



From Multimodal Generative Models to Dynamic World Modeling

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https://liuziwei7.github.io

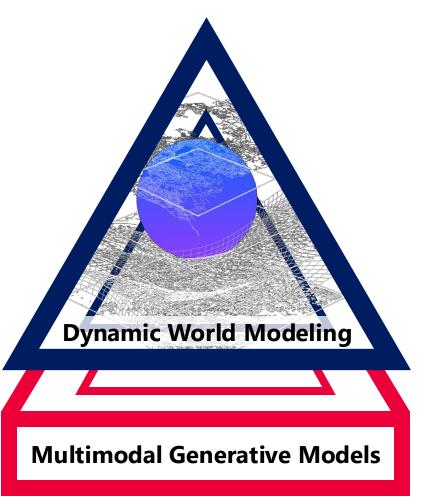






Be Physical

How to Model Material and Illumination



Be Social

How to Model Social Interactions

Be Dynamic How to Model

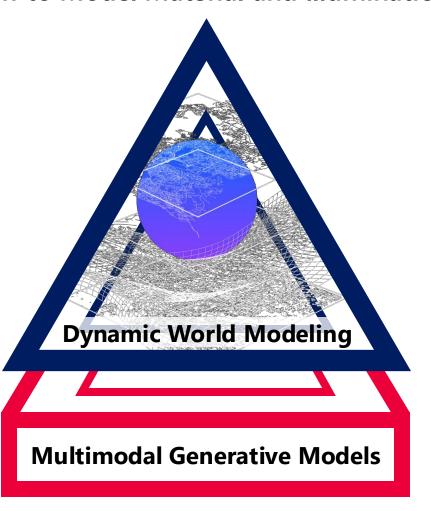
Dynamic Scenes





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How to Model Social
Interactions

Be Dynamic How to Model Dynamic Scenes





Be Physical: 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

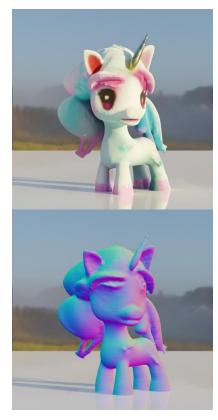




- High-resolution Generative 3D Representation
 - Parameter-efficient
 - Surface-only
 - As compact as possible
 - Scalable Tokenization
 - Rapid tensorization from input
 - Reversible conversion to GLB mesh
 - Differentiable Rendering
- Modelling of Physical Light Transport
 - Well-defined Geometry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







Our Goal

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





"A cute unicorn"







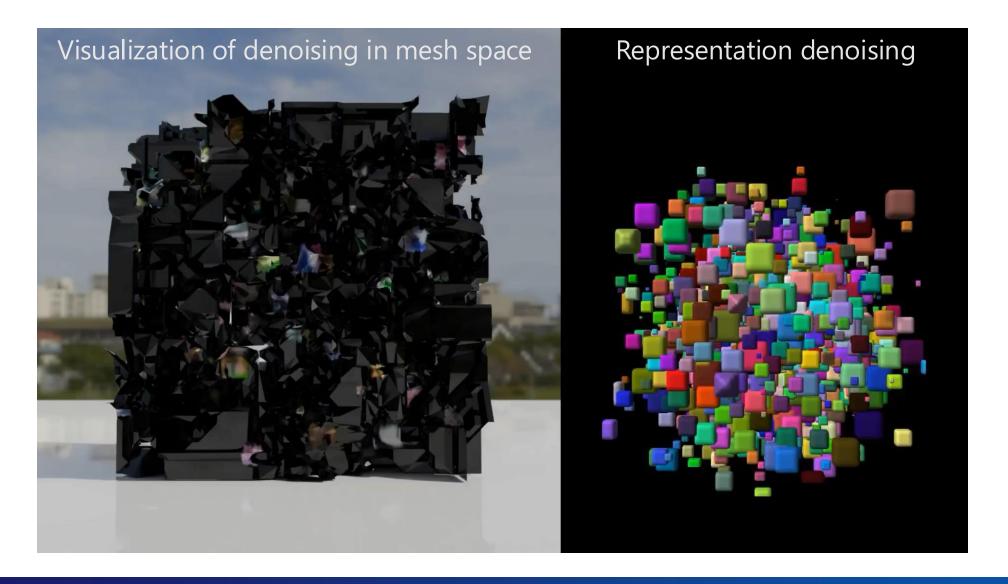
A Single Image / Texts

High-quality 3D Asset Ready for Blender 70

Key Idea: Primitive Diffusion



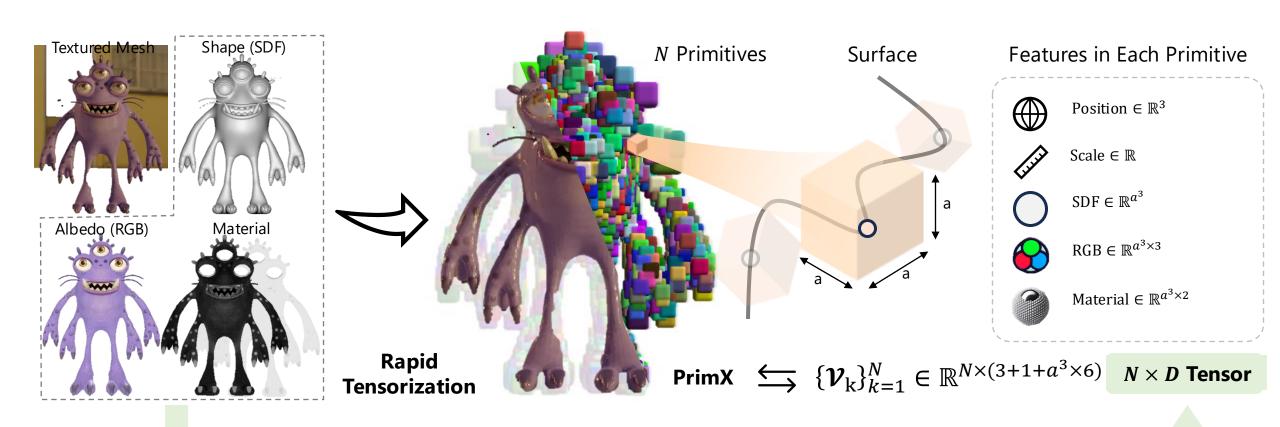




Stage I: Geometry, Texture, Materials into N×D Primitives NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE





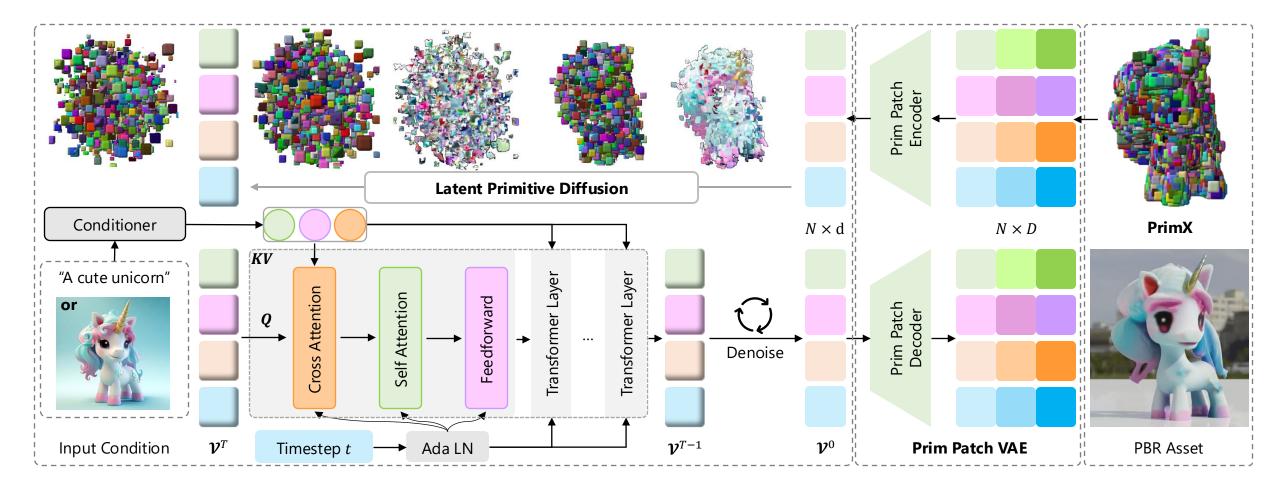


Tensorize a Textured Mesh into NxD Primitives

Stage II: Latent Primitive Diffusion



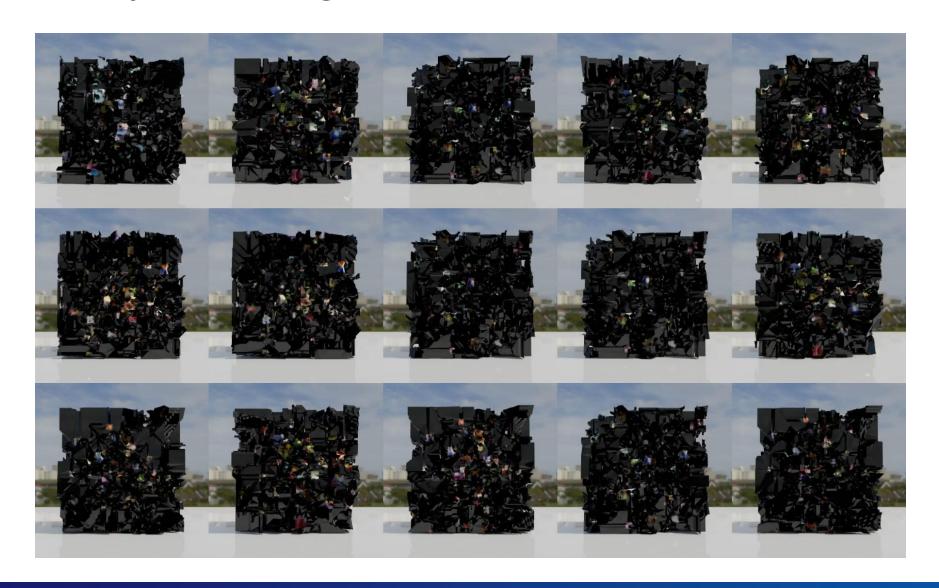




Gallery: Denoising in 5 Seconds



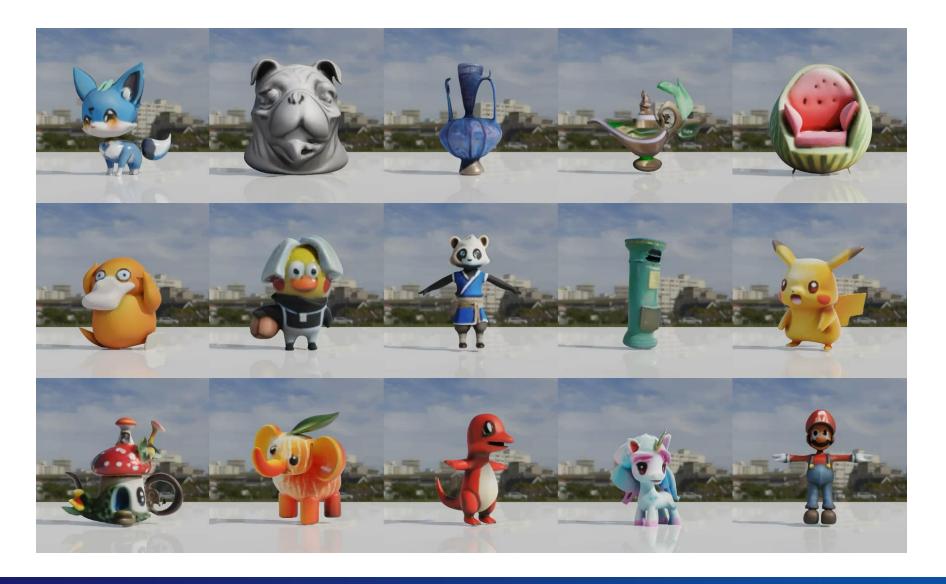




Gallery: Ready for Graphics Engines











Be Physical: Neural LightRig



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

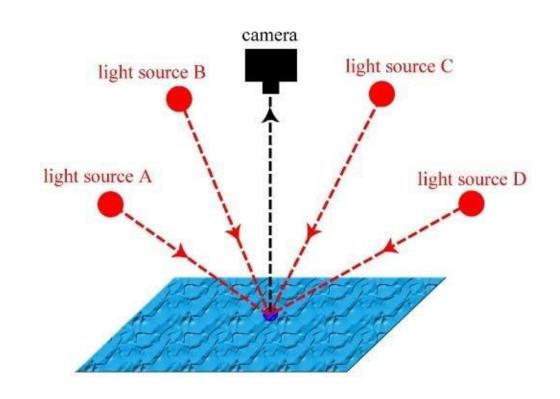
Zexin He, Tengfei Wang, Xin Huang, Xingang Pan, Ziwei Liu CVPR 2025

A Long-Standing Challenge – Inverse Rendering





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



^[1] Robert J. Woodham. Photometric method for determining surface orientation from multiple images. 1989.

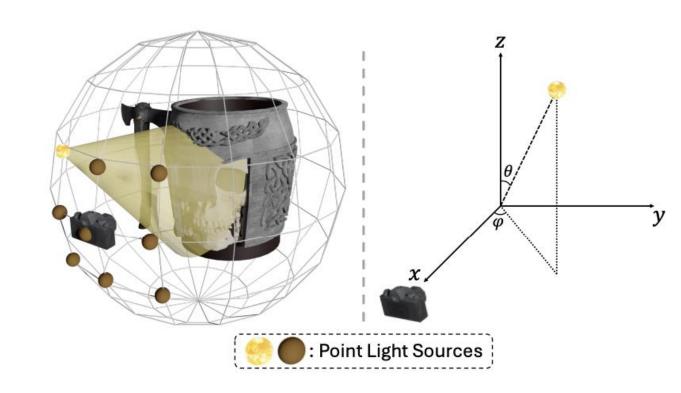
^[2] Image source: https://www.researchgate.net/profile/Lyndon-Smith-4/publication/325473321/figure/fig1/AS:666789923020804@1535986514936/The-principle-of-photometric-stereo-which-employs-a-single-camera-to-capture-multiple_W640.jpg.

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] Lymin 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



Stage I: Multi-Light Diffusion

Stage II: Large G-Buffer Model

Quantitative Evaluations





Surface Normal Estimation

Method		Mean ↓	Median ↓	3° ↑	5° ↑	7.5 ° ↑	11.25° ↑	22.5 ° ↑	30 ° ↑
RGB↔X [57]	T	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	<u>97.162</u>
Marigold [25]		8.652	7.078	<u>25.219</u>	42.289	58.062	72.873	92.326	96.742
StableNormal [53]		<u>8.034</u>	<u>6.568</u>	21.393	<u>43.917</u>	<u>63.740</u>	<u>78.568</u>	<u>93.671</u>	96.785
Ours		6.413	4.897	38.656	56.780	70.938	82.853	95.412	98.063

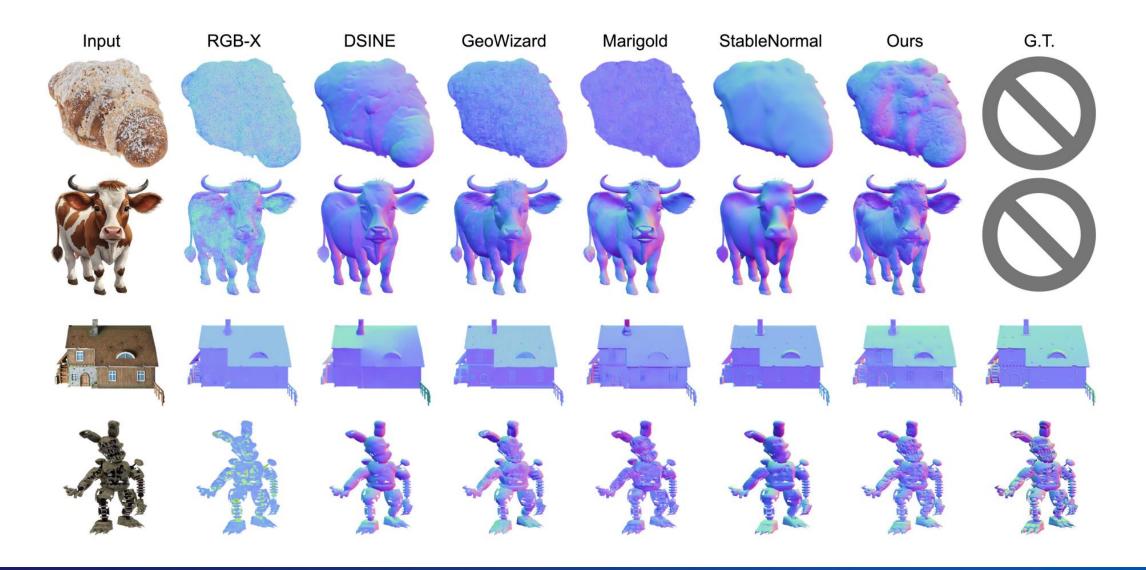
PBR Estimation and Single-Image Relighting

Method	Albedo		Roughness		Metallic		Relighting			Latency
	PSNR ↑	$\mathbf{RMSE}\downarrow$	PSNR ↑	$\mathbf{RMSE}\downarrow$	PSNR ↑	$\mathbf{RMSE}\downarrow$	PSNR ↑	SSIM ↑	LPIPS \downarrow	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	<u>27.98</u>	<u>0.9474</u>	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



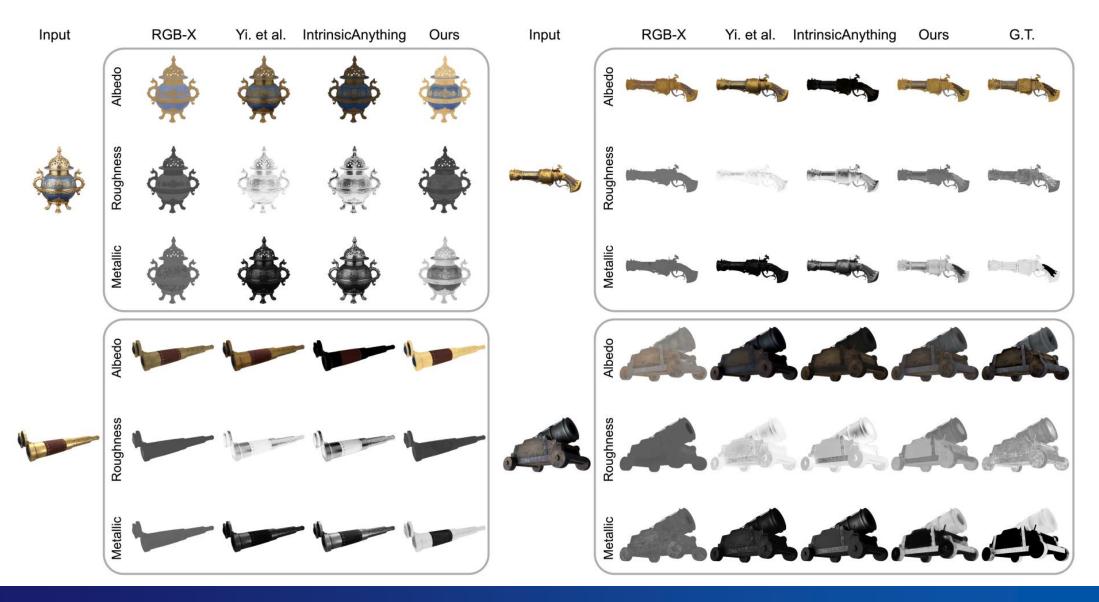




PBR Material Estimation







Single-Image Relighting



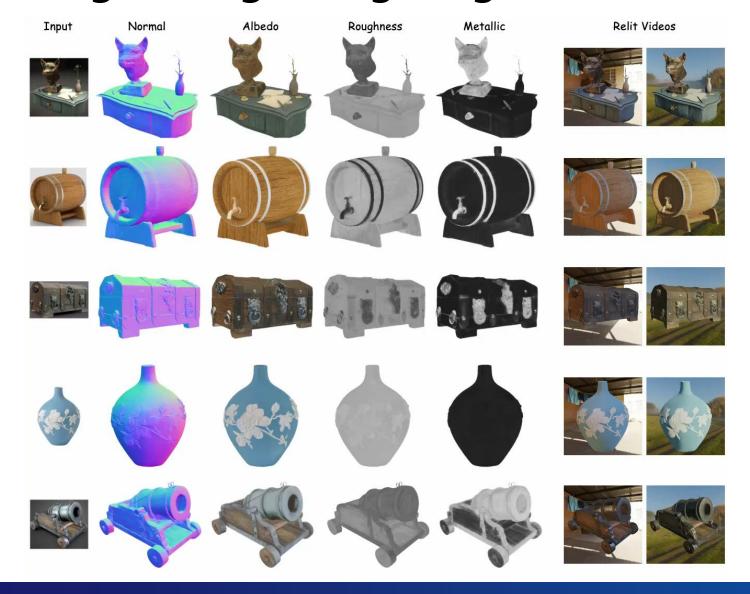


Input	Environment	RGB-X	DiLightNet	IC-Light	Yi. et al.	IntrinsicAnything	Ours	G.T.
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Single-Image Relighting





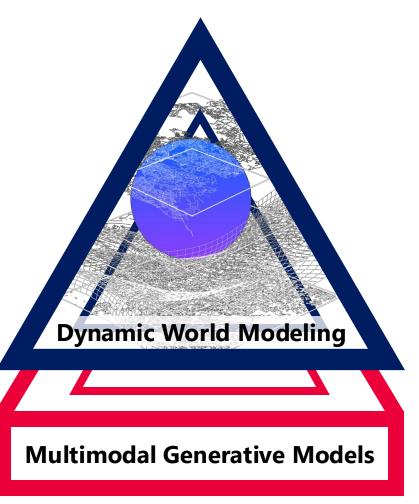






Be Physical

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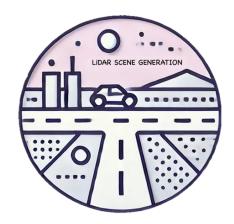


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Be Dynamic: DynamicCity



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

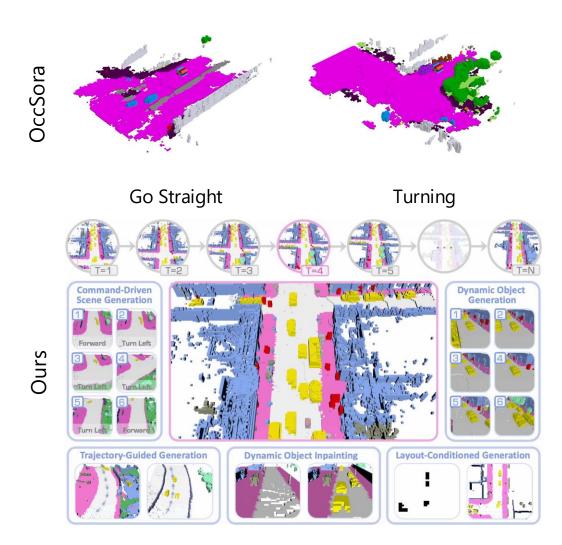
Hengwei Bian, Lingdong Kong, Haozhe Xie, Liang Pan, Yu Qiao, Ziwei Liu ICLR 2025 Spotlight

Challenges





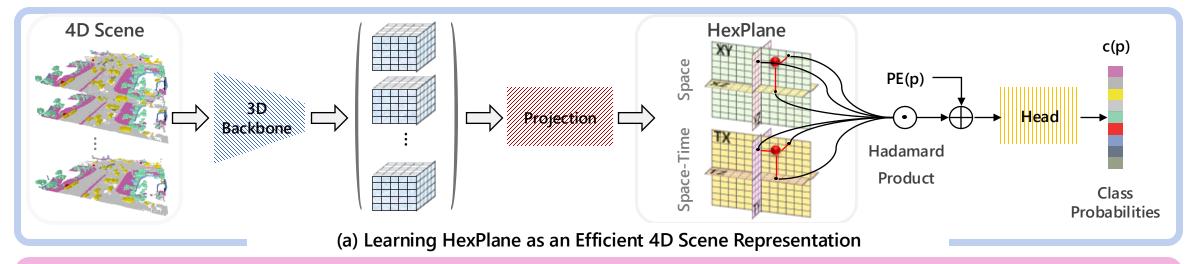
- Inefficient VAEs for 4D data
 - low compression
 - poor reconstruction
- Suboptimal generation quality
- Limited control over the generation process

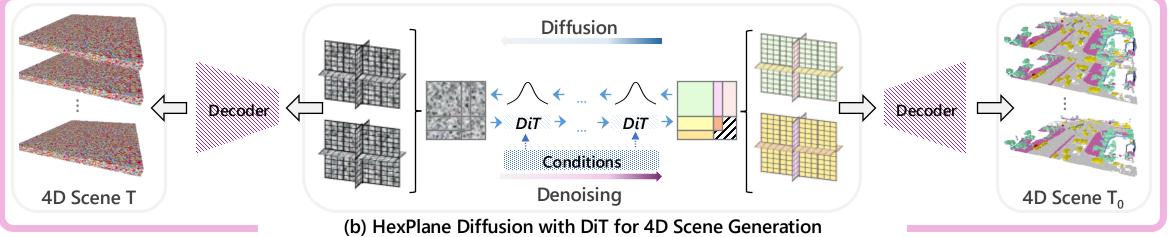


DynamicCity: 4D Occupancy Generation









Unconditional 4D Generation



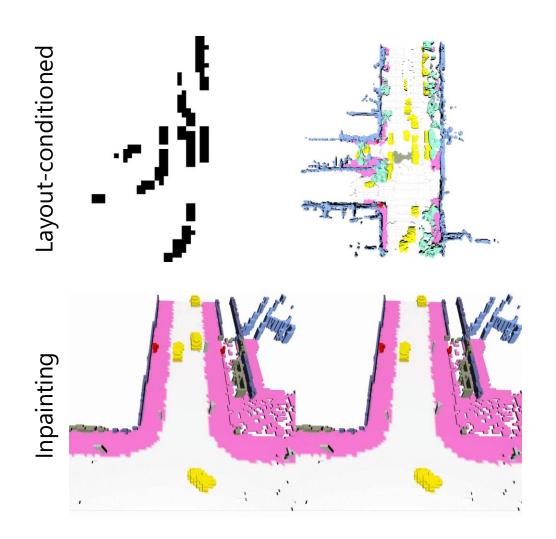


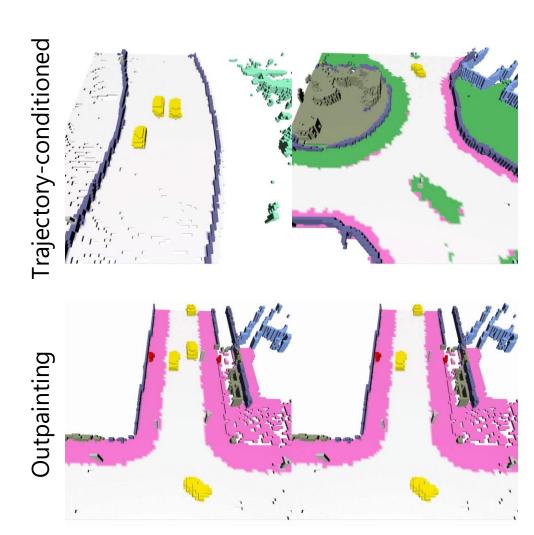


Conditional 4D Generation















Be Dynamic: CityDreamer4D



CityDreamer4D: Compositional Generative Model of Unbounded 4D Cities

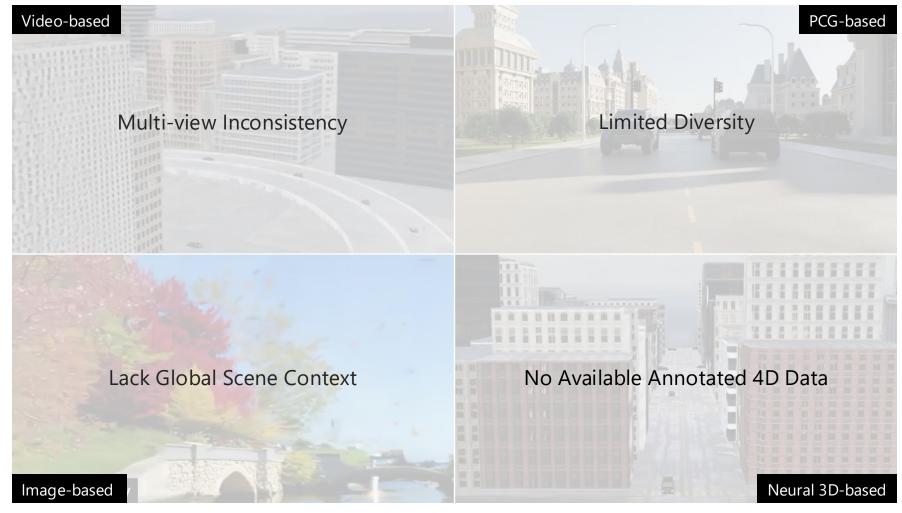
Haozhe Xie, Zhaoxi Chen, Fangzhou Hong, Ziwei Liu

arXiv 2501.08983

Challenges







- [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







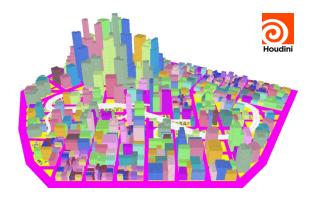


Generated 3D City

3D Assets (Small set for Visualization)

City Prototype





3D Instance Annotation

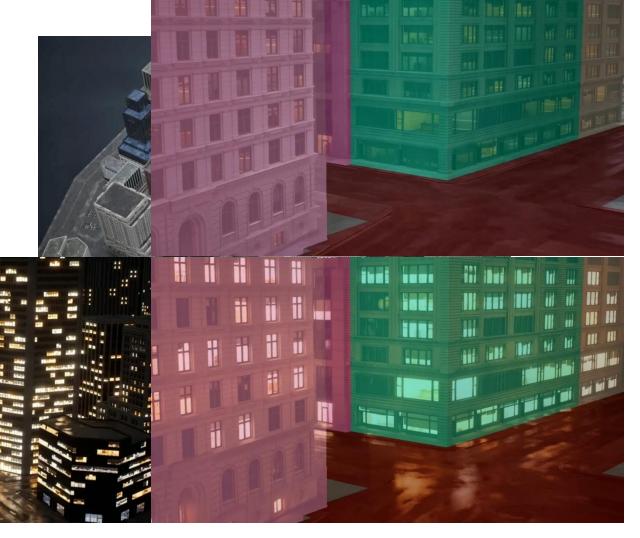


The CityTopia Dataset





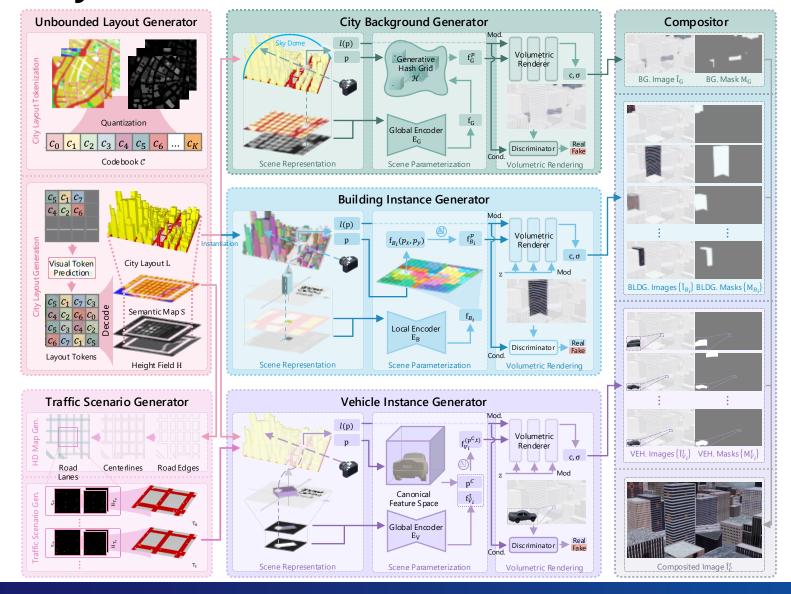




CityDreamer4D Framework







Comparison to SOTA Methods



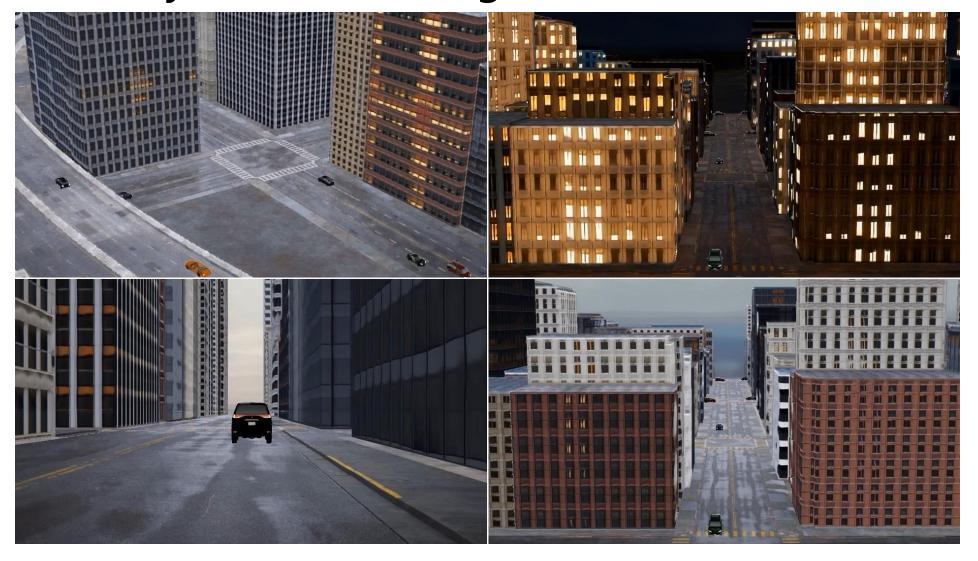




Arbitrary View Rendering





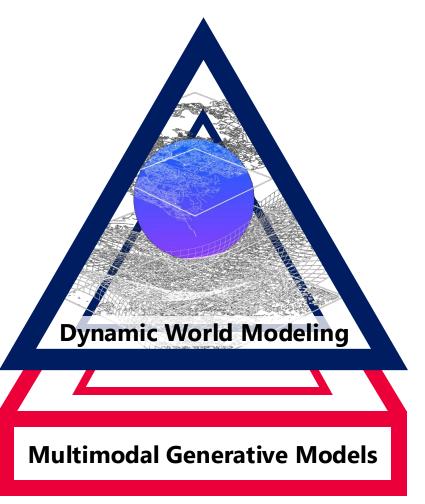






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Be Social: SOLAMI

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

Single And Service And Service

Digital





- 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.

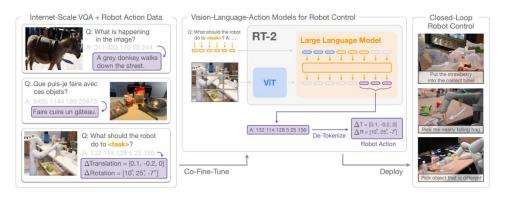
Motivation: Avatar as Virtual Robot







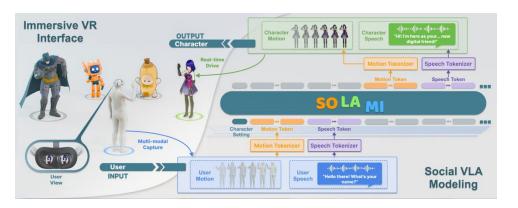
Robot
3D Agent with Real Embodiment
(Real-world Task & Interaction)



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



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



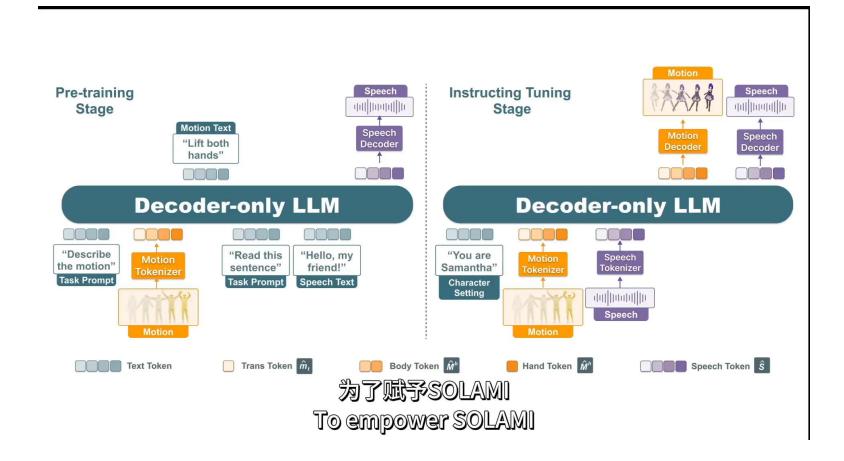
Social VLA for Immersive Interaction with 3D Characters

Training Recipe





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

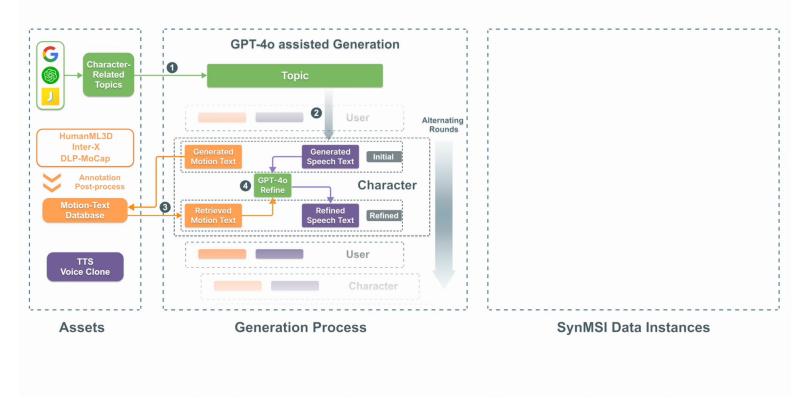


Data Generation





- 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

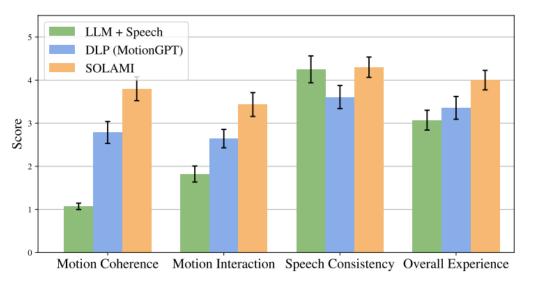


Table 1. Quantitative results of baselines and SOLAMI. ' \uparrow '(' \downarrow ') indicates that the values are better if the metrics are larger (smaller). We run all the evaluations 5 times and report the average metric. The best results are in bold and the second best results are underlined.

Methods	Motion Metrics					Inference		
Methods	$FID\downarrow$	Diversity [↑]	PA-MPJPE↓	Angle Error↓	VC Similarity↑	Context Relevance↑	Character Consistency↑	Latency ↓
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]	4.254	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>	0.387	0.820	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>	2.639

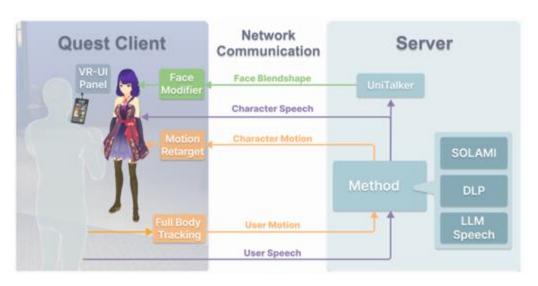
Demo: VR Interface

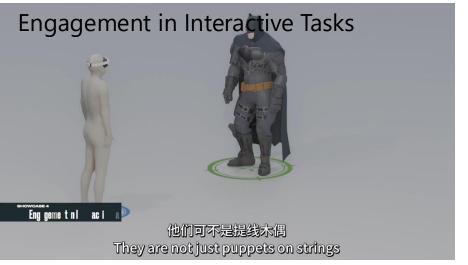


















Be Social: EgoLife



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

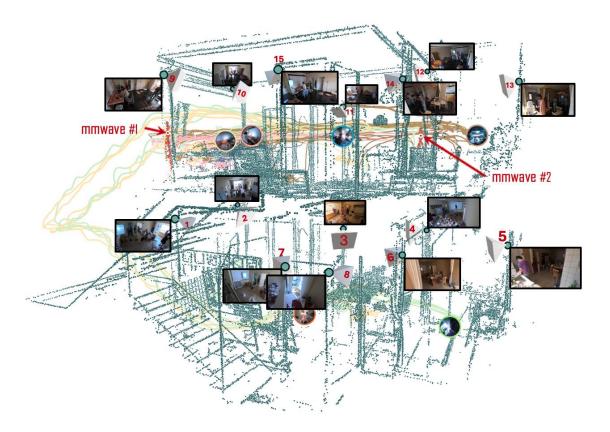


Each one wearing Meta Aria glasses (almost) all day long.

The EgoLife Collected Data









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

The EgoLife Timeline





DA	×y 1	DAY 2	DAY 3	DAY 4	DAY 5	DAY 6	DAY 7	
11 12 13 14	17 18 19 20 21 22 10 11 12 京 京 京 京 京 京 京 京 京 京 京 京 京 京 京 京 京	13 15 16 17 18 20 21 22	10 11 14 15 16 17 18 19 20 21 22	10 11 12 13 15 16 17 18 19 20 21 22	11 12 14 15 16 17 18 19 20 21 22 4	10 11 12 13 14 15 16 17 19 20 21 22	10 11 12 13 14 15 17 18 19 20	
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(
Social×183 🗸 Housekeeping×145 🖶 Cooking×86 📜 Shopping×74 🔟 Dining×67 🧩 Party×64 🥙 Arts & Craftwork×57								
∠ Leisure ×	∠ Leisure×49 Games×46 Music & Dance×45 Outing×40 Setup×35 Meeting×31 Commuting×15							

The EgoLifeQA Benchmark

 $6 \times 500 = 3000 \text{ QAs}$







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: Shure sang after Jake asked us to dance.



@ Day 1 11:46:59.050



Day 4: 11:34:05.400



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

A. RMB 2 B. RMB3 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



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



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

Answer: A. Evidence: I made a shopping list, and already got fruit, etc., but ...





































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:











I had coffee a total of five times, three of which were while doing crafts...



Day 6: 19:50:19.750

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

A. Choizst

Jake

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.



HabitInsight

Personal Habit Patterns



RelationMap Interpersonal Interaction Patterns

The EgoLifeQA Benchmark



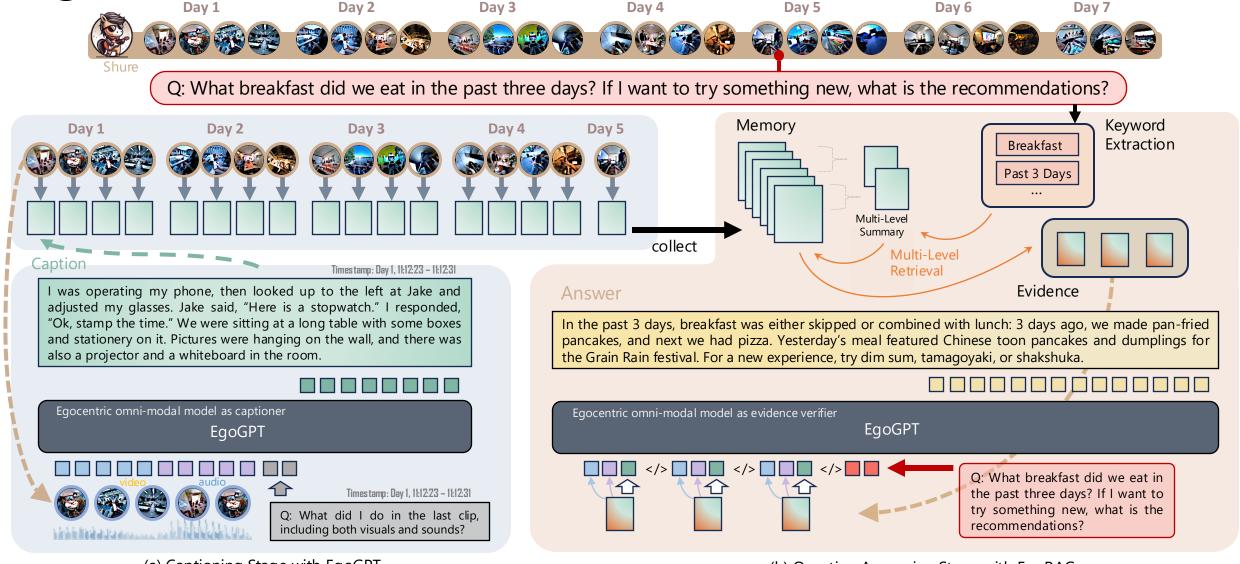




EgoButler







(a) Captioning Stage with EgoGPT

(b) Question Answering Stage with EgoRAG

EgoButler – The EgoGPT Component





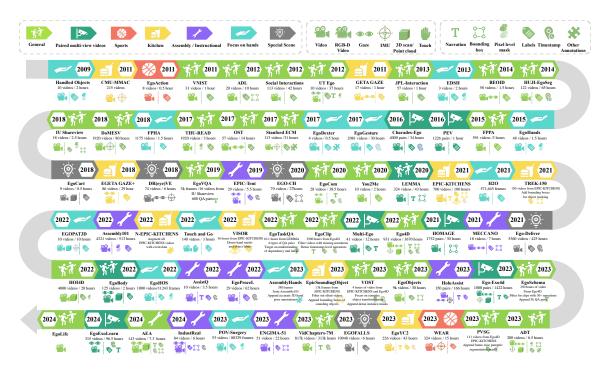
LLaVA-OneVision (Qwen2 as LLM)

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	

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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 EgoRAG Component





[...] picked up a spoon, and DAY 1 11:26

picked up a glass of milk from the table [...]

should I put this?" then said, "I'll do it." Tasha

started stirring the bread in the bowl [...] then

[...] Katrina asked, "Where DAY 1 19:11

reminded, "There's still a bottle of fresh milk [...]

Boosted by EgoGPT, EgoButler achieves SOTA:

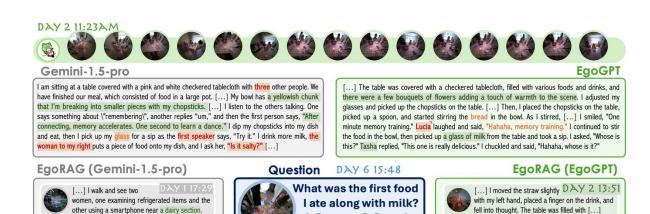
- In-depth egocentric video familiarity
- Omni-modal comprehension effectively integrating both visual and audio signals

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
- Ø Better Person Identification Modeling
- Pattern Tracker: Building a habit and behavior pattern engine for continuous insight generation



A. Banana B. Pancake

Correct Ans: B

D. Cookie

B. Pancake

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.

C. Eggs

A. Banana

I'm holding chopsticks and DAY 2 13:4

picking up a piece of food from a small, white bowl

people are standing around a long table with food.

I speak a sentence, but my voice isn't in English.

of rice, placing it onto [...] the rice bowl.

I enter a room where several

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



egolife







Extremely Long, Egocentric,

Interpersonal, Multi-view, Multi-modal, Daily Life Video Understanding



More to explore:

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

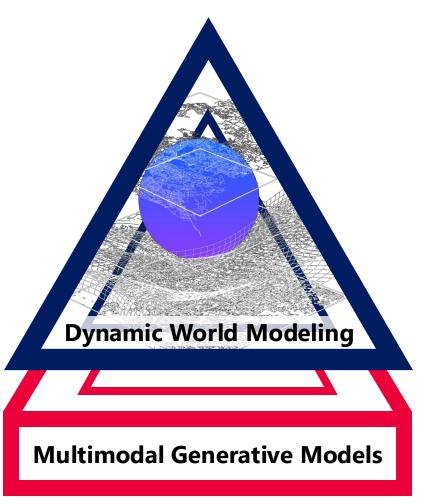
egolife-ai.github.io





Be Physical

How to Model Material and Illumination



Be Dynamic

Dynamic Scenes

How to Model

Be Social

How to Model Social Interactions





Thank You

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