Building Visual Intelligence

Songyou Peng
Google DeepMind

Meta Sep 29, 2025



Grounding

Reconstruct and understand 3D

Scaling

Foundation Model for Generalization

Reasoning

Solve complicated tasks

Action

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Learn to **Reconstruct** and **understand** 3D World



ConvOccNet
ECCV 2020 (Spotlight)



MonoSDF NeurlPS 2022



 CE-SLAM
 NICER-SLAI

 /PR 2022
 3DV 2024 (Or



Shape As Points
NeurlPS 2021 (Oral)



UNISURF ICCV 2021 (Oral)

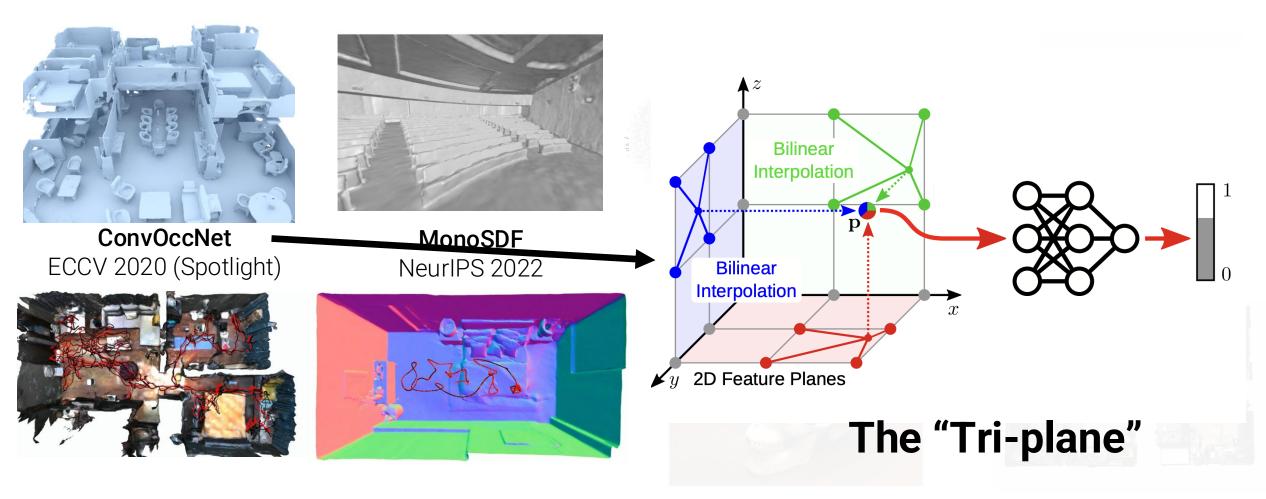


KiloNeRF ICCV 2021



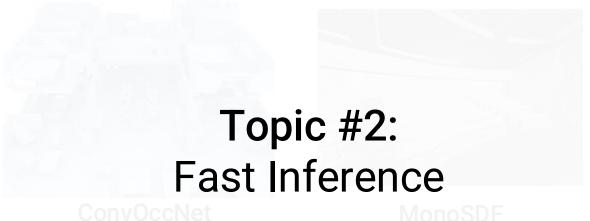
OpenScene CVPR 2023 ₂

Learn to Reconstruct and Understand 3D World

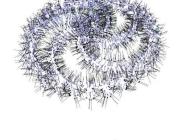


NICE-SLAM CVPR 2022 NICER-SLAM 3DV 2024 (Best Honor. Men.) UNISURF ICCV 2021 (Oral) OpenScene CVPR 2023

Learn to Reconstruct and Understand 3D World









Shape As Points NeurlPS 2021 (Oral)













Learn to Reconstruct and Understand 3D World



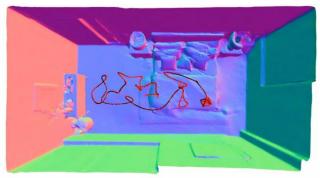
ConvOccNet
V 2020 (Spotlight)



NICE-SLAM

CVPR 2022

MonoSDF NeurIPS 2022



NICER-SLAM
3DV 2024 (Best Paper Honorable)



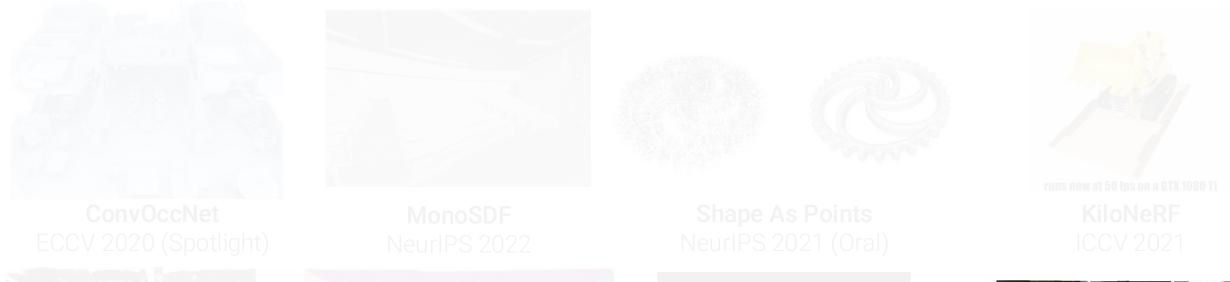


UNISURF ICCV 2021 (Oral)

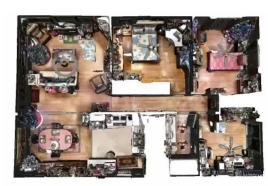


OpenScene CVPR 2023

Learn to Reconstruct and Understand 3D World



Topic #4:
Open-vocabulary 3D Scene Understanding



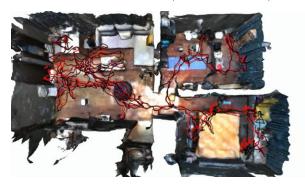
NICE-SLAM CVPR 2022 NICER-SLAM 3DV 2024 (Oral)

UNISURF ICCV 2021 (Oral) OpenScene CVPR 2023 8

Learn to Reconstruct and Understand 3D World

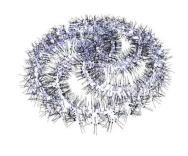


ConvOccNet ECCV 2020 (Spotlight)



MonoSDF NeurIPS 2022





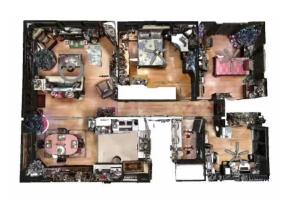
Shape As Points NeurlPS 2021 (Oral)



UNISURF ICCV 2021 (Oral)



KiloNeRF ICCV 2021



OpenScene CVPR 2023 9

NICE-SLAM CVPR 2022

NICER-SLAM
3DV 2024 (Best Paper Honorable)

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Solve complicated tasks

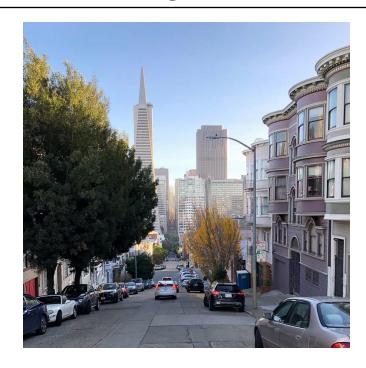
Action

Current Focus at GDM

Teaching Multimodal LLMs to Think in Space

Pre-training for

Gemini



X billion tokens for **spatial grounding**, **multiview consistency**, **high-level semantics**, etc

Post-training for ♦ Gemini



The model can **think with images**, and actively conduct information seeking

Building Visual Intelligence

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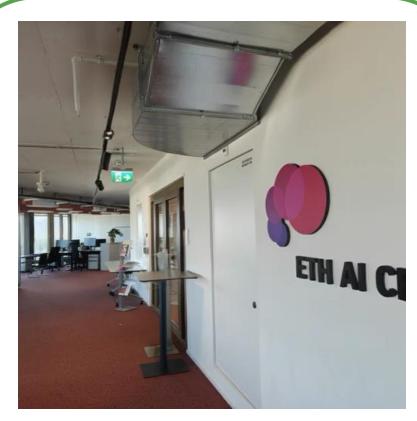
Reasoning

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Foundation Model for Visual Intelligence

From 2 Views to 10 Million



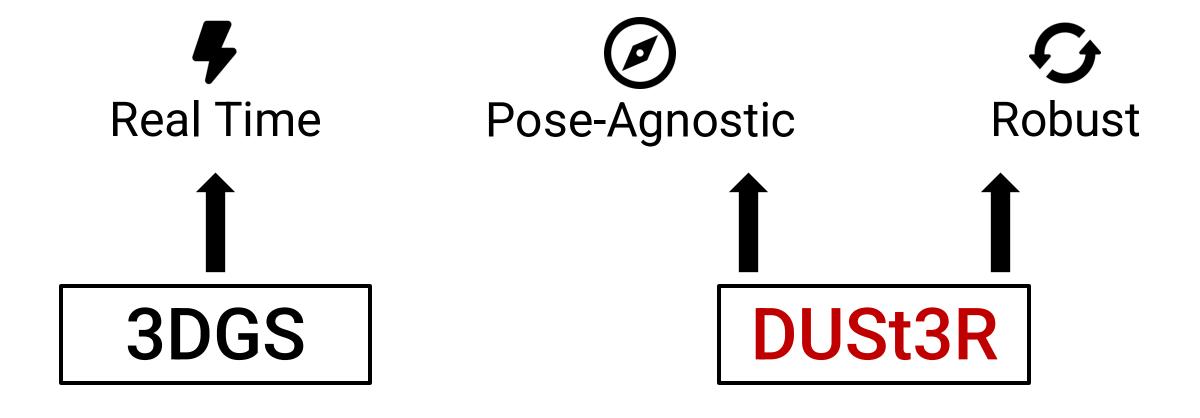
NoPoSplat ICLR 2025 (Oral)



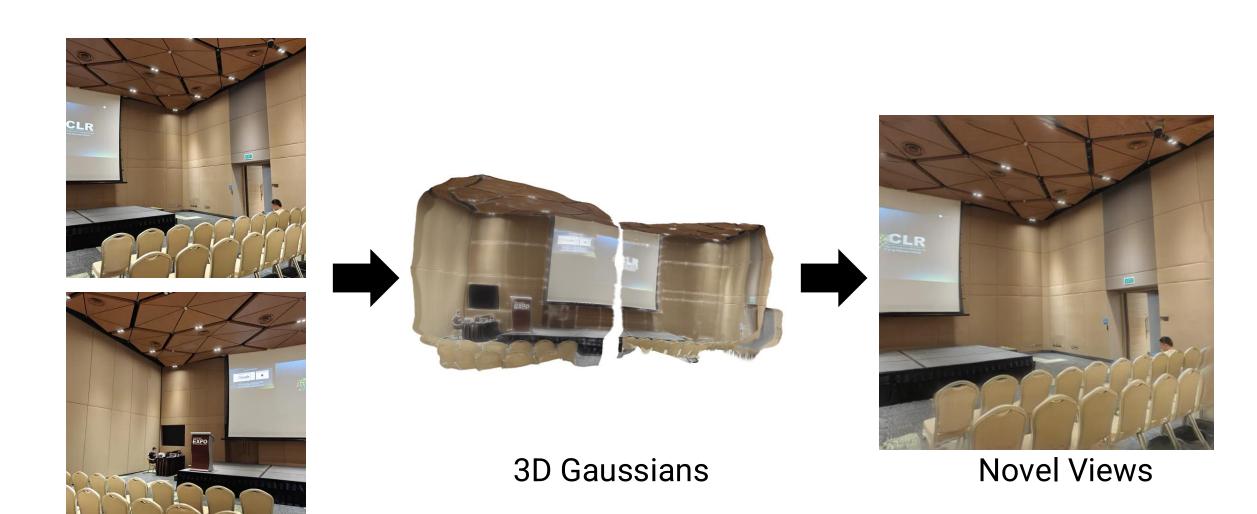
Visual Chronicles
ICCV 2025 (Highlight)

An Ideal 3D Modelling Pipeline

Instant, Pose-Free, Real-World 3D Everywhere



Goal: Unposed Feedforward 3DGS















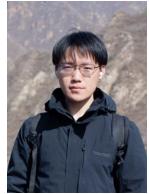
No Pose, No Problem

Surprisingly Simple 3D Gaussian Splats from Sparse Unposed Images

(a.k.a NoPoSplat)



ICLR 2025 (Oral, top 1.8%)



Botao Ye



Sifei Liu



Haofei Xu



Xueting Li

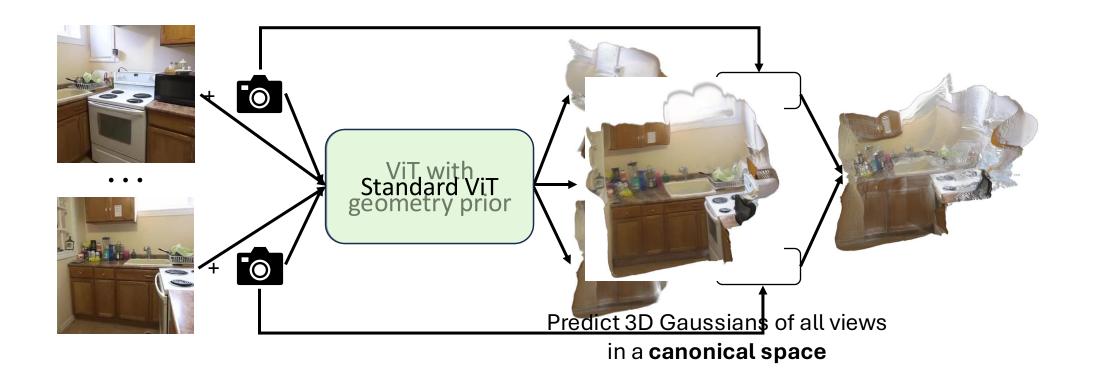




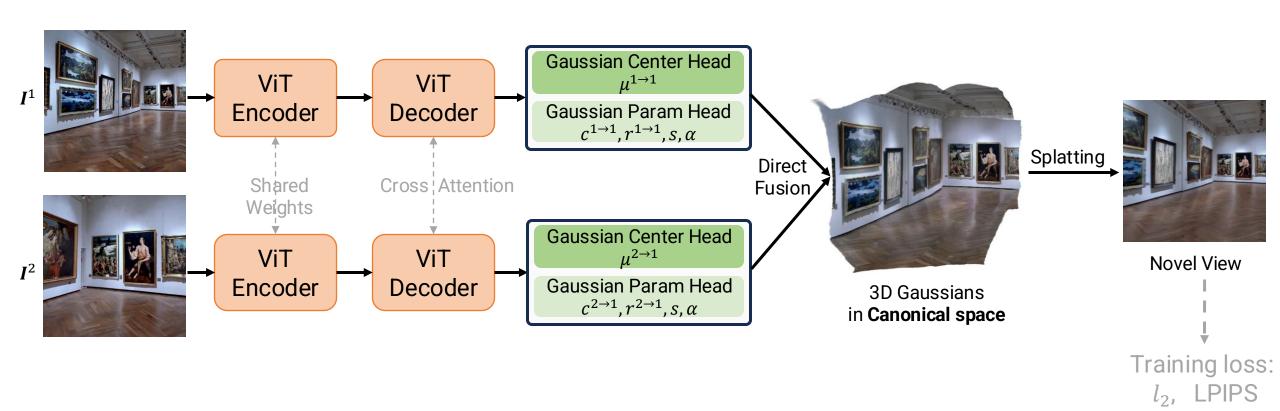
Marc Pollefeys Ming-Hsuan Yang Songyou Peng



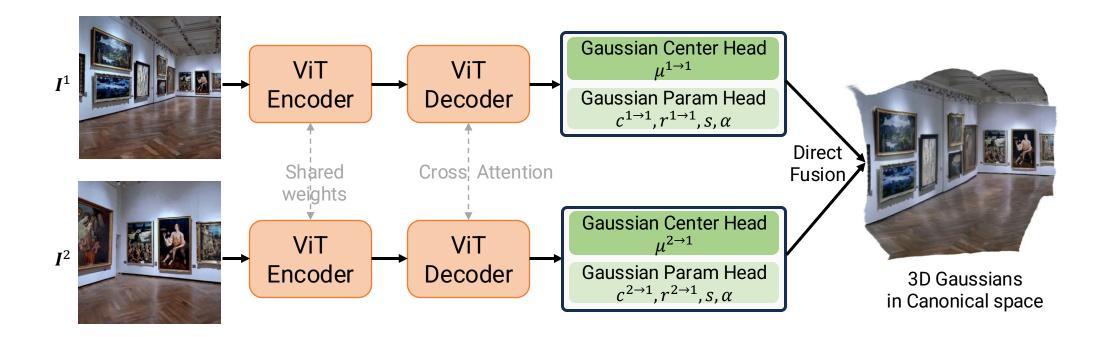
Previous Feed-forward 3DGS



Architecture

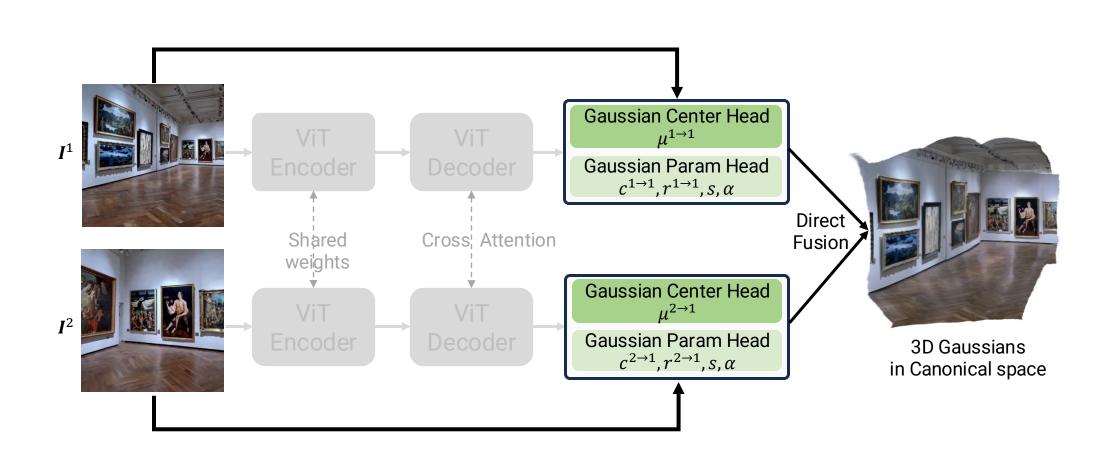


Issue 1: Blurry Rendering



Issue 1: Blurry Rendering

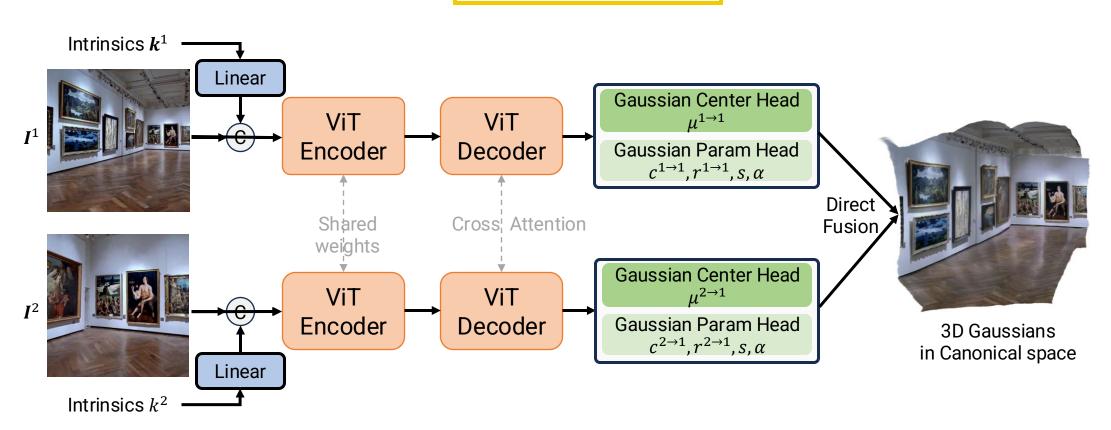
Solution: Add a shortcut!



Issue 2: Scale Ambiguity

Solution: Add the intrinsic embeddings!

$$p = K(RP + t)$$



Issue 3: Inaccurate Pose Estimation

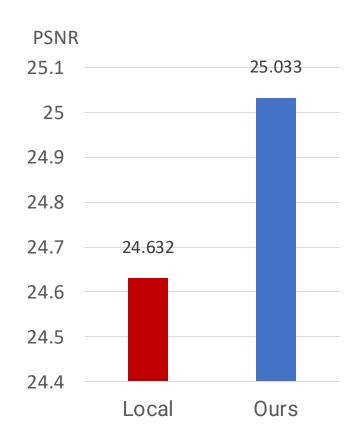
Solution: coarse-to-fine estimation

- Coarse stage: run RANSAC-PnP on Gaussian centers
- Refine stage: optimize with photometric loss

PnP	Photometric	5°	10°	20°
✓	✓	0.318	0.538	0.717
✓		0.287	0.506	0.692
	✓	0.017	0.027	0.051

Ablation

Canonical Gaussian prediction



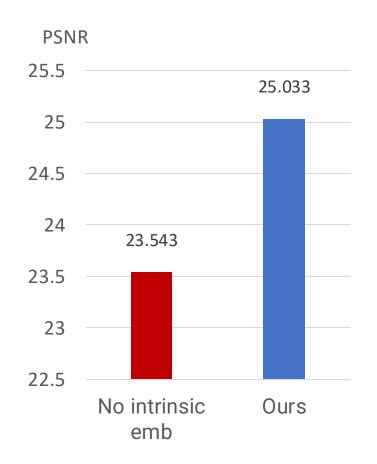




Canonical

Ablation

Intrinsic embedding





No Intrinsic Emb



Ours

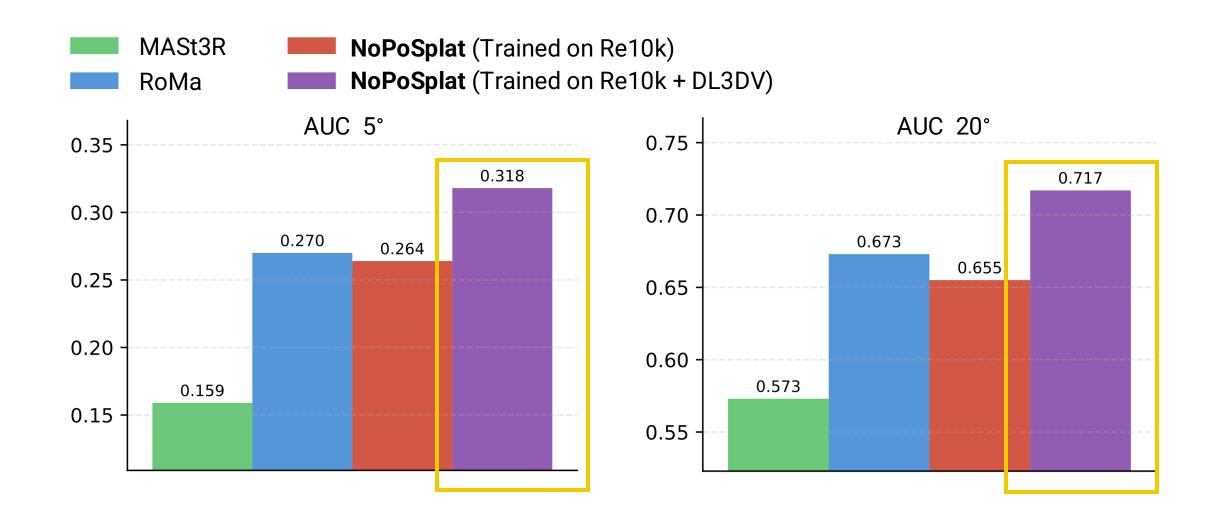


GT

What is More...

Accurate Pose Estimation

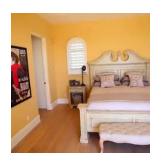
Evaluation on ScanNet



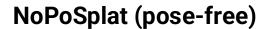
High Quality Geometry

Input Images







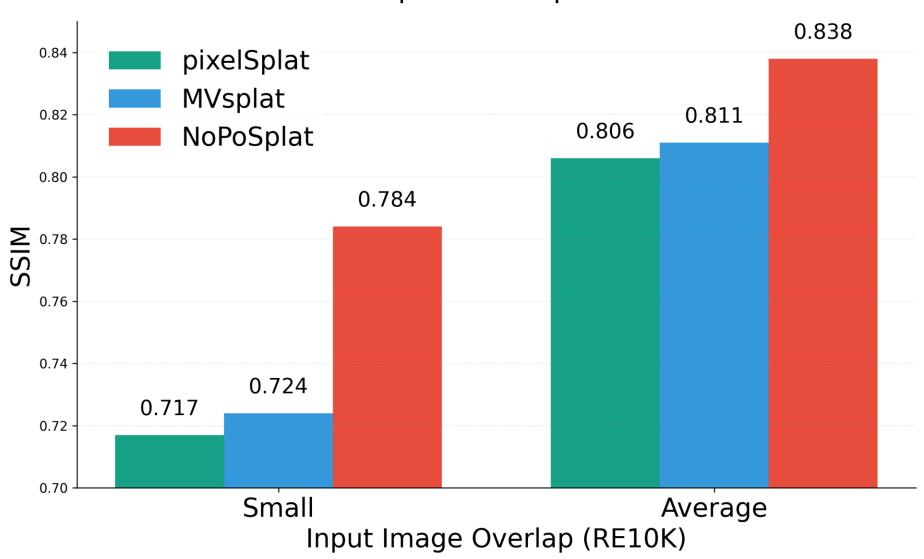




MVSplat (pose-required)

Appearance Quality

Better even than pose-required methods!

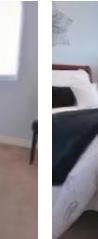


Appearance Quality

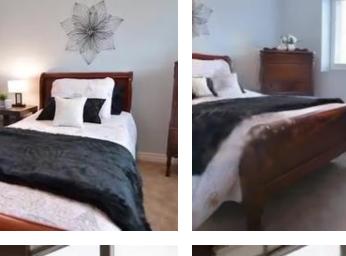
Input Views



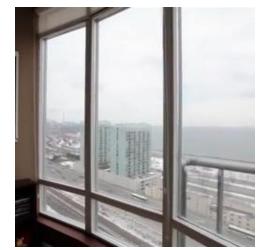
MVSplat



NoPoSplat





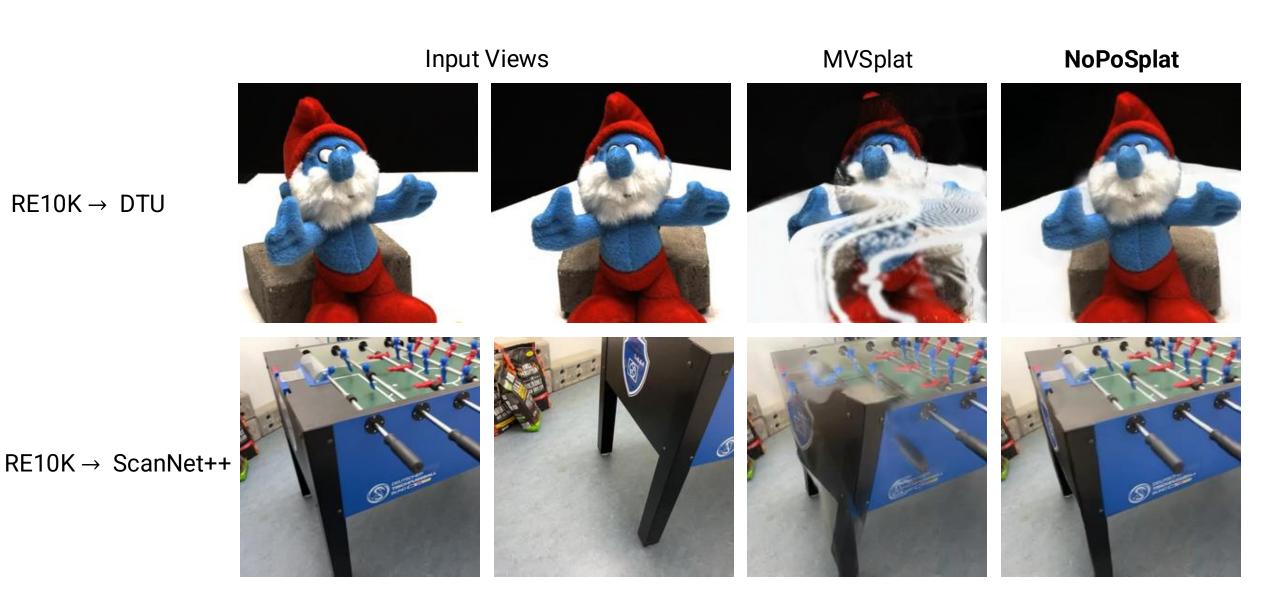








Cross-Dataset Generalization

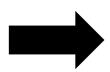


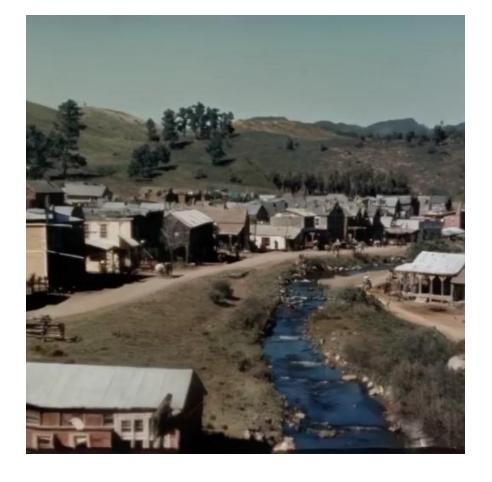
In-the-Wild Data

Images extracted from OpenAI Sora









Input Images

Novel Views

In-the-Wild Data

Images from Tanks & Temples









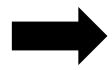
Novel Views

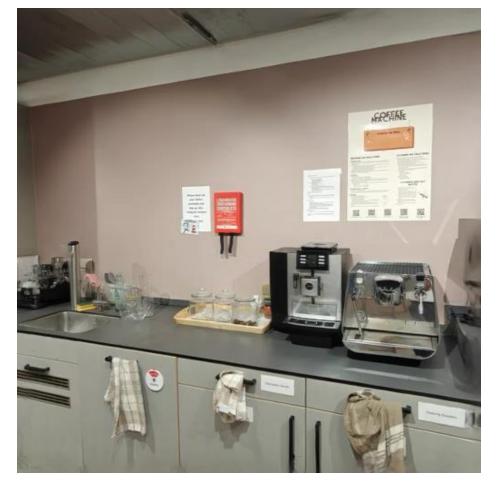
In-the-Wild Data

iPhone images









Input Images

Novel Views

Take-home Messages

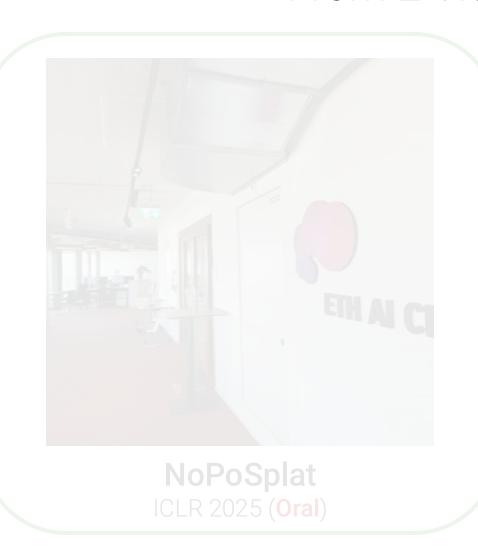
Feedforward NVS can be surprisingly simple!

• Side product: SoTA relative pose estimation

Foundation model rocks!

Foundation Model for Visual Intelligence

From 2 Views to 10 Million



Visual Chronicles ICCV 2025 (Highlight)







Visual Chronicles

Using Multimodal LLMs to Analyze Massive Collections of Images

ICCV 2025 (Highlight)





Boyang Deng



Songyou Peng



Kyle Genova



Gordon Wetzstein



Noah Snavely



Leo Guibas



Tom Funkhouser

Motivation

What are the interesting changes happened in the time-lapses?



The bridge was painted in a bright blue color.



The restaurant **extended a dining structure outside**.

Motivation

What are the interesting changes happened in the time-lapses?





- Open-ended queries
- Not too challenging for humans
- What if we have **millions** of time-lapses?
- What if we want to know **trends of changes**?
- Quite challenging for any CV models!
 - No "interesting change" detectors.
 - No ImageNet of interesting changes.

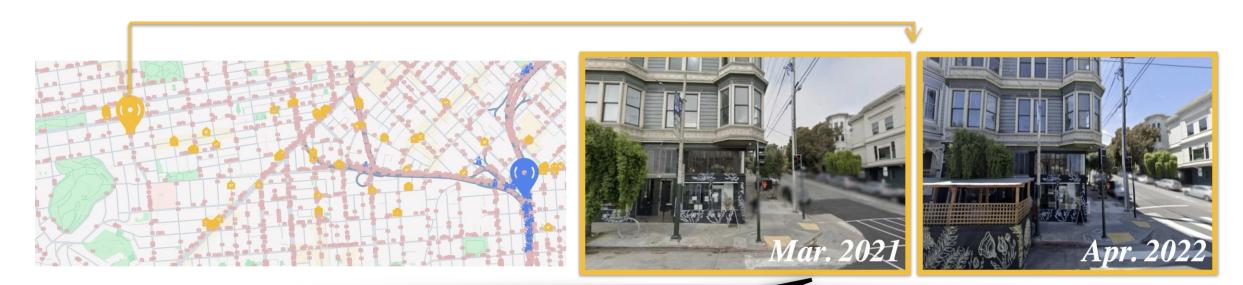








Massive Collections of Images (20M per City)



... added outdoor dining. (seen 1482 times in 🔯)









Massive Collections of Images (20M per City)



... overpass painted **blue**. (seen 481 times in 🛣)

How to Approach Trend Discovery?

MLLMs as an essential tool

Brute Force #1: Directly ask LLMs w/o any data?

- Abstract answers, e.g. "Increased focus on sustainability".
- No evidence Hard to verify any trends.

Brute Force #2: Feed all images to MLLMs and ask?

- Gemini could take up to 8K images at a time
- Boring output: Half of the output is about addition / removal of scaffolding

Visual Chronicles

Step 1: Use MLLMs for Local Change Detection

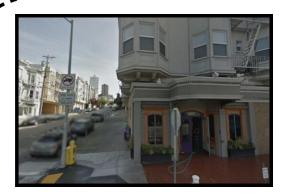


Image A (Mar. 2011)

MLLM



Image B (Feb. 2014)



Image C (Oct. 2015) ..

(Image $B \rightarrow$ Image C): An advertisement board was put up in front of the store.

Visual Chronicles

Step 2: find trends among local changes (3M per city)

(Image $B \rightarrow$ Image C): An advertisement board was put up in front of the store.

Brute Force: Feed all changes to LLMs?

Very limited input and output

Ours: Two-step hybrid approach

- 1. Produce visual trend proposals
- 2. Verify which proposed trends are supported by N changes

Visual Chronicles – Trend Discovery

How to produce visual trend proposals?

(Image $B \rightarrow$ Image C): An advertisement board was put up in front of the store.

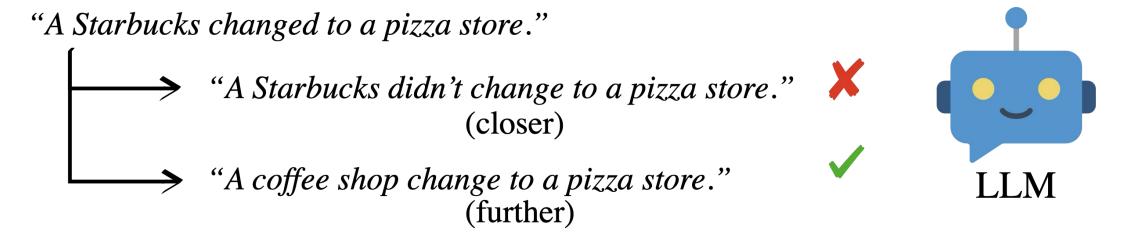
- 1. Encode local changes to text embedding
- 2. Sort them based on the lengths
- 3. NMS with to find the top 500 trend proposals

Visual Chronicles – Trend Discovery

How to verify which proposal are supported?

Use distance in the text embedding space with a tighter threshold

It cannot capture subtle similarities!



Ours: Pick top 1,500 changes for each proposal, use LLMs to verify

Visual Chronicles

First use of MLLMs for massive scale analysis of images



Image A (Mar. 2011)



Image B (Feb. 2014)



Step 1:

Change

detection

_ocal

Image C (Oct. 2015) .

MLLM

(Image $B \rightarrow$ Image C): An advertisement board was put up in front of the store.

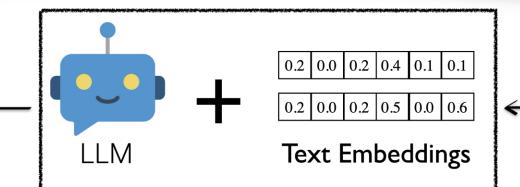
Step 2:

Trend discovery

Trend:

"... added an advertisement board."

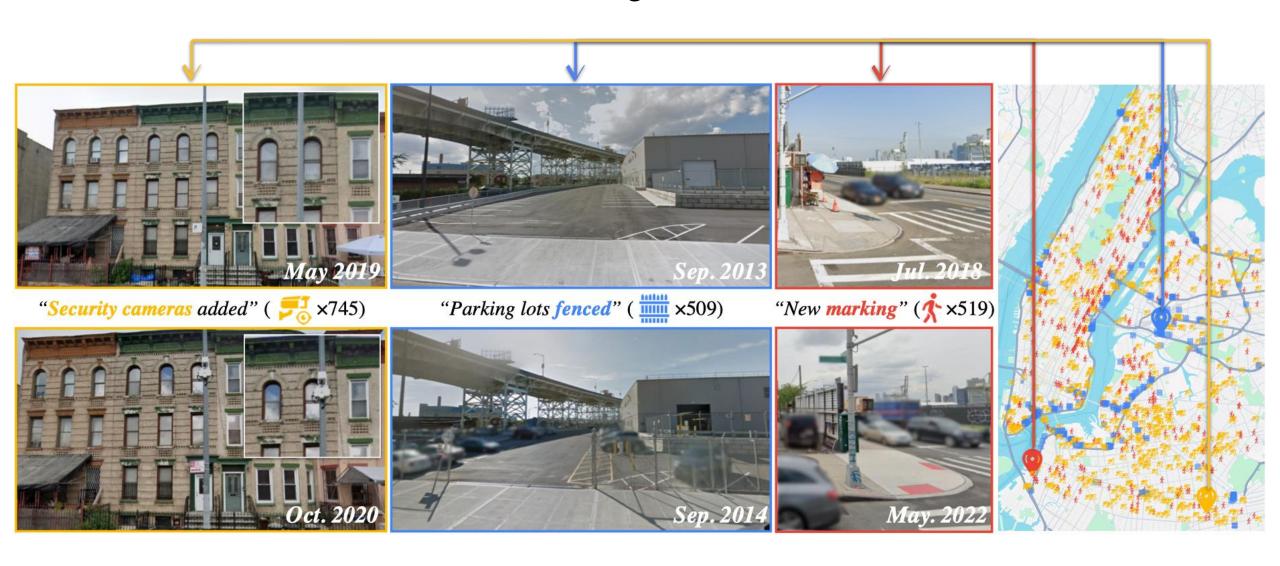
(observed 780 times)



Discover fascinating trends in San Francisco



Discover fascinating trends in New York



Support temporally conditioned search, e.g. "since 2020"









Outdoor Dining (seen 1482 times)

Blue Overpass (seen 481 times)

"Central freeway gets \$31 million 'Coronado Blue' paint job

... started in June 2021 ... to be done in May 2024."

The San Francisco Standard

Support semantically conditioned search, e.g. "retail store"

Some retail stores opened in NYC, 2011 - 2023.



Juice Shops (318 opened)



Bakeries (512 opened)

Some retail stores closed in NYC, 2011 - 2023.



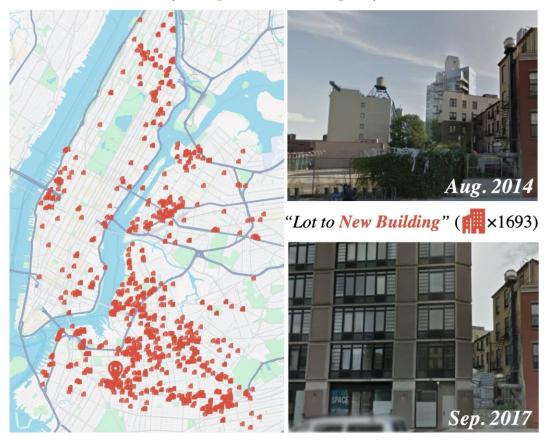
Banks (1614 closed)



Groceries (741 closed)

Other interesting applications

Where are new buildings built in NYC? (A Spatial Insight)



What are the unusual things in NYC? (A Non-Temporal Query)



Another Case Study

"Added Graffiti" were spotted ~3x more post-2020 (3152 times) than pre-2020 (1150 times).





"San Francisco deals with increasing graffiti ...
Especially after COVID ..."



"As part of the unprecedented COVID pandemic, the Board of Supervisors temporarily suspended Public Works' enforcement of the San Francisco Graffiti Ordinance ..."



We must be careful when drawing socioeconomic conclusion.

Take-home Messages

 We study the open-ended analysis of massive image collection

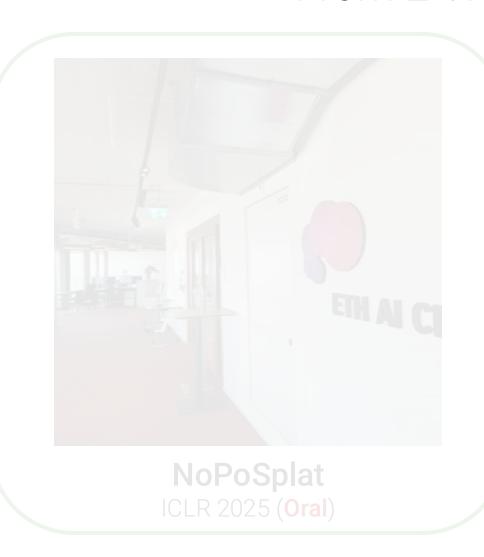
MLLMs as a critical tool to this problem

Design a practical and effective system

Find interesting insights about SF and NYC

Foundation Model for Visual Intelligence

From 2 Views to 10 Million





Visual Chronicles ICCV 2025 (Highlight)

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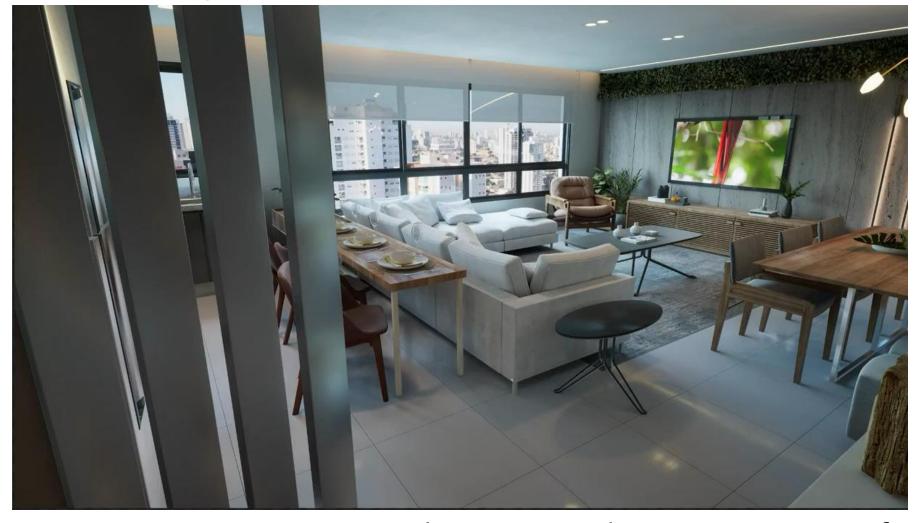
Solve complicated tasks

Action

Agent and tool use

My Vision

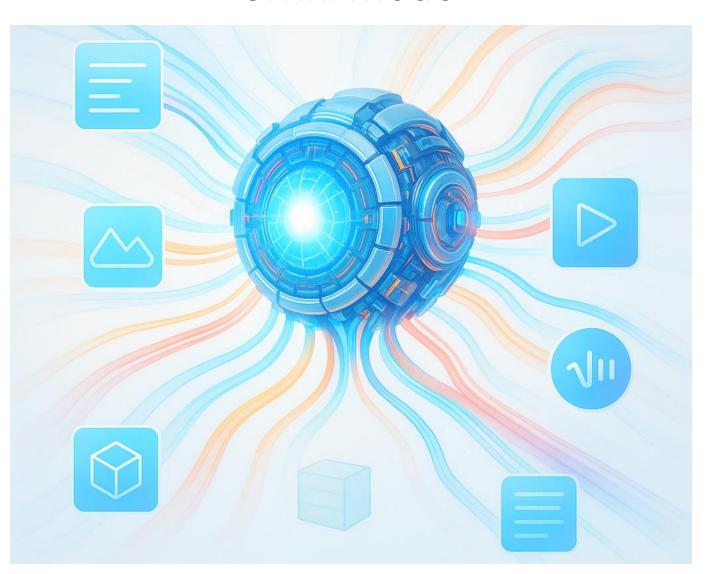
Agentic perception is the future



Perception → Reasoning → Tools→ New Observation → Refinement

What is next?

Omni Model



Building Visual Intelligence

Songyou Peng



