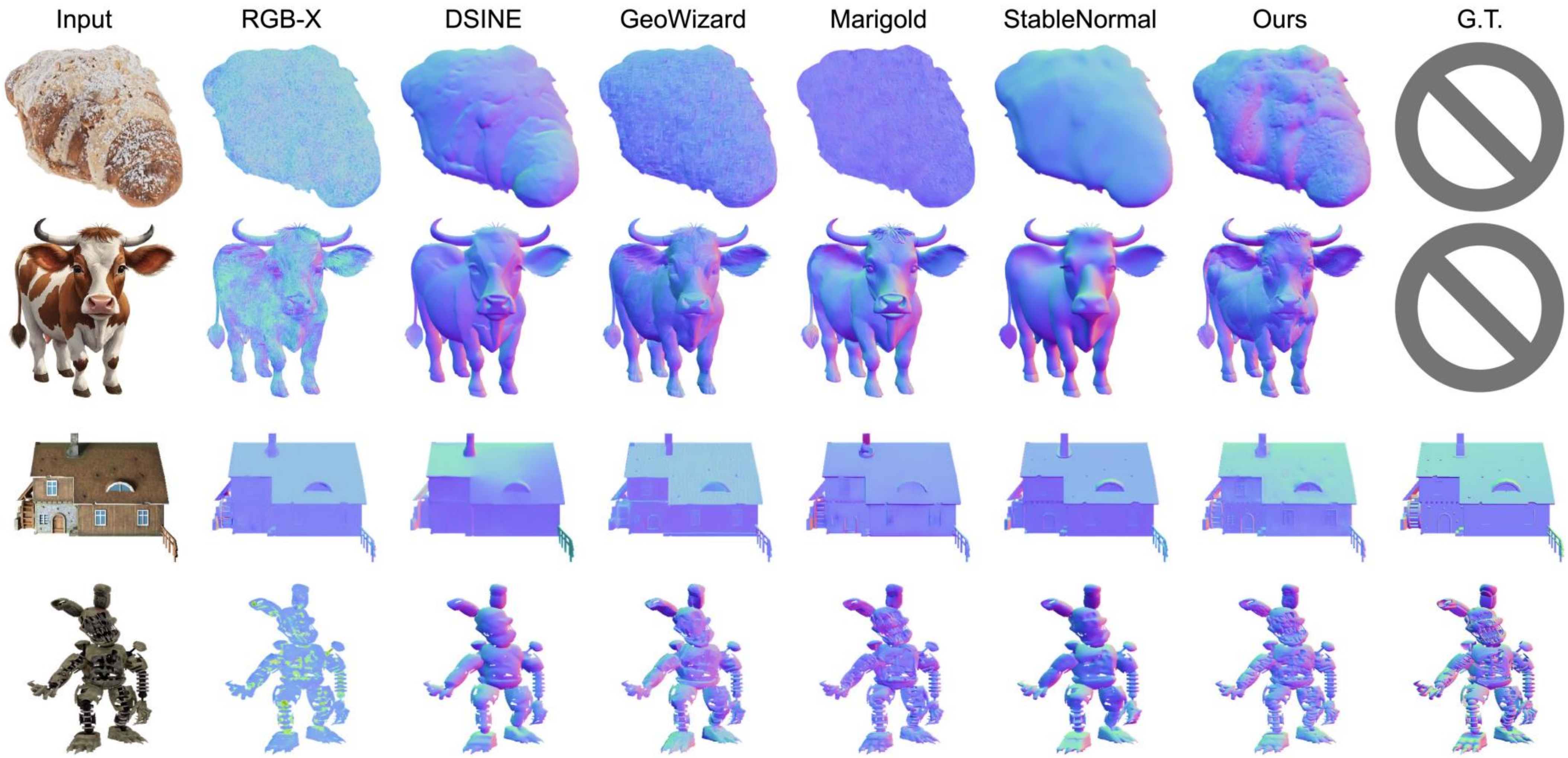
- Surface Normal Estimation

Method	Mean ↓	Median ↓	3° ↑	5° ↑	7.5° ↑	11.25° ↑	22.5° ↑	30° ↑
RGB↔X [57]	14.847	13.704	11.676	23.073	35.196	49.829	75.777	86.348
DSINE [2]	9.161	7.457	23.565	41.751	57.596	72.003	90.294	95.297
GeoWizard [16]	8.455	6.926	22.245	40.993	58.457	74.916	93.315	97.162
Marigold [25]	8.652	7.078	25.219	42.289	58.062	72.873	92.326	96.742
StableNormal [53]	8.034	6.568	21.393	43.917	63.740	78.568	93.671	96.785
Ours	**6.413**	**4.897**	**38.656**	**56.780**	**70.938**	**82.853**	**95.412**	**98.063**

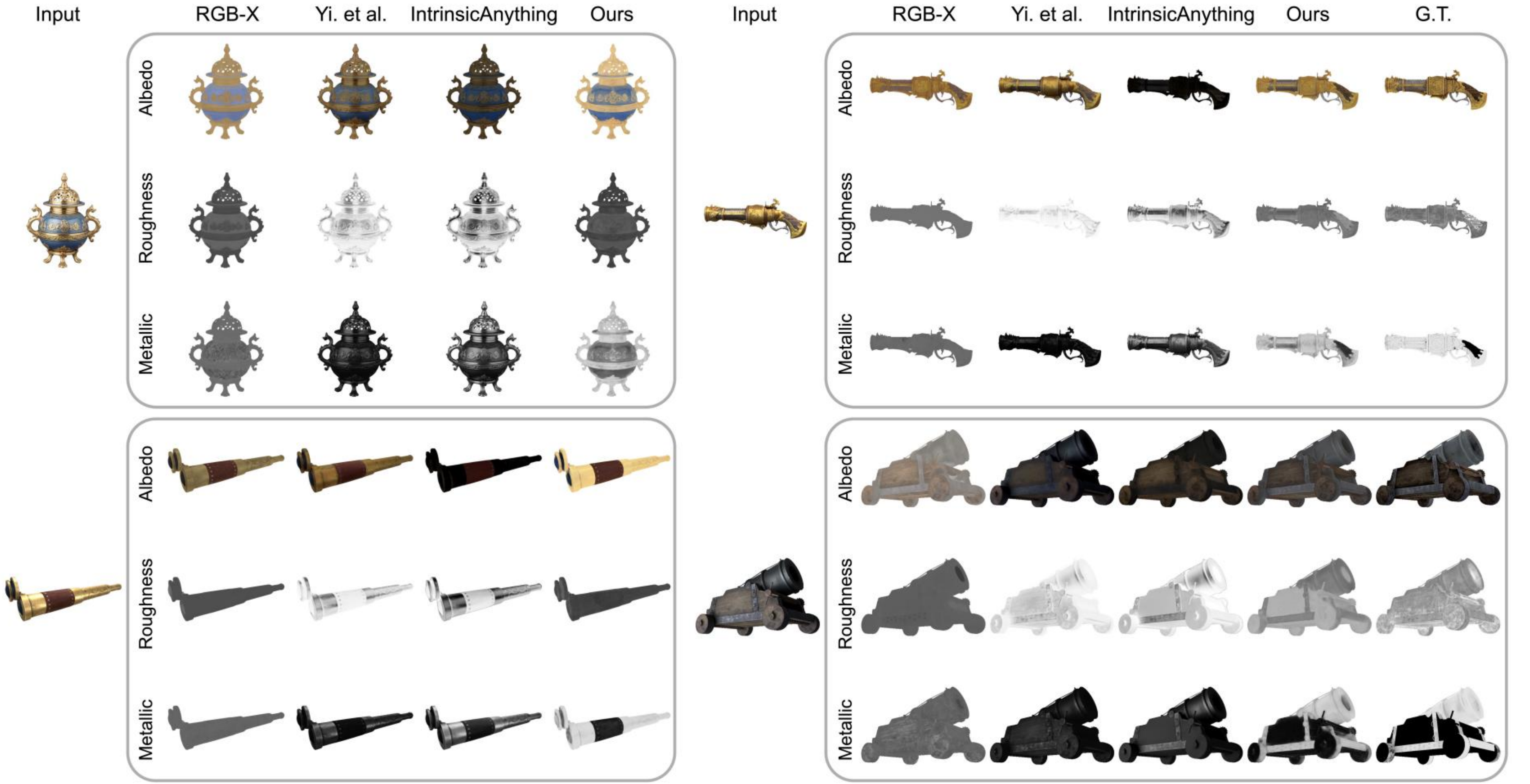
- PBR Estimation and Single-Image Relighting

Method	Albedo		Roughness		Metallic		Relighting			Latency
	PSNR ↑	RMSE ↓	PSNR ↑	RMSE ↓	PSNR ↑	RMSE ↓	PSNR ↑	SSIM ↑	LPIPS ↓	Average Time ↓
RGB↔X [57]	16.26	0.176	19.21	0.134	16.65	0.199	20.78	0.8927	0.0781	15s
Yi. et al [54]	21.10	0.106	16.88	0.180	20.30	0.144	26.47	0.9316	0.0691	5s
IntrinsicAnything [8]	23.88	0.078	17.25	0.172	22.00	0.134	27.98	0.9474	0.0490	2min
DiLightNet [56]	-	-	-	-	-	-	22.68	0.8751	0.0981	30s
IC-Light [60]	-	-	-	-	-	-	20.29	0.9027	0.0638	1min
Ours	**26.62**	**0.054**	**23.44**	**0.085**	**26.23**	**0.109**	**30.12**	**0.9601**	**0.0371**	5s

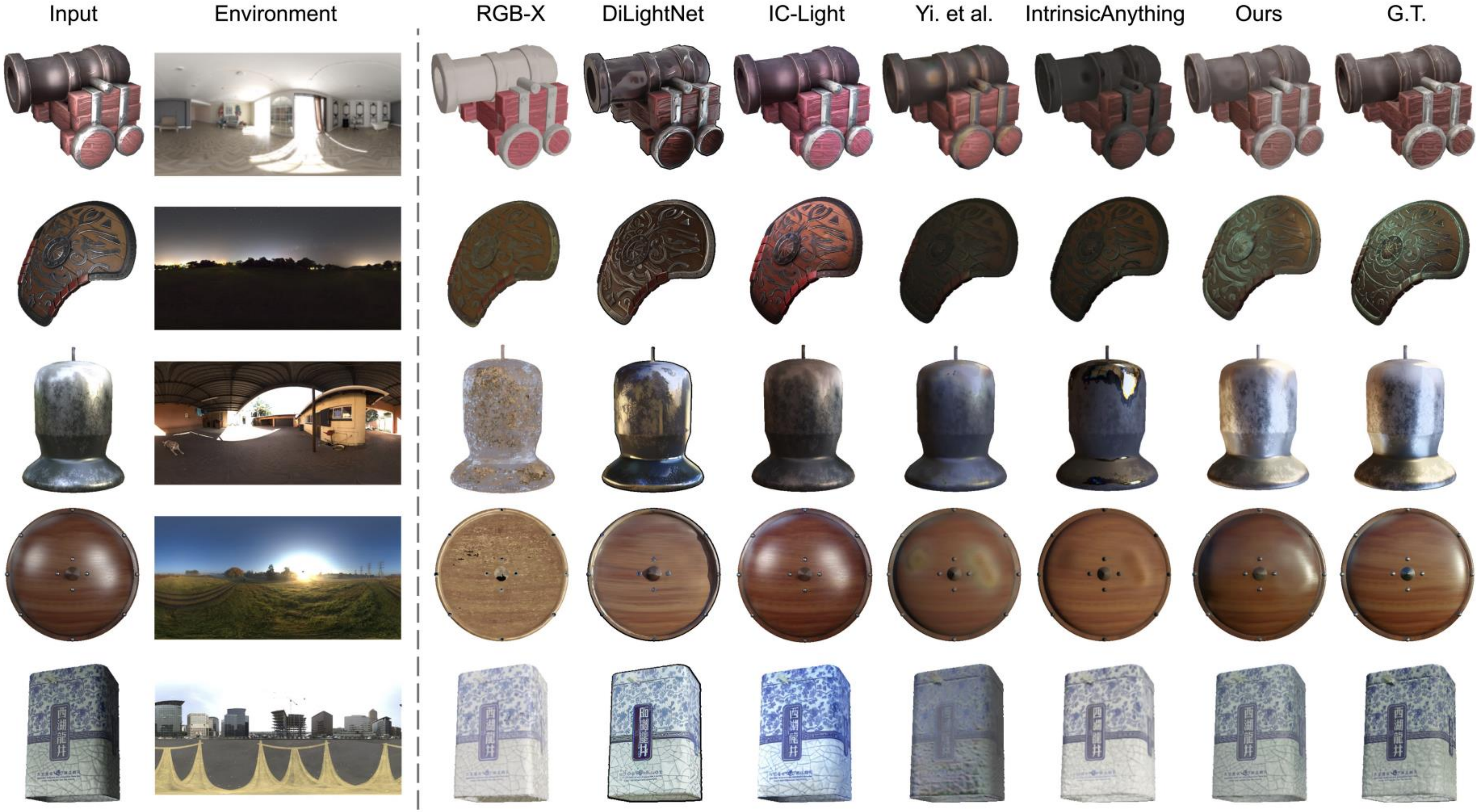
Surface Normal Estimation



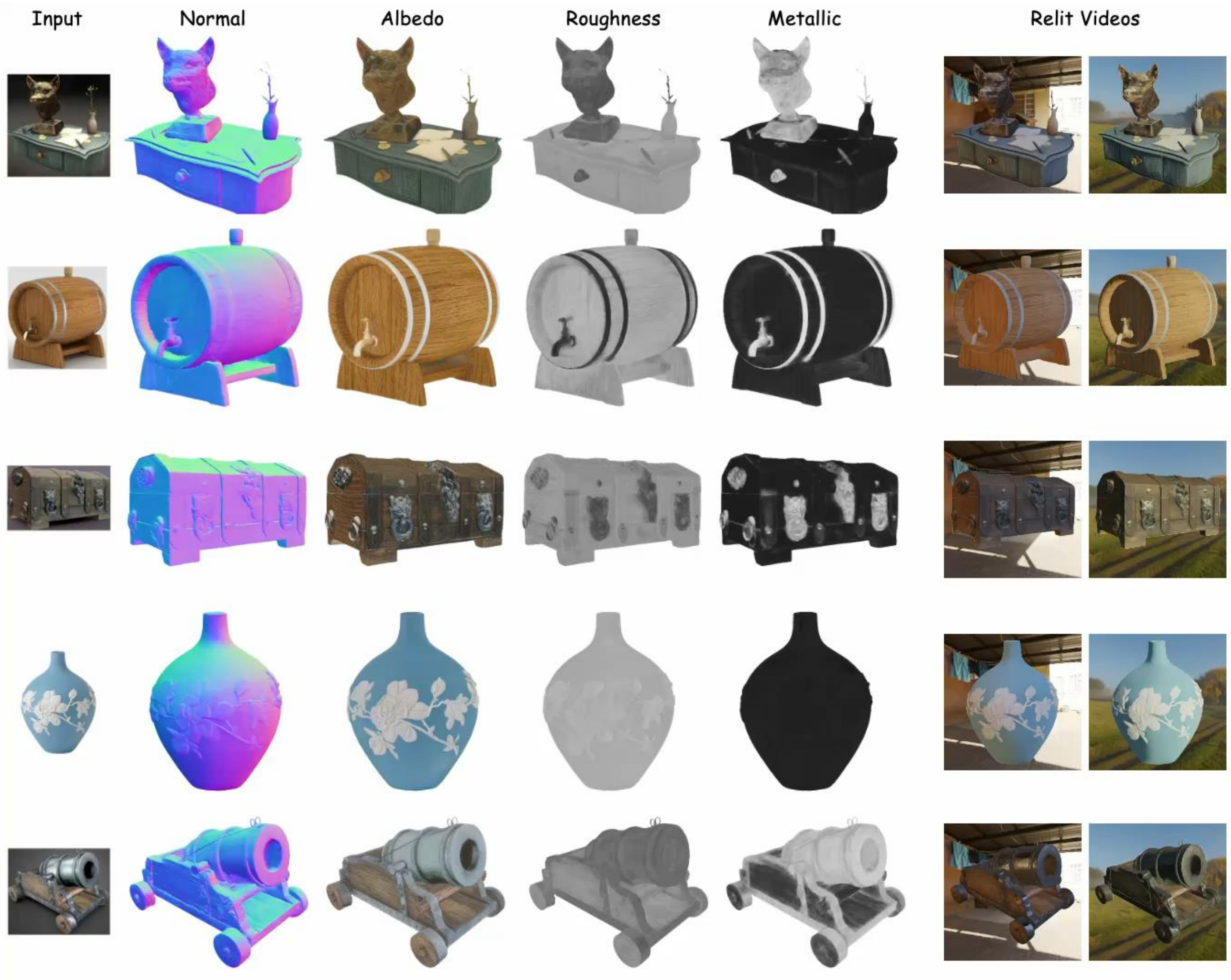
PBR Material Estimation



Single-Image Relighting



Single-Image Relighting



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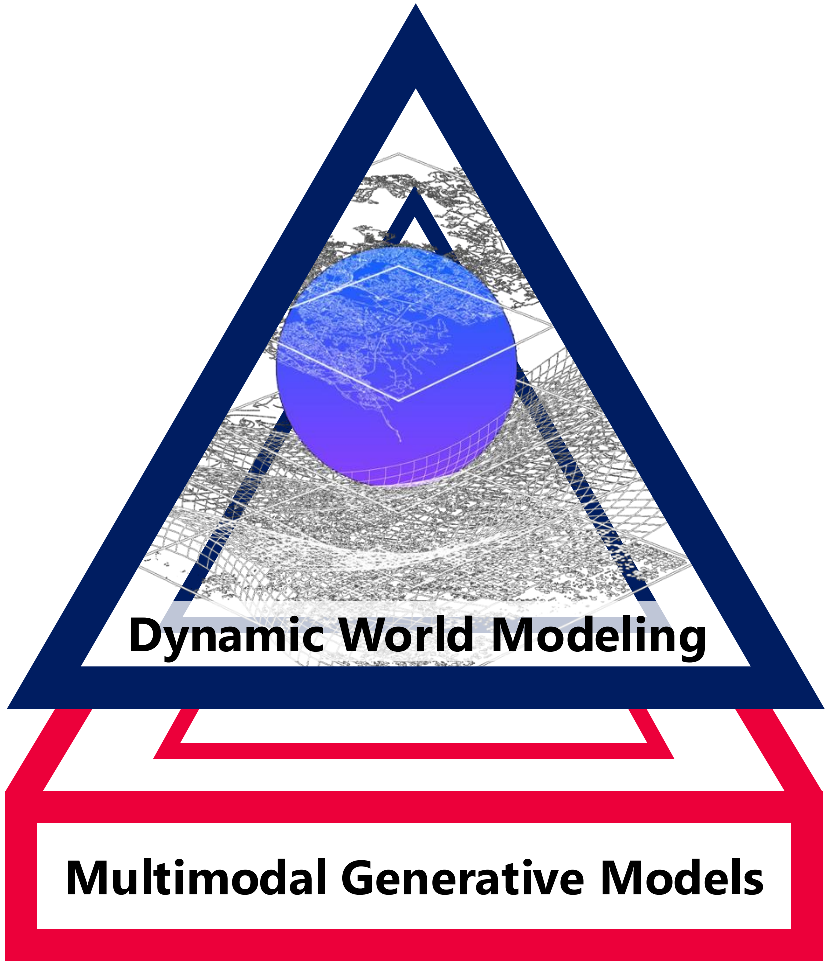

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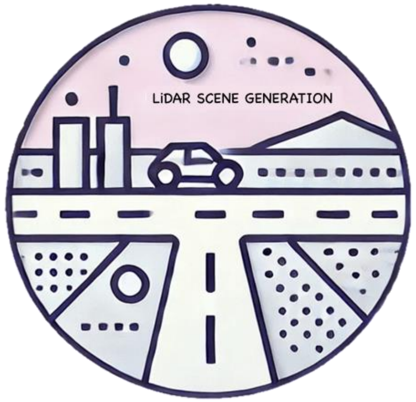


Be Dynamic: DynamicCity

3DTopia/DynamicCity

DynamicCity: Large-Scale 4D Occupancy Generation from Dynamic Scenes

Hengwei Bian, Lingdong Kong, Haozhe Xie, Liang Pan, Yu Qiao, Ziwei Liu

ICLR 2025 Spotlight

Challenges

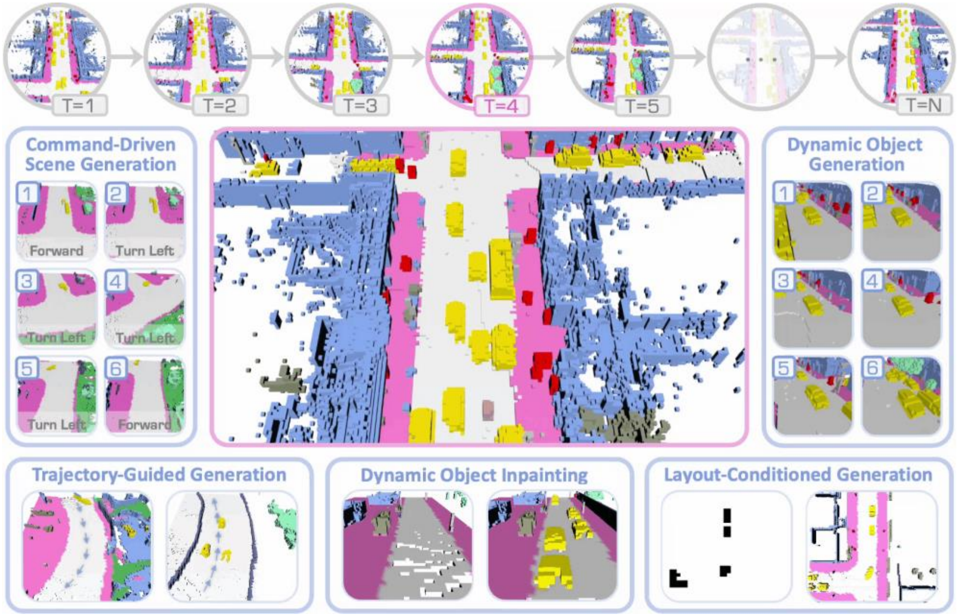
- Inefficient VAEs for 4D data
  - low compression
  - poor reconstruction
- Suboptimal generation quality
- Limited control over the generation process

OccSora

Go Straight

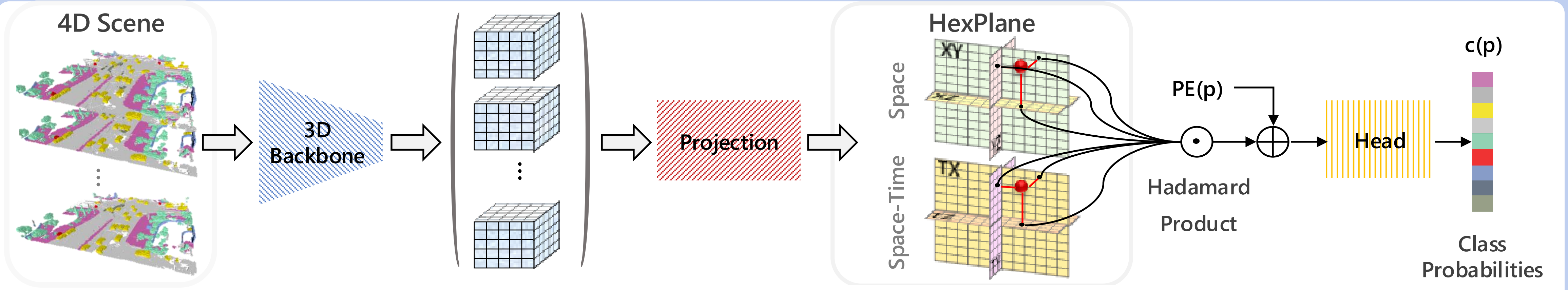
Turning

Ours

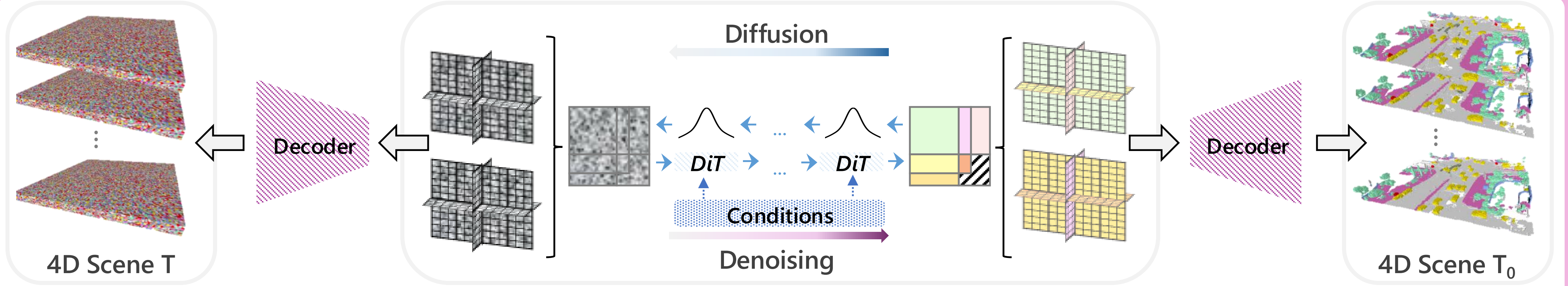


OccSora: 4D Occupancy Generation Models as World Simulators for Autonomous Driving. arXiv 2405.20337.

DynamicCity: 4D Occupancy Generation



(a) Learning HexPlane as an Efficient 4D Scene Representation

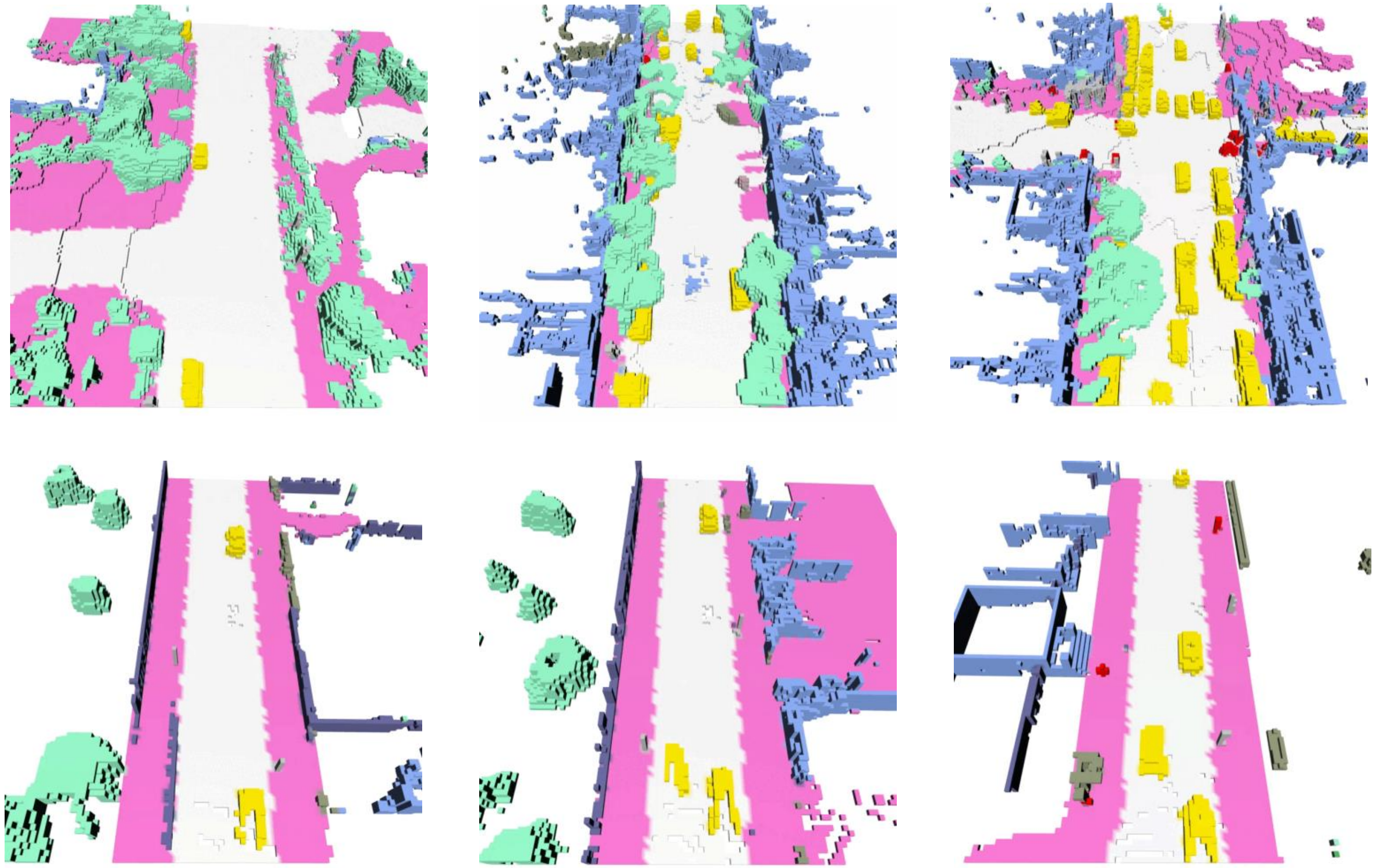


(b) HexPlane Diffusion with DiT for 4D Scene Generation

Unconditional 4D Generation

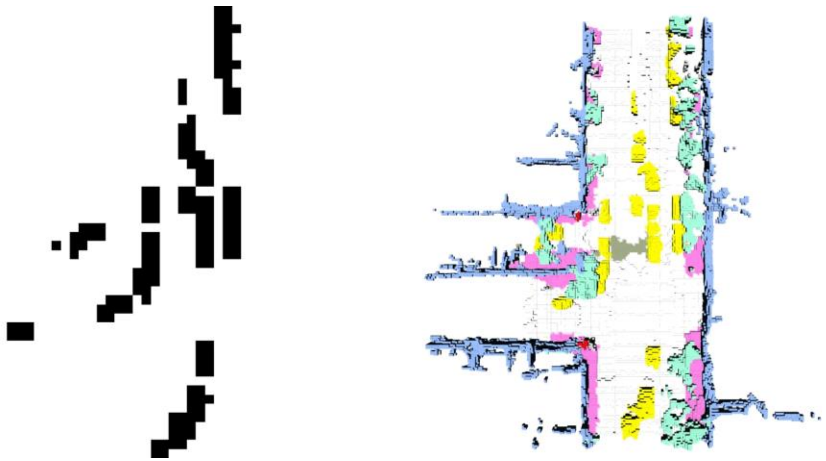
Occc3D-Waymo

CarlaSC

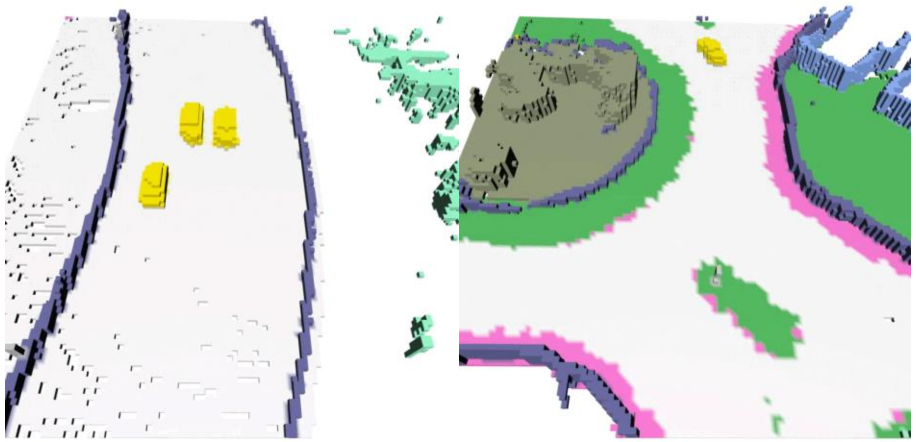


Conditional 4D Generation

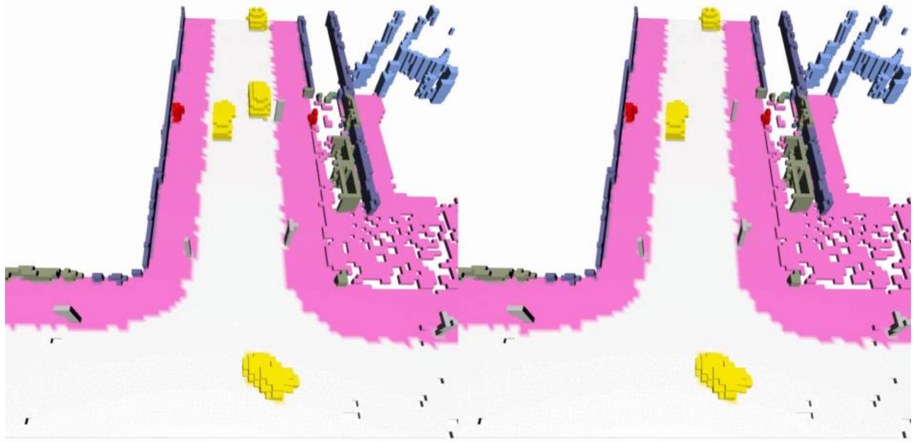
Layout-conditioned



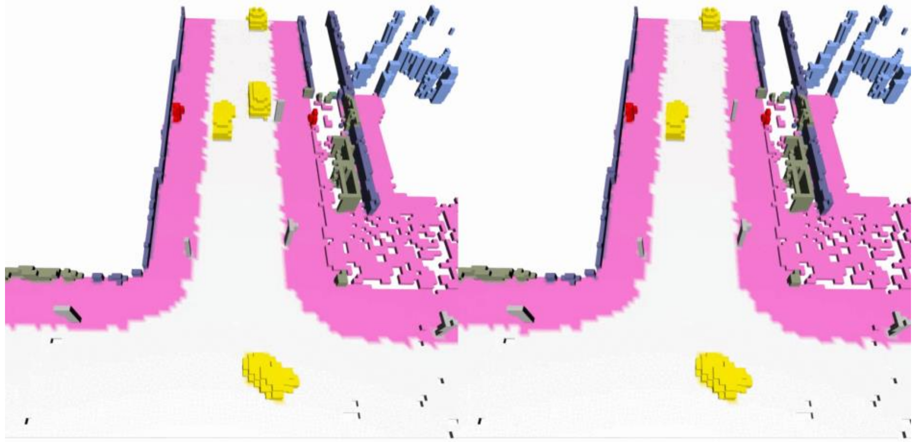
Trajectory-conditioned



Inpainting



Outpainting



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Be Dynamic: CityDreamer4D

hzxie/CityDreamer4D

CityDreamer4D: Compositional Generative Model of Unbounded 4D Cities

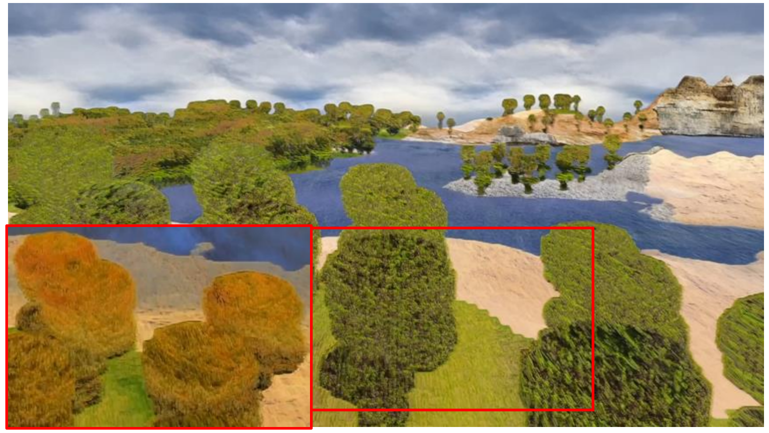
Haozhe Xie, Zhaoxi Chen, Fangzhou Hong, Ziwei Liu

arXiv 2501.08983

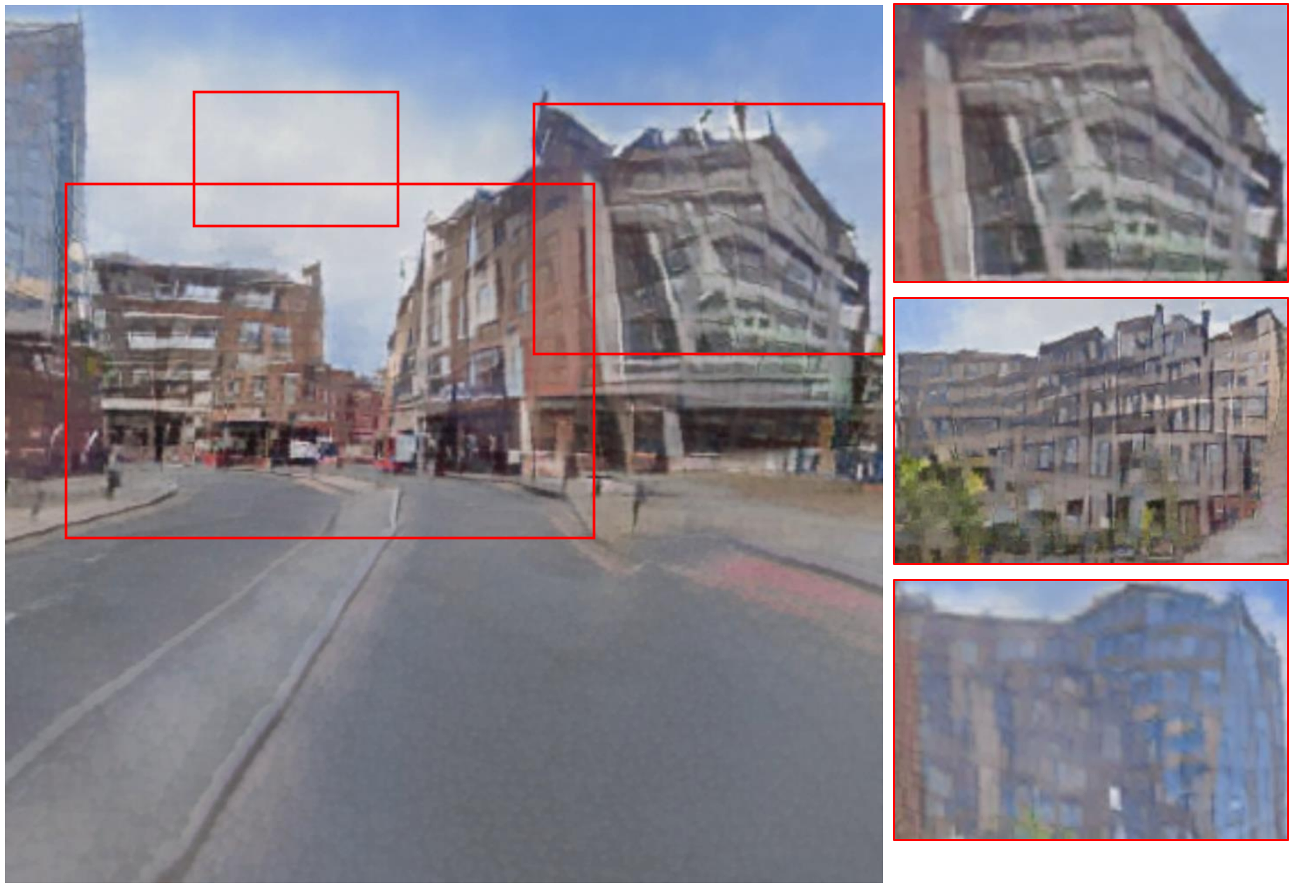
How to Generate Unbounded 3D Cities?

- Creating cities are more challenging than natural scenes

GANCraft [CVPR'21]

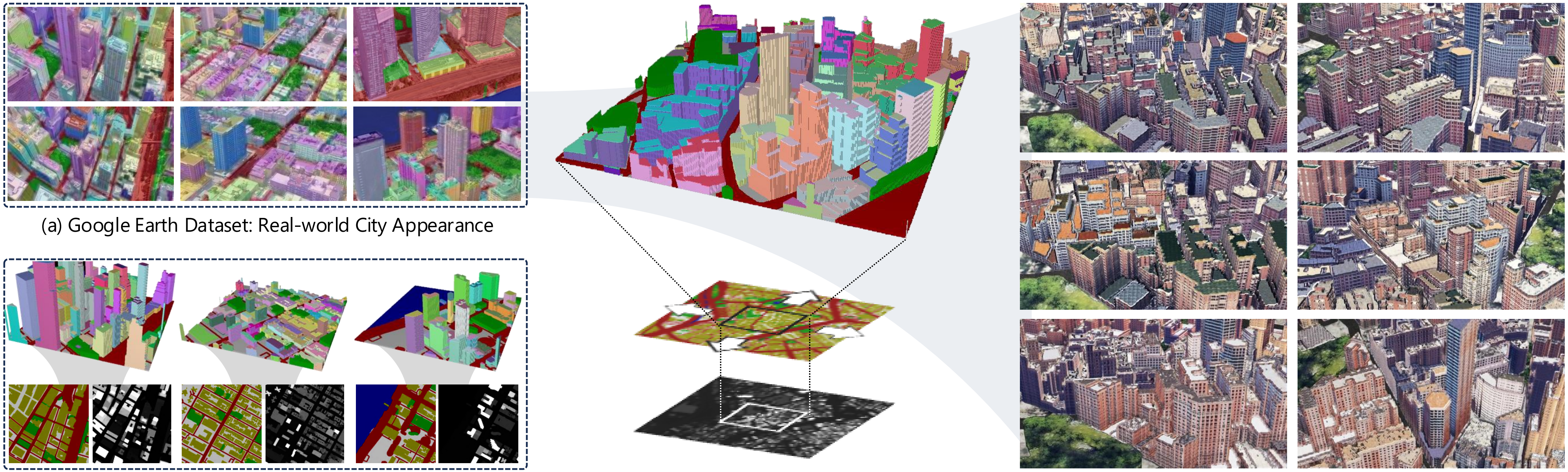


SceneDreamer [TPAMI'23]



InfiniCity [ICCV'23]

Learning 3D City from Unannotated 2D Images



(a) Google Earth Dataset: Real-world City Appearance

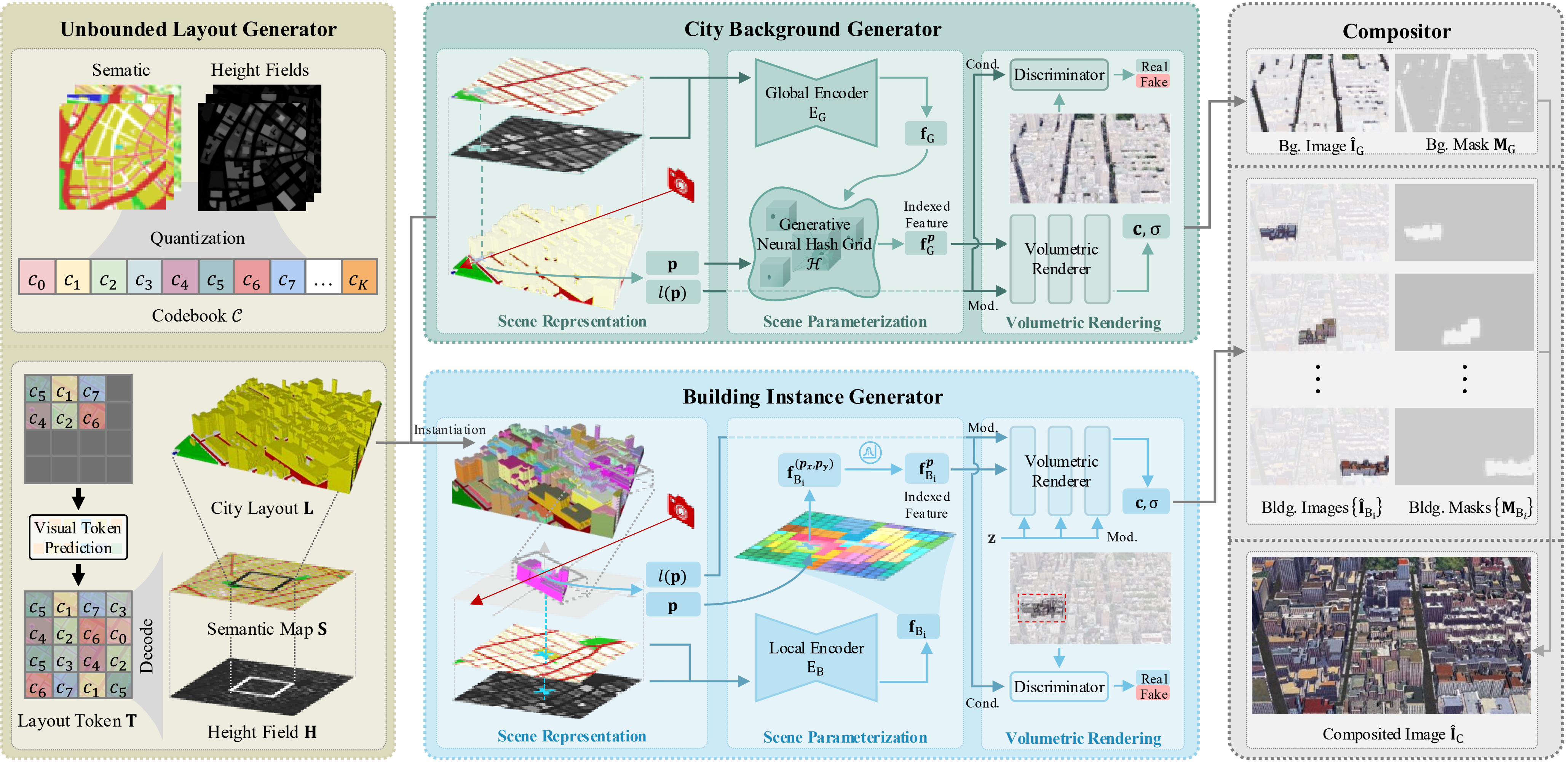
(b) OSM Dataset: Real-world City Layout

(c) Unbounded City Layout Generation

(d) CityDreamer Generated 3D Cities

CityDreamer: Compositional Generative Model of Unbounded 3D Cities. CVPR 2024.

CityDreamer Framework



CityDreamer: Compositional Generative Model of Unbounded 3D Cities. CVPR 2024.

Rendering in Unreal Engine 5

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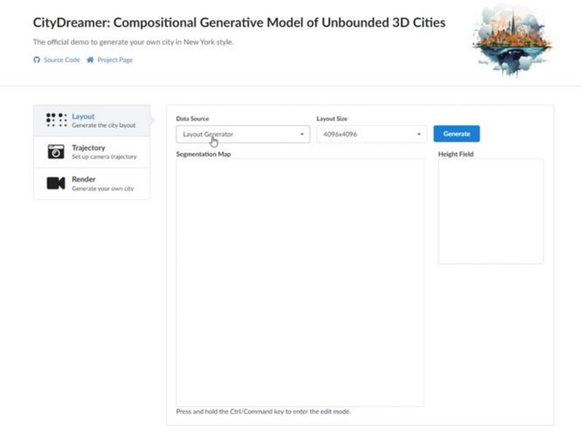
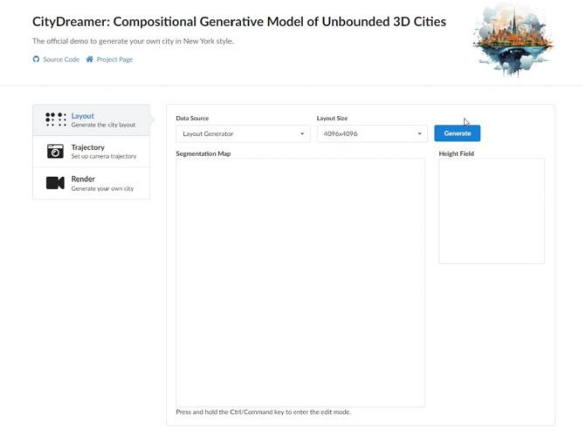




CityDreamer: Compositional Generative Model of Unbounded 3D Cities. CVPR 2024.

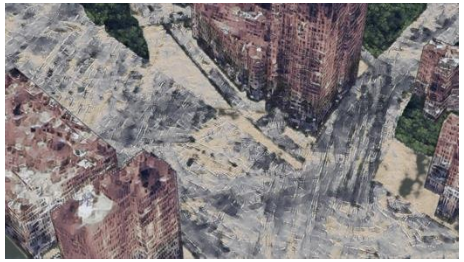
How to Make the City Generation Faster?

- Challenge 1

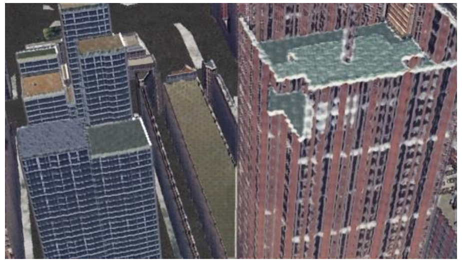
  NeRF-based Methods are Not Efficient

Pers.Nature *(5.99 FPS)*

InfiniCity *(Unknown)*



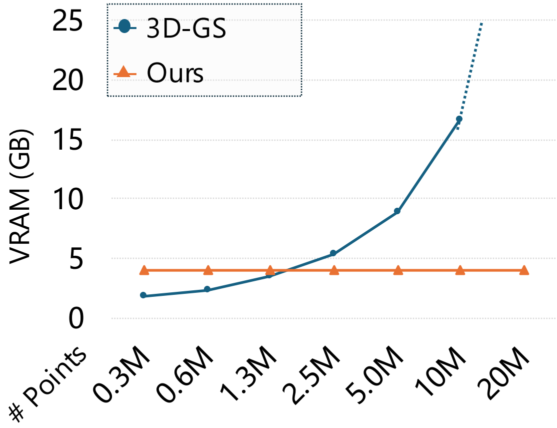
SceneDreamer *(1.61 FPS)*

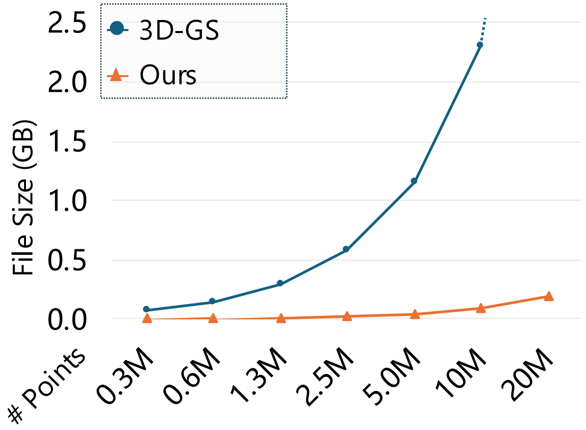


CityDreamer *(0.18 FPS)*

- Challenge 2

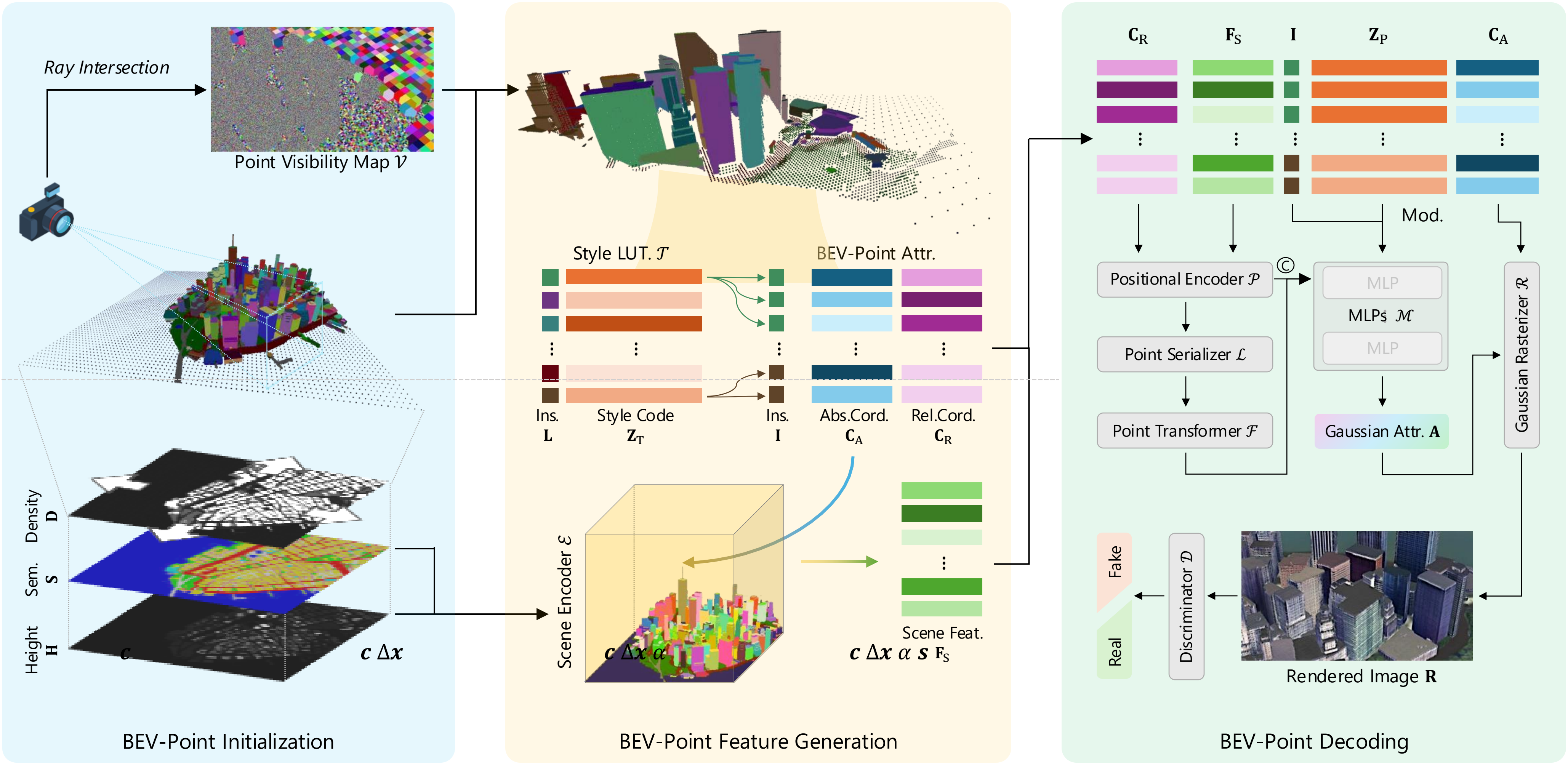
  3D-GS are not Storage Efficient





GaussianCity: Generative Gaussian Splatting for Unbounded 3D City Generation. CVPR 2025.

GaussianCity Framework



GaussianCity: Generative Gaussian Splatting for Unbounded 3D City Generation. CVPR 2025.

60x Faster City Generation with GaussianCity

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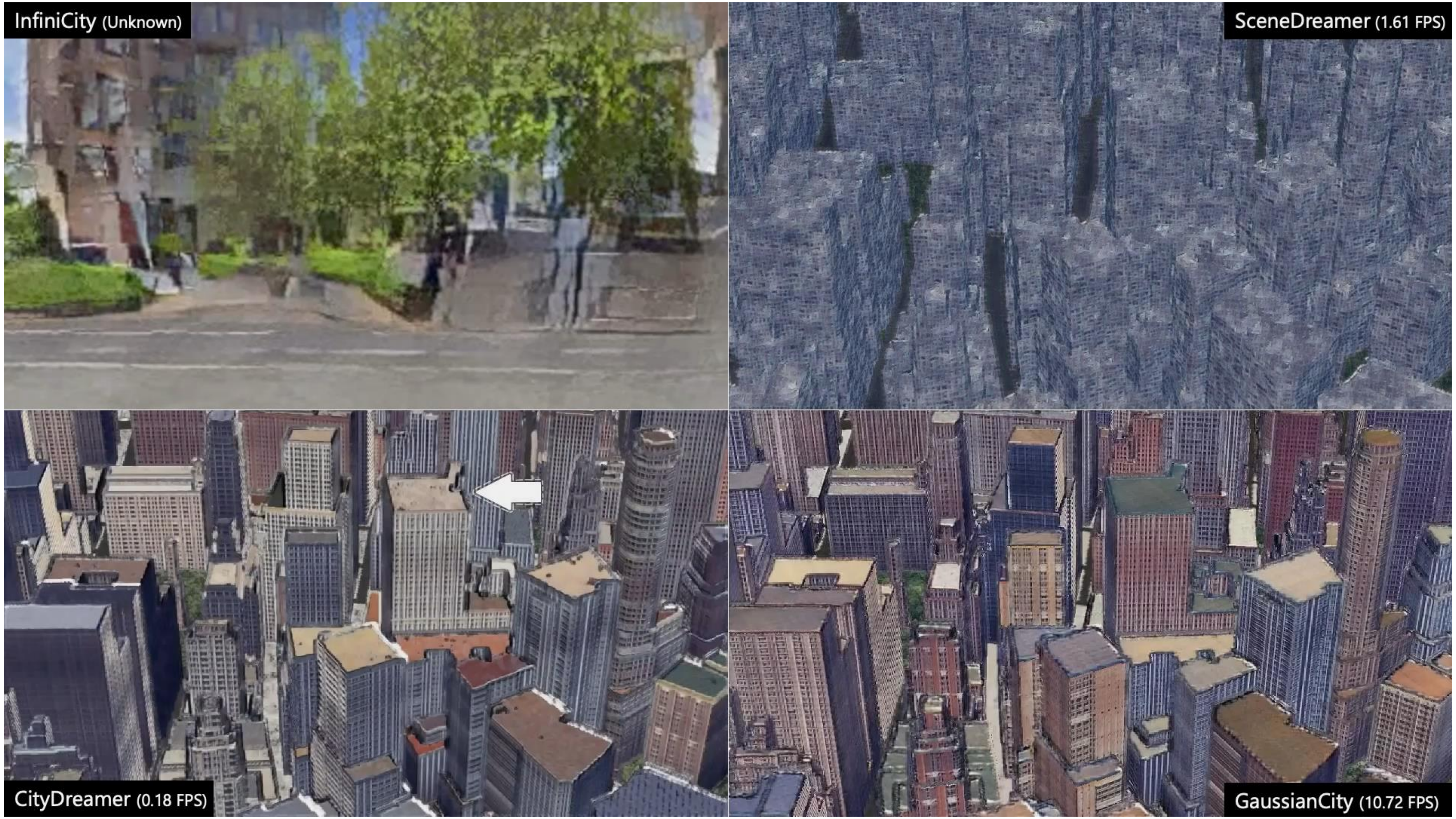
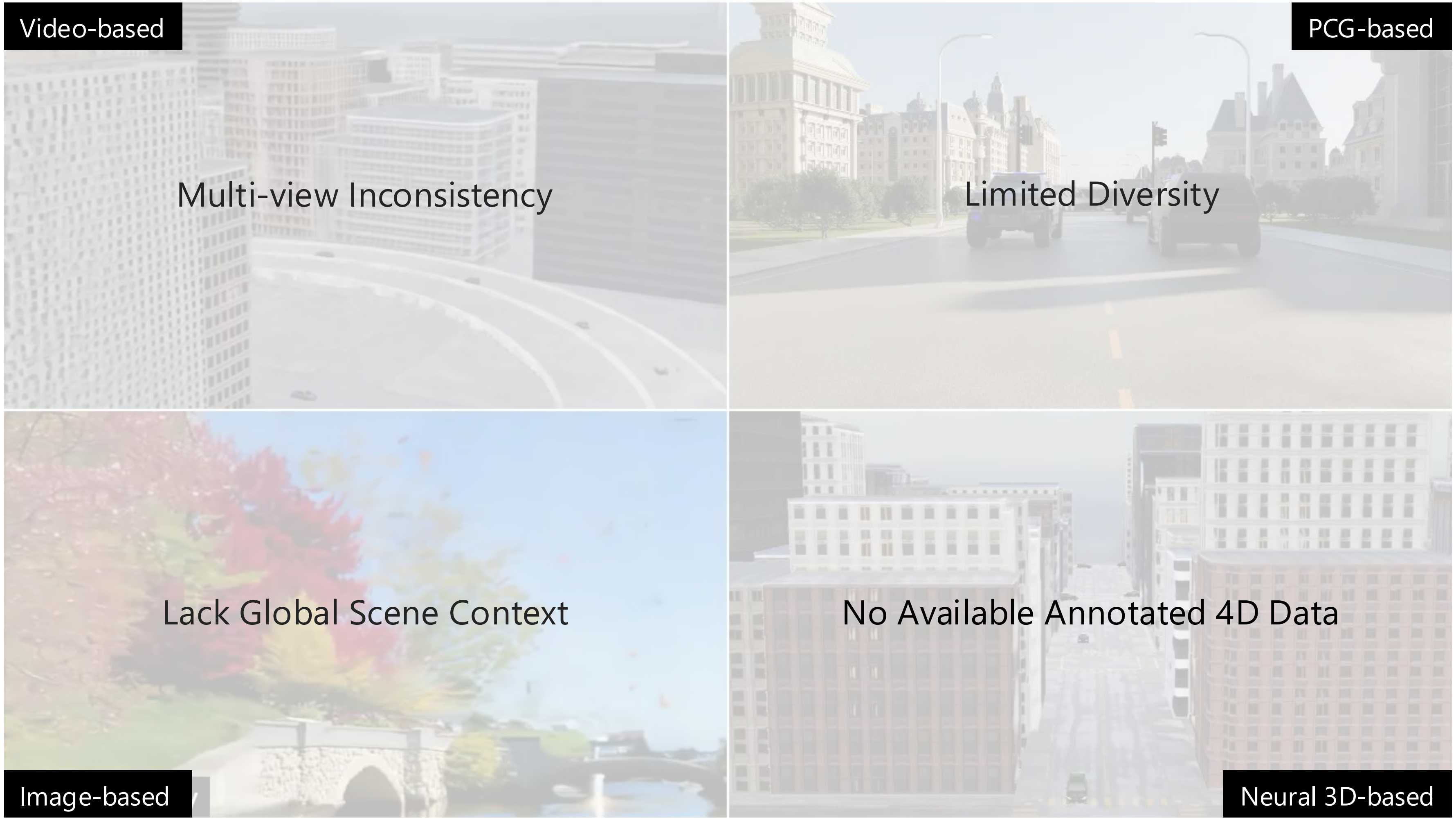


GaussianCity: Generative Gaussian Splatting for Unbounded 3D City Generation. CVPR 2025.

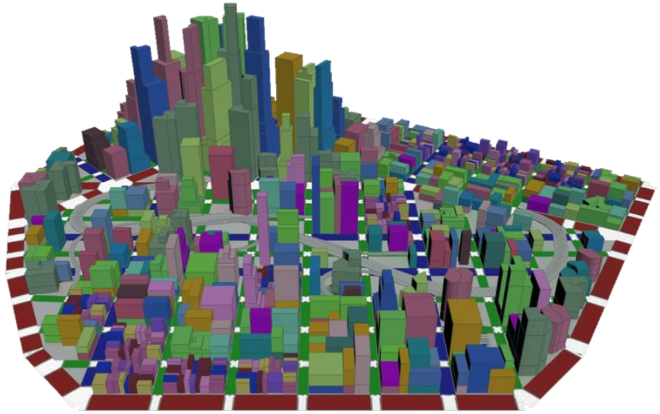
How to Generate 4D Cities?



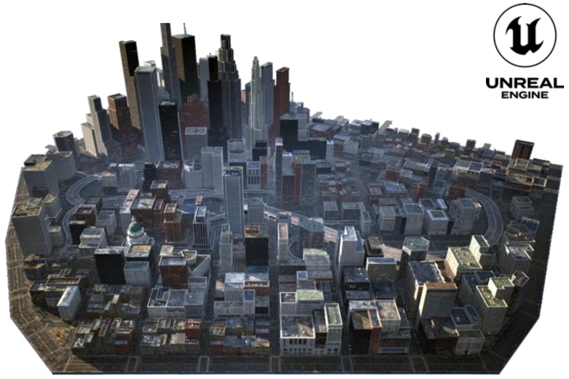
[1] Wonderjourney: Going from Anywhere to Everywhere. CVPR 2024.
[2] CityX: Controllable Procedural Content Generation for Unbounded 3D Cities. arXiv 2407.17572.
[3] DimensionX: Create Any 3D and 4D Scenes from a Single Image with Controllable Video Diffusion. arXiv 2411.04928.

Learning 4D City from 3D Data Annotations

3D Assets
(Small set for Visualization)



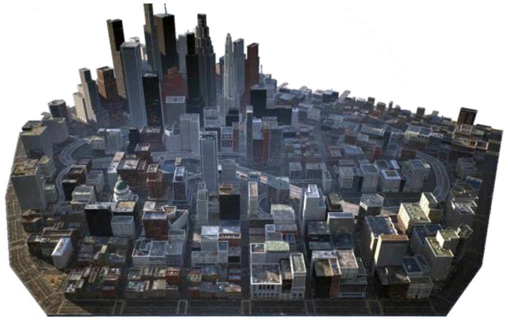
City Prototype

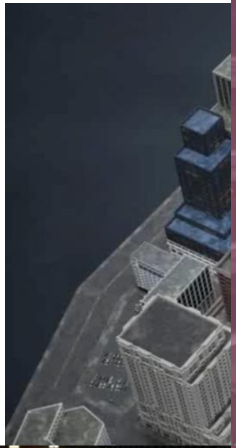


Generated 3D City

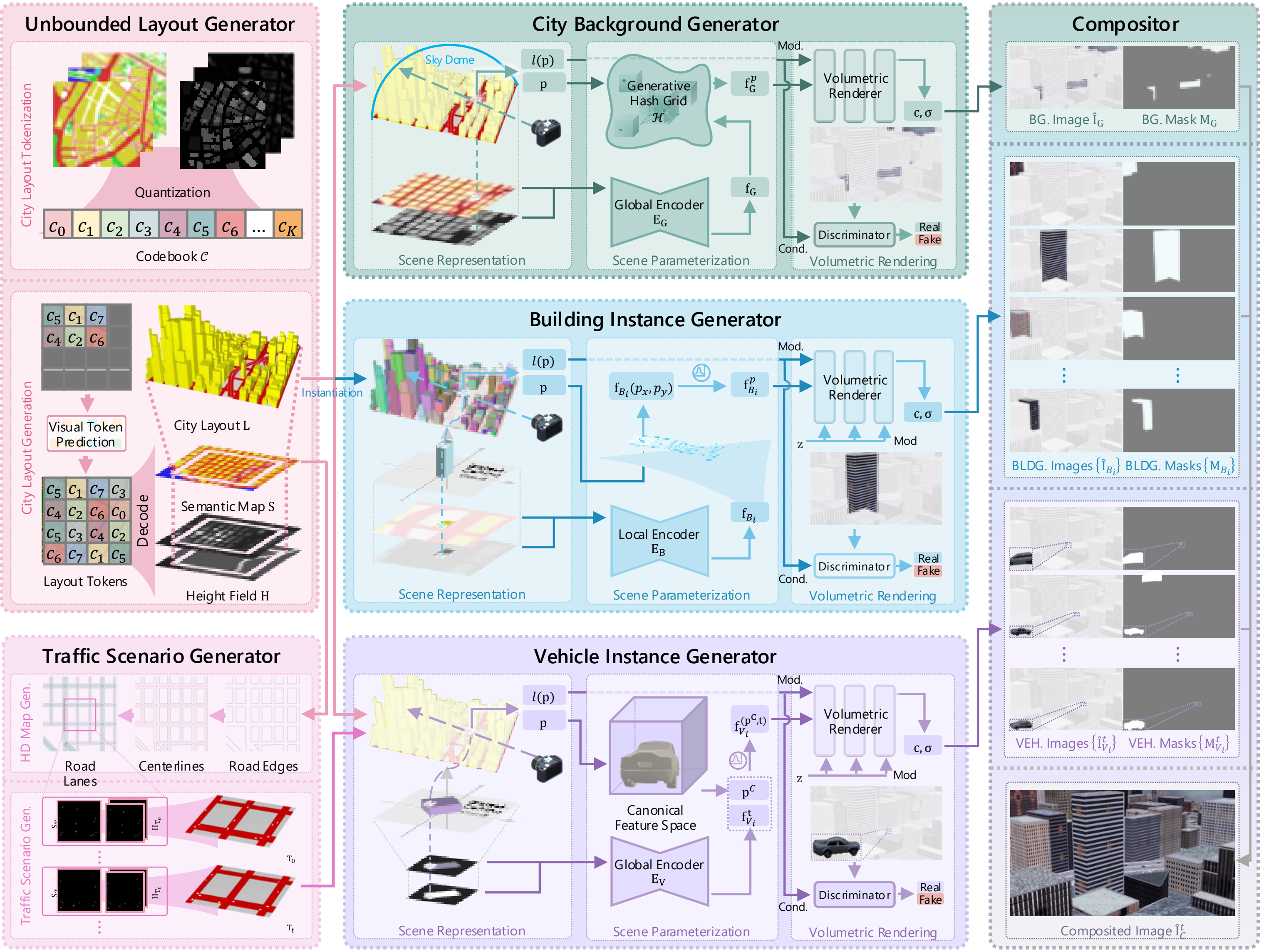
3D Instance Annotation

The CityTopia Dataset





CityDreamer4D Framework



Comparison to SOTA Methods

Arbitrary View Rendering

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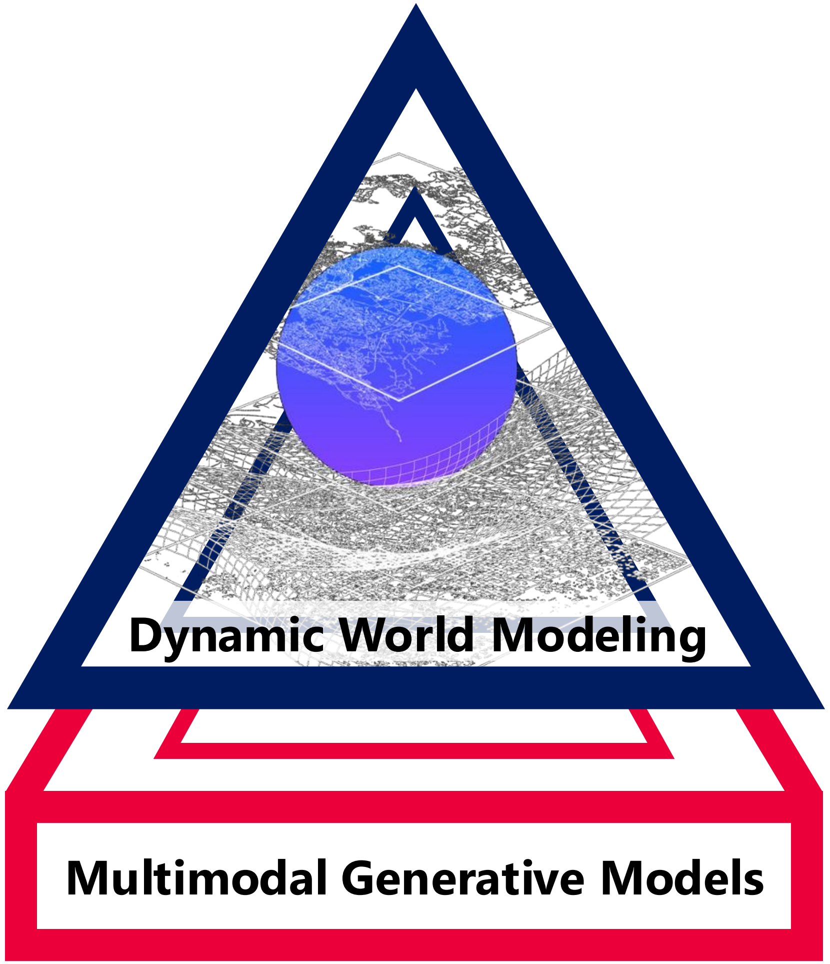
Be Dynamic

How to Model Dynamic Scenes



Be Social

How to Model Social Interactions

Be Social: SOLAMI

SOLAMI: Social Vision-Language-Action Modeling for Immersive Interaction with 3D Autonomous Characters

Jianping Jiang, Weiye Xiao, Zhengyu Lin, Huaizhong Zhang, Tianxiang Ren, Yang Gao, Zhiqian Lin, Zhongang Cai, Lei Yang, Ziwei Liu

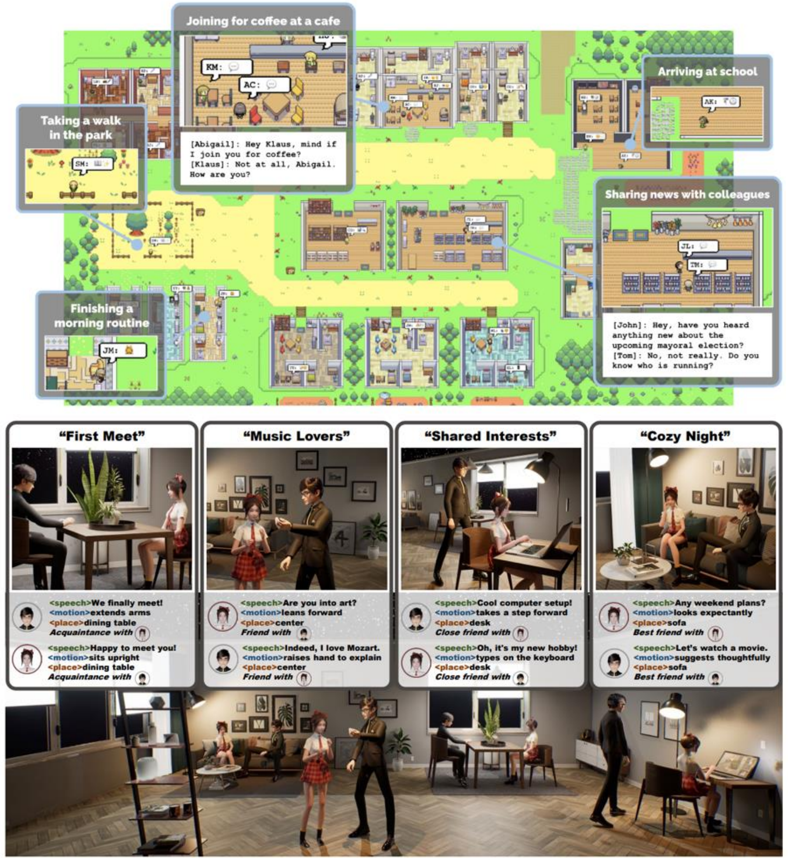
CVPR 2025

3D Characters with Social Intelligence

- Modeling with LLM-Agent Framework

Generative Agents [1]

Digital Life Project [2]

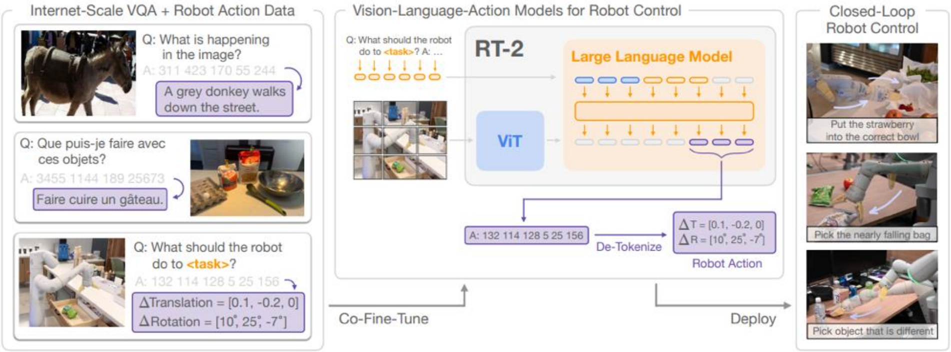


- Limitations
  - Scalable Formulation
  - Multimodal Coherence
  - Latency

[1] Generative Agents: Interactive Simulacra of Human Behavior. UIST 2023.
[2] Digital Life Project: Autonomous 3D Characters with Social Intelligence. CVPR 2024.

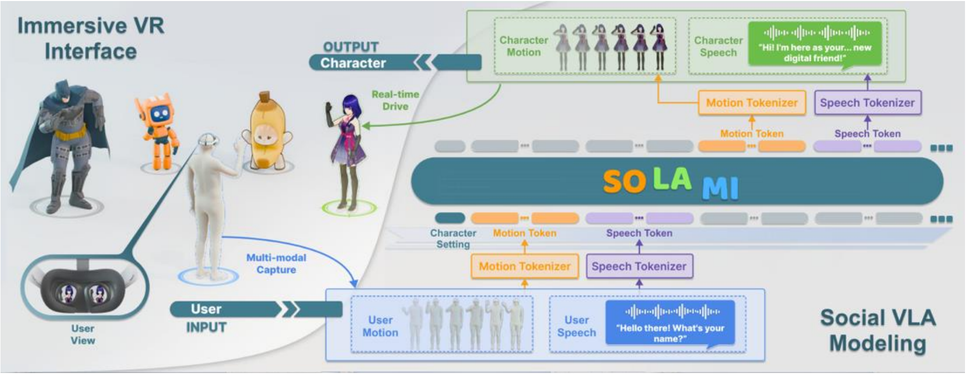
Motivation: Avatar as Virtual Robot

Robot
3D Agent with Real Embodiment
(Real-world Task & Interaction)



RT-2 [1]:Vision-Language-Action Models

3D Avatar
3D Agent with Virtual Embodiment
(Natural Appearance & Behavior)

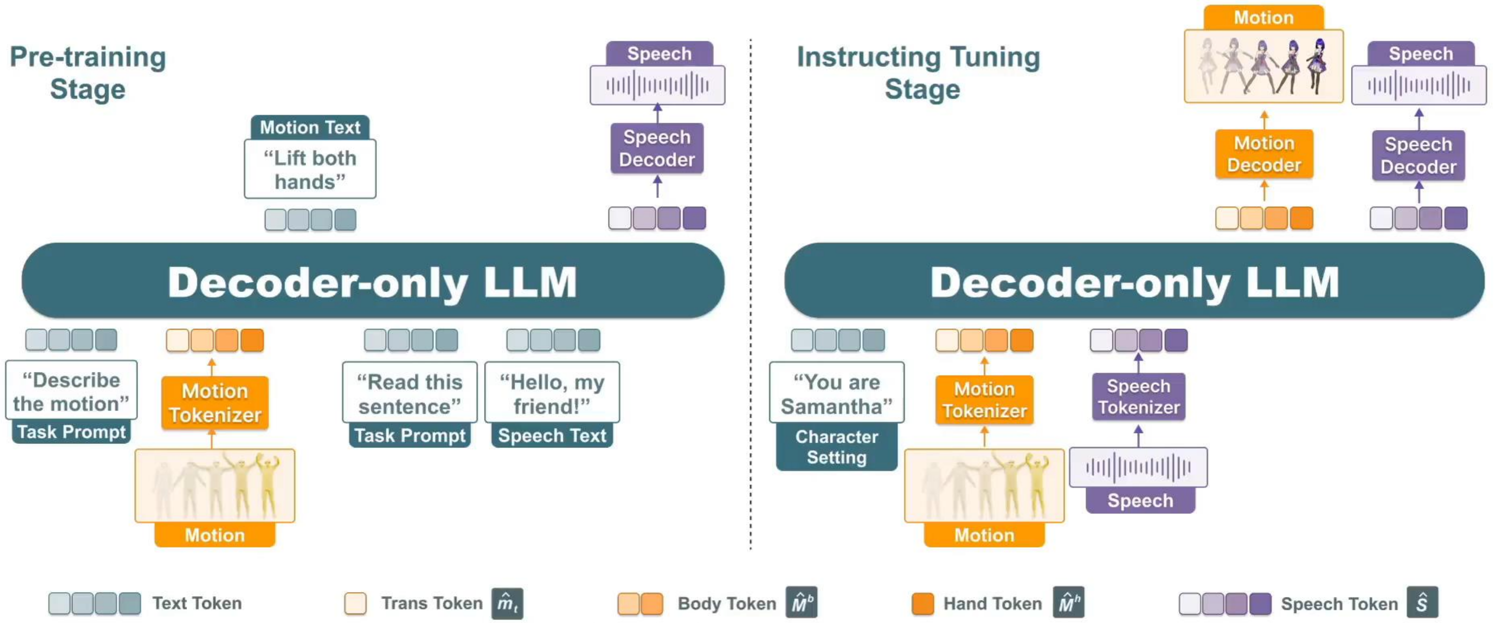


Social VLA for Immersive Interaction with 3D Characters

[1] RT-2: Vision-Language-Action Models Transfer Web Knowledge to Robotic Control. CoRL 2023.

Training Recipe

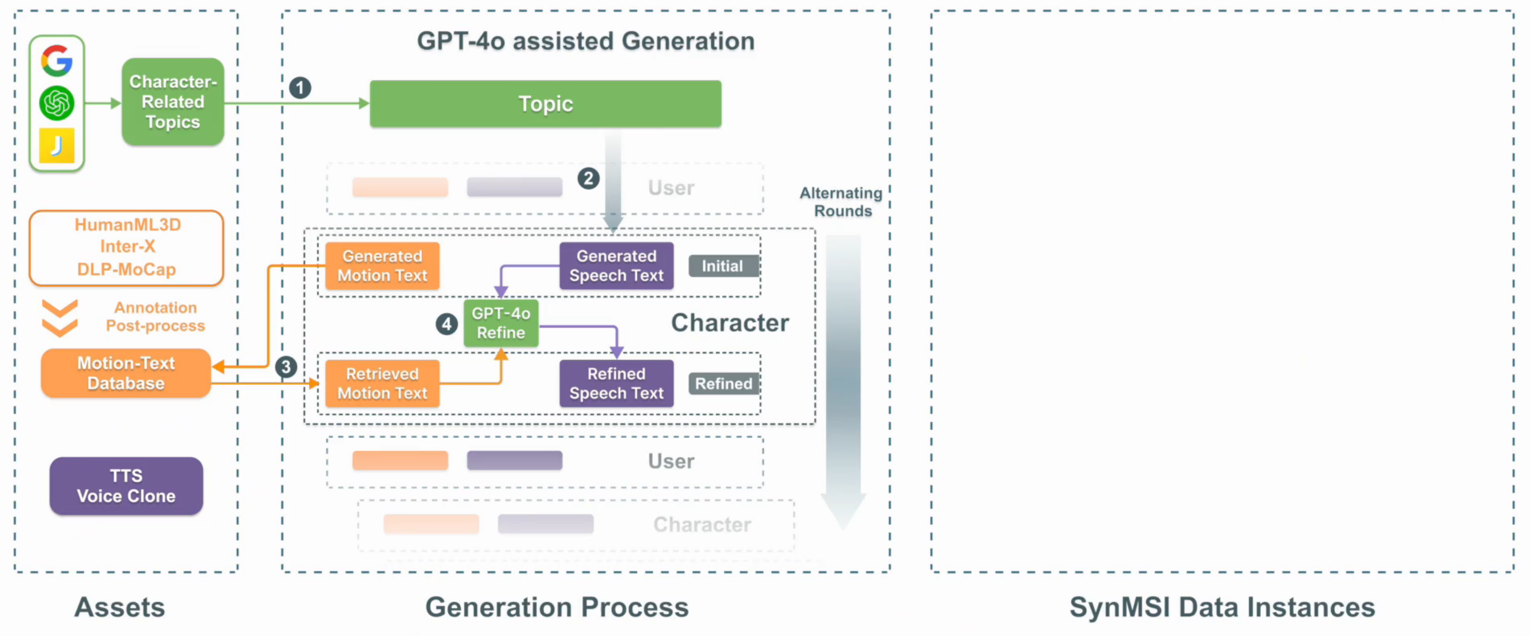
- Training Stages
  - Stage1: Motion & Speech Tokenizer Training
  - Stage2: Motion-Text-Speech Alignment with Multi-Task Pretraining
  - Stage3: Instruction Tuning for Multimodal Chat



为了赋予SOLAMI
To empower SOLAMI

Data Generation

- Multimodal Chat Data Synthesize
  - LLM-Generated Scripts
    - Diverse Topics
    - Refined Process
  - Motion-Text Dataset
    - Large-Scale



Evaluation: Quantitative & Qualitative

- Compared to Speech-Only Method
  - Better User Experience
- Compared to LLM-Agent Framework
  - Low Latency & Multimodal Coherence
  - Alignment Tax on Text

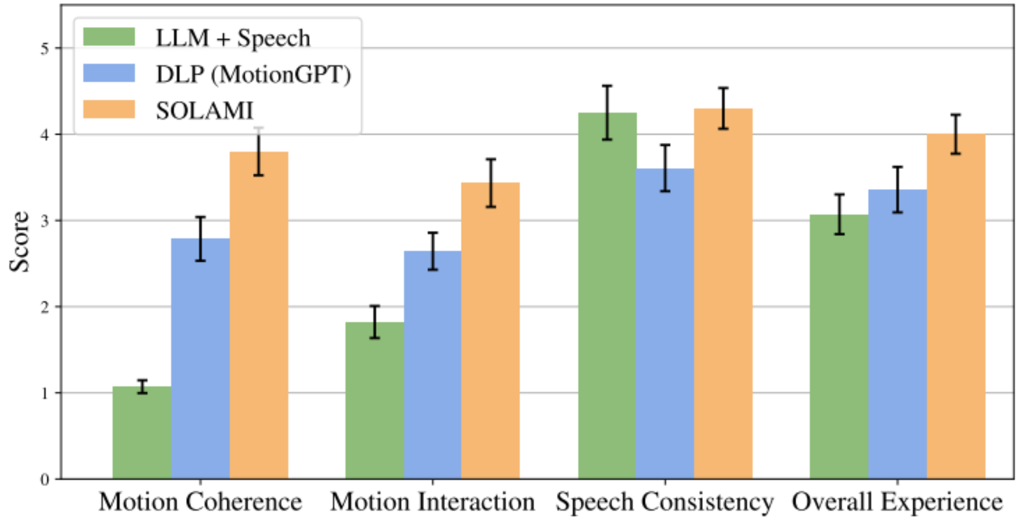
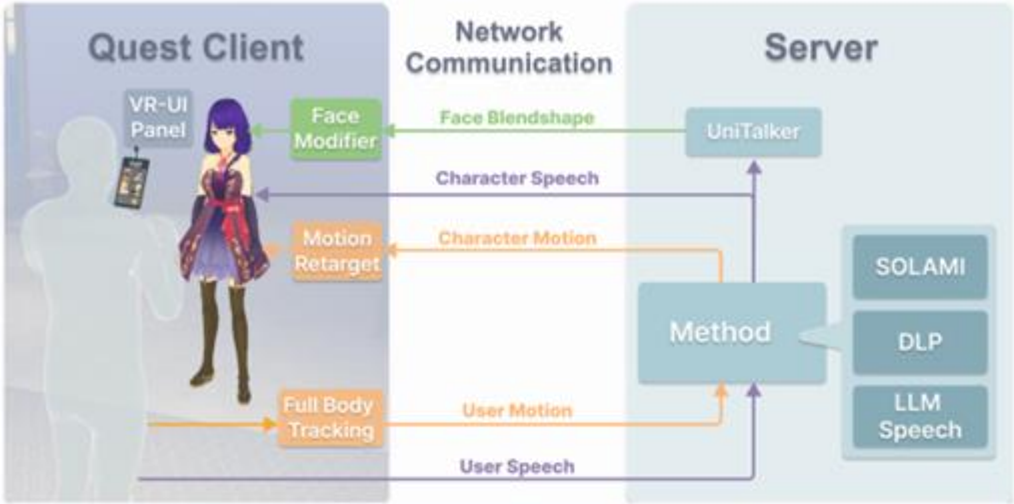


Table 1. **Quantitative results of baselines and SOLAMI.** '↑'('↓') indicates that the values are better if the metrics are larger (smaller). We run all the evaluations 5 times and report the average metric. The best results are in bold and the second best results are underlined.

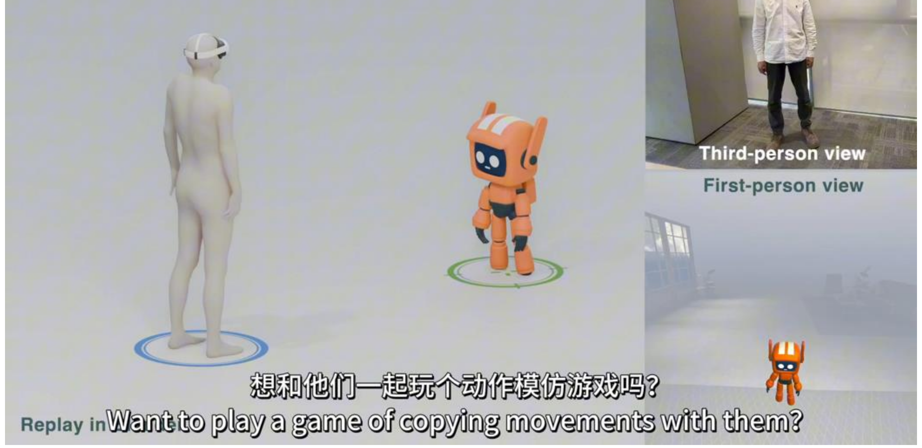
Methods	Motion Metrics				Speech Metrics			Inference Latency ↓
	FID↓	Diversity↑	PA-MPJPE↓	Angle Error↓	VC Similarity↑	Context Relevance↑	Character Consistency↑	
SynMSI Dataset	-	9.136	-	-	-	4.888	4.893	-
LLM+Speech (Llama2) [69]	-	-	-	-	0.818	3.527	**3.859**	3.157
AnyGPT (fine-tune) [81]	-	-	-	-	0.819	3.502	3.803	**2.588**
DLP (MotionGPT) [17]	<u>4.254</u>	8.259	165.053	0.495	0.812	<u>3.577</u>	3.785	5.518
SOLAMI (w/o pretrain)	5.052	<u>8.558</u>	<u>159.709</u>	<u>0.387</u>	<u>0.820</u>	3.541	3.461	2.657
SOLAMI (LoRA)	15.729	8.145	167.149	0.400	0.770	3.251	3.423	2.710
SOLAMI (full params)	**3.443**	**8.853**	**151.500**	**0.360**	**0.824**	**3.634**	<u>3.824</u>	<u>2.639</u>

Demo: VR Interface

Comprehension of Body Language



Execution of Motion Commands



Engagement in Interactive Tasks

Be Social: EgoLife

EvolvingLMMs-Lab/EgoLife

EgoLife: Towards Egocentric Life Assistant

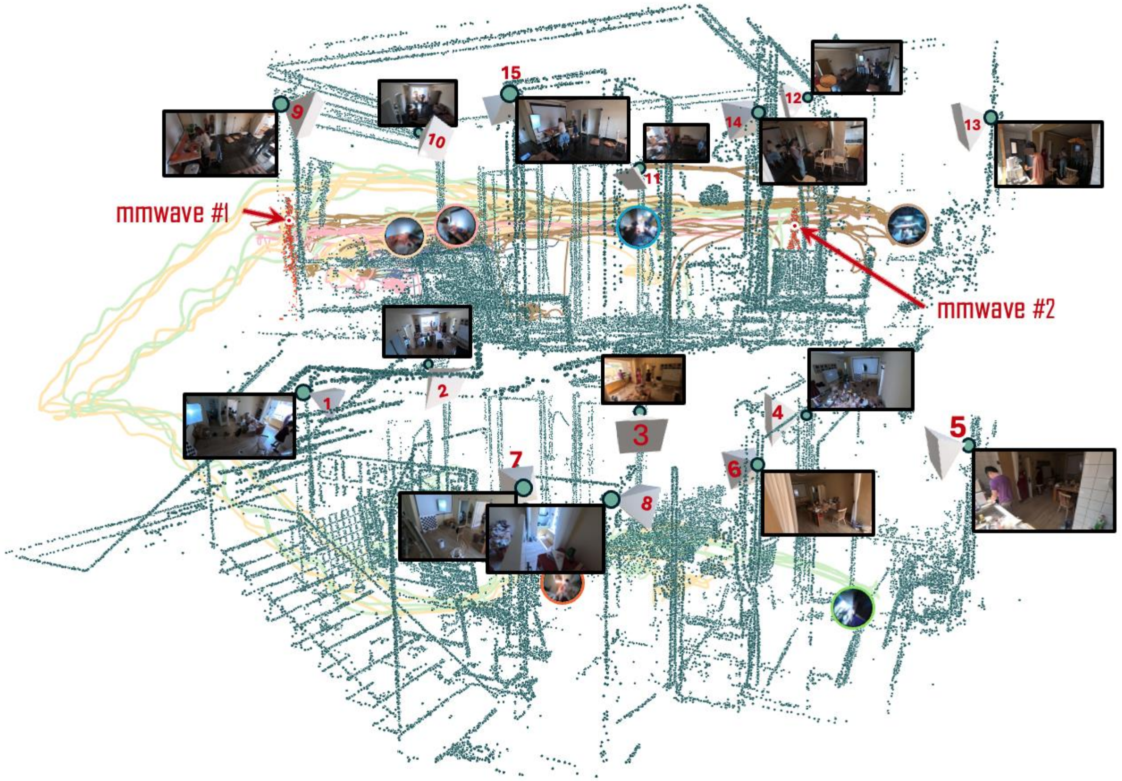
Jingkang Yang, Shuai Liu, Hongming Guo, Yuhao Dong, Xiamengwei Zhang, Sicheng Zhang, Pengyun Wang, Zitang Zhou, Binzhu Xie, Ziyue Wang, Bei Ouyang, Zhengyu Lin, Marco Cominelli, Zhongang Cai, Yuanhan Zhang, Peiyuan Zhang, Fangzhou Hong, Joerg Widmer, Francesco Gringoli, Lei Yang, Bo Li, Ziwei Liu

CVPR 2025

We invited 6 people living together for 7 days in egolife

Each one wearing Meta Aria glasses (almost) all day long.

The EgoLife Collected Data



Ego video, audio, mmwave, wifi, Ego/Exo signals synchronization.

The EgoLife Timeline

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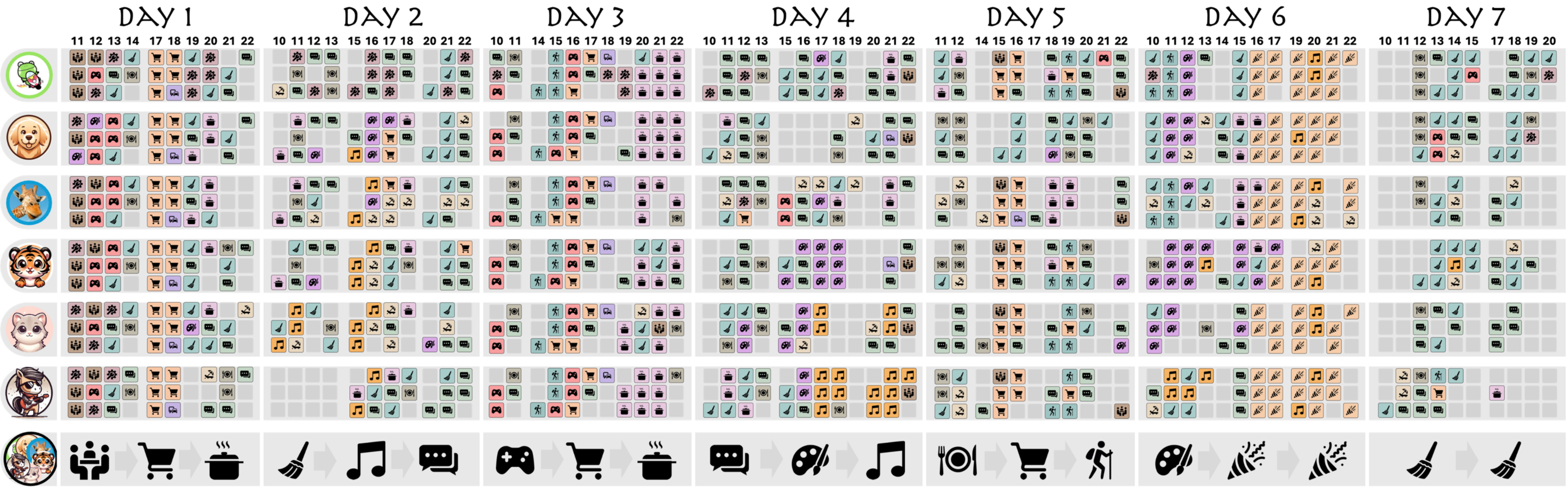

Social ×183 Housekeeping ×145 Cooking ×86 Shopping ×74 Dining ×67 Party ×64 Arts & Craftwork ×57
Leisure ×49 Games ×46 Music & Dance ×45 Outing ×40 Setup ×35 Meeting ×31 Commuting ×15

The EgoLifeQA Benchmark

6 x 500 = 3000 QAs

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EventRecall — Past Events of Interest

Day 1: 21:48:21.200

What was the first song mentioned after planning to dance?

A. Why Not Dance B. Mushroom
C. I Wanna Dance with Somebody
D. Never Gonna Give You Up

Answer: A. Evidence: @ Day 1 11:46:59.050
Shure sang after Jake asked us to dance.

EntityLog — Past Objects of Interest

Day 4: 11:34:05.400

Which price is closest to what we paid for one yogurt?

A. RMB 2 B. RMB 3
C. RMB 4 D. RMB 5

Answer: B. Evidence:
The yogurt is on sale, RMB19.9 for 6 cups
@ Day 3: 17:00:04.450

TaskMaster — Tasks Assignment and Review

Many things are in my cart already. What items that we previously discussed have I not bought yet?

A. Milk
B. Chicken wings
C. Strawberries
D. Bananas

Day 5: 16:20:46.350

Answer: A. Evidence:
I made a shopping list, and already got fruit, etc., but ...
D5-15:10 15:57 … 16:14

HabitInsight — Personal Habit Patterns

Day 4: 12:08:50.600

What activity do I usually do while drinking coffee?

A. Scrolling through TikTok
B. Texting on the phone
C. Tidying up the room
D. Doing Craftwork

Answer: D. Evidence:
D1-16:14 D2-10:40 D2-10:52 … D4-11:39
I had coffee a total of five times, three of which were while doing crafts...

RelationMap — Interpersonal Interaction Patterns

Day 6: 19:50:19.750

Shure is playing the guitar now. Who else usually joins us playing guitar together?

A. Choizst
B. Jake
C. Nicous
D. Lucia

Answer: C. Evidence:
D4-17:19 D4-17:22 D4-22:00 D5-22:52
Nicous played the guitar with Shure and me twice, more frequently than anyone else.

The EgoLifeQA Benchmark

EgoButler

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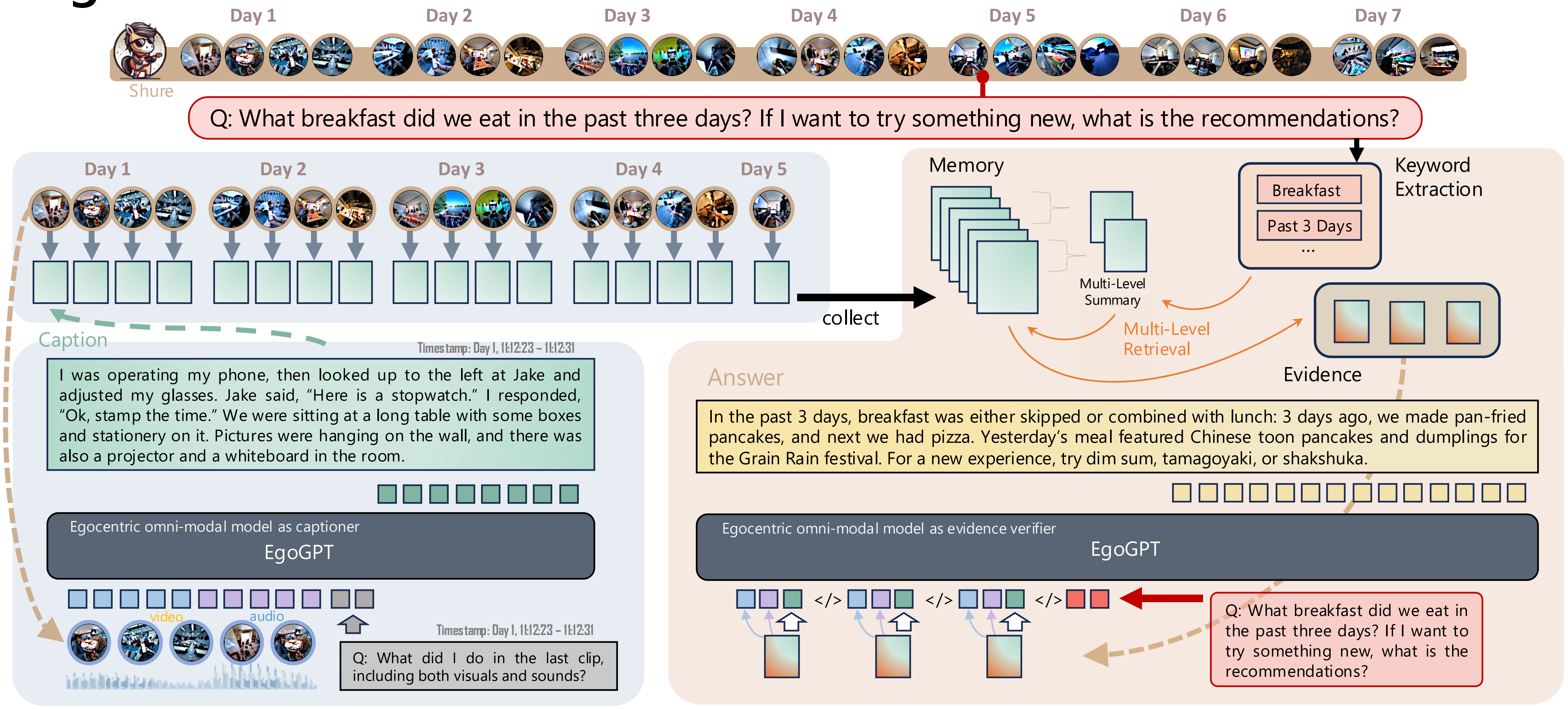
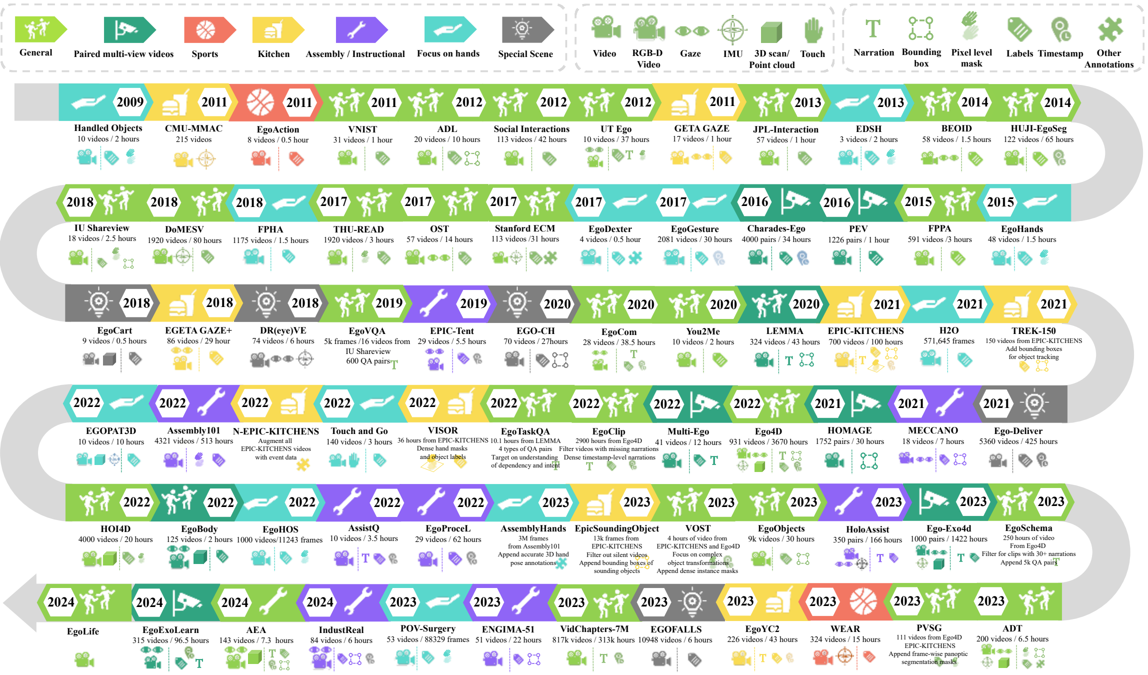


(a) Captioning Stage with EgoGPT

(b) Question Answering Stage with EgoRAG

EgoButler – The EgoGPT Component

LLaVA-OneVision (Qwen2 as LLM) → Whisper as audio encoder, SFT an audio projector on Qwen2 with ASR datasets → LLaVA-OneVision that supports audio → SFT on EgoIT and EgoLife → EgoGPT



Overview of Classic Egocentric Dataset

Performance of EgoGPT-7B. The table presents a comprehensive comparison of EgoGPT against state-of-the-art commercial and open-source models on existing egocentric benchmarks. With EgoIT and EgoLife Day 1 data, EgoGPT achieve impressive performance on ego setting.

Model	#Param	#Frames	EgoSchema	EgoPlan	EgoThink
GPT-4v [95]	-	32	56.6	38.0	65.5
Gemini-1.5-Pro [96]	-	32	72.2	31.3	62.4
GPT-4o [97]	-	32	72.2	32.8	65.5
LLaVA-Next-Video [98]	7B	32	49.7	29.0	40.6
LongVA [99]	7B	32	44.1	29.9	48.3
IXC-2.5 [100]	7B	32	54.6	29.4	56.0
InternVideo2 [101]	8B	32	55.2	27.5	43.9
Qwen2-VL [94]	7B	32	66.7	34.3	59.3
Oryx [57]	7B	32	56.0	33.2	53.1
LLaVA-OV [55]	7B	32	60.1	30.7	54.2
LLaVA-Videos [102]	7B	32	57.3	33.6	56.4
EgoGPT (EgoIT)	7B	32	73.2	32.4	61.7
EgoGPT (EgoIT+EgoLifeD1)	7B	32	75.4	33.4	61.4

EgoButler – The EgoGPT Component

LLaVA-OneVision (Qwen2 as LLM) → Whisper as audio encoder, SFT an audio projector on Qwen2 with ASR datasets → LLaVA-OneVision that supports audio → SFT on EgoIT and EgoLife → EgoGPT

Dataset Composition of EgoIT-99K. We curated 9 classic egocentric video datasets and utilized their annotations to generate captioning and QA instruction-tuning data for fine-tuning EgoGPT, #AV indicates the number of videos with audio used for training.

Dataset	Duration	#Videos (#AV)	#QA
Ego4D [5]	3.34h	523 (458)	1.41K
Charades-Ego [25]	5.04h	591 (228)	18.46K
HoloAssist [29]	9.17h	121	33.96K
EGTEA Gaze+ [26]	3.01h	16	11.20K
IndustReal [28]	2.96h	44	11.58K
EgoTaskQA [93]	8.72h	172	3.59K
EgoProceL [27]	3.11h	18	5.90K
Epic-Kitchens [4]	4.15h	36	10.15K
ADL [24]	3.66h	8	3.23K
Total	**43.16h**	**1529 (686)**	**99.48K**

Performance of EgoGPT-7B. The table presents a comprehensive comparison of EgoGPT against state-of-the-art commercial and open-source models on existing egocentric benchmarks. With EgoIT and EgoLife Day 1 data, EgoGPT achieve impressive performance on ego setting.

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EgoGPT (EgoIT+EgoLifeD1)	7B	32	75.4	33.4	61.4

EgoButler – The EgoRAG Component

Boosted by EgoGPT, EgoButler achieves SOTA:

- In-depth egocentric video familiarity
- Omni-modal comprehension — effectively integrating both visual and audio signals

Powered by EgoRAG, EgoGPT enables:

- Week-long memory retrieval, answering complex, long-horizon questions
- Robust grounding and context-aware reasoning, where others often fail

Limitations

- ❗ One-Time Retrieval → Agentic Search
- 🧠 Better Person Identification Modeling
- 🔁 Pattern Tracker: Building a habit and behavior pattern engine for continuous insight generation

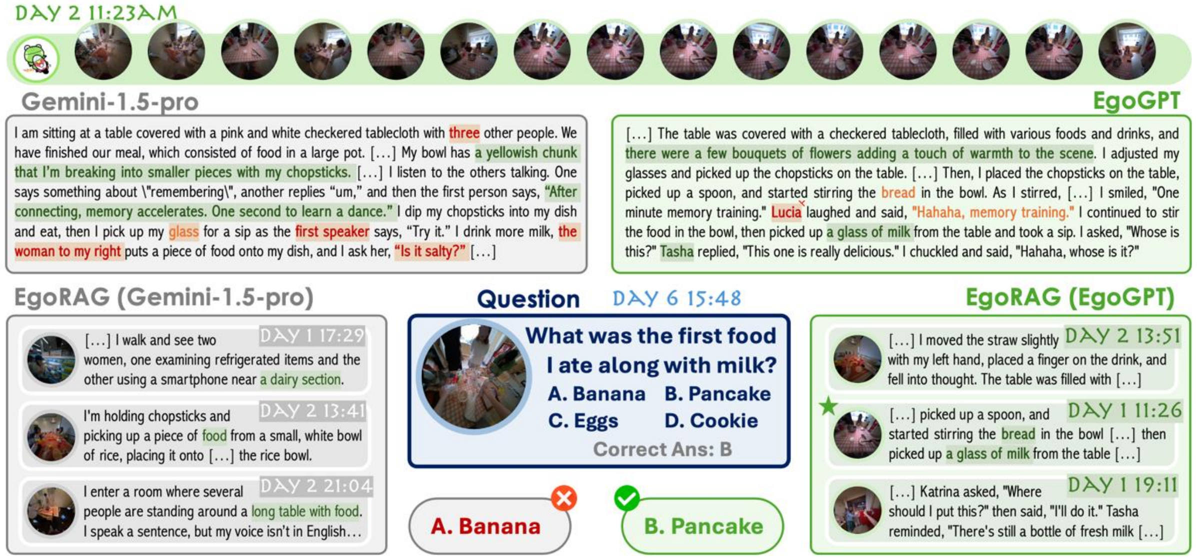

Table 5. **Performance comparison of EgoGPT with state-of-the-art models on EgoLifeQA benchmarks.** For a fair comparison on EgoLifeQA, EgoGPT was replaced with the corresponding models in the EgoButler pipeline to evaluate their performance under the same conditions. Models that provide captions for EgoLifeQA use 1 FPS for video sampling.

Model	#Frames	Audio	Identity	EgoLifeQA					
				EntityLog	EventRecall	HabitInsight	RelationMap	TaskMaster	Average
Gemini-1.5-Pro [95]	-	✓	✗	36.0	37.3	45.9	30.4	34.9	36.9
GPT-4o [96]	1 FPS	✗	✗	34.4	42.1	29.5	30.4	44.4	36.2
LLaVA-OV [55]	1 FPS	✗	✗	36.8	34.9	31.1	22.4	28.6	30.8
EgoGPT (EgoIT-99K)	1 FPS	✓	✗	35.2	36.5	27.9	29.6	36.5	33.1
EgoGPT (EgoIT-99K+D1)	1 FPS	✓	✓	39.2	36.5	31.1	33.6	39.7	36.0

Towards **Extremely Long, Egocentric, Interpersonal, Multi-view, Multi-modal, Daily Life** Video Understanding

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More to explore:

Dense Caption, Transcript, Gaze, Multiple Third-Person View, SLAM

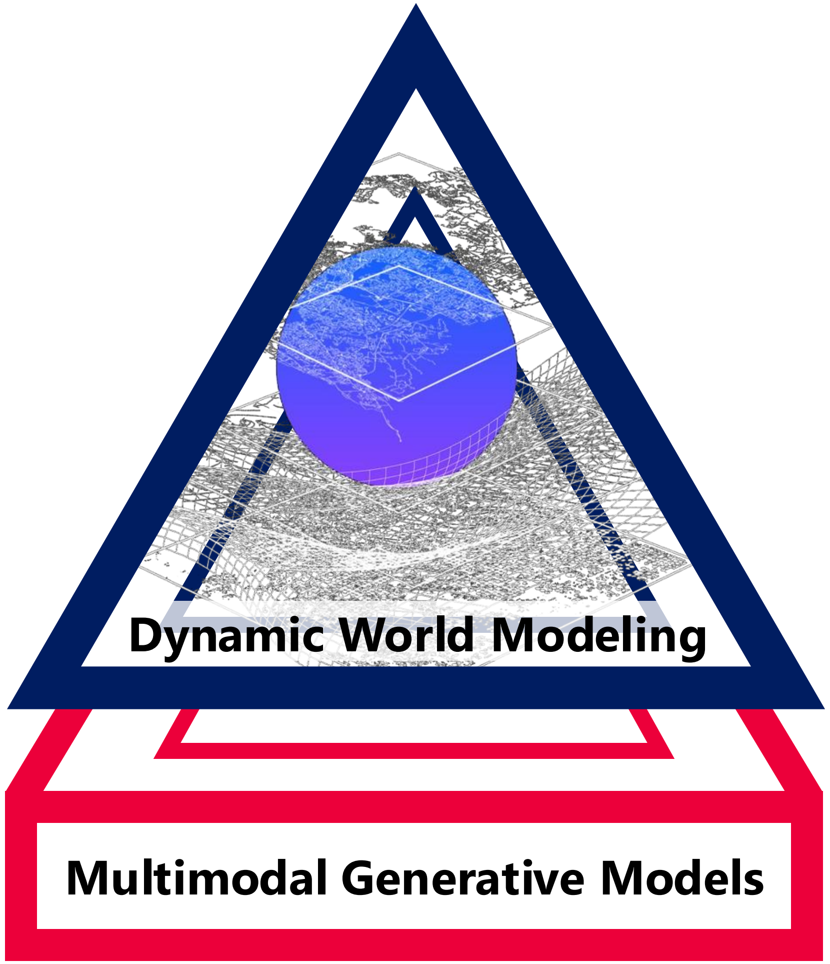
egolife-ai.github.io

Be Physical

How to Model Material and Illumination

Be Dynamic

How to Model Dynamic Scenes



Be Social

How to Model Social Interactions

Thank You

Ziwei Liu 刘子纬

Nanyang Technological University