Grounding Foundation Models to the Real World

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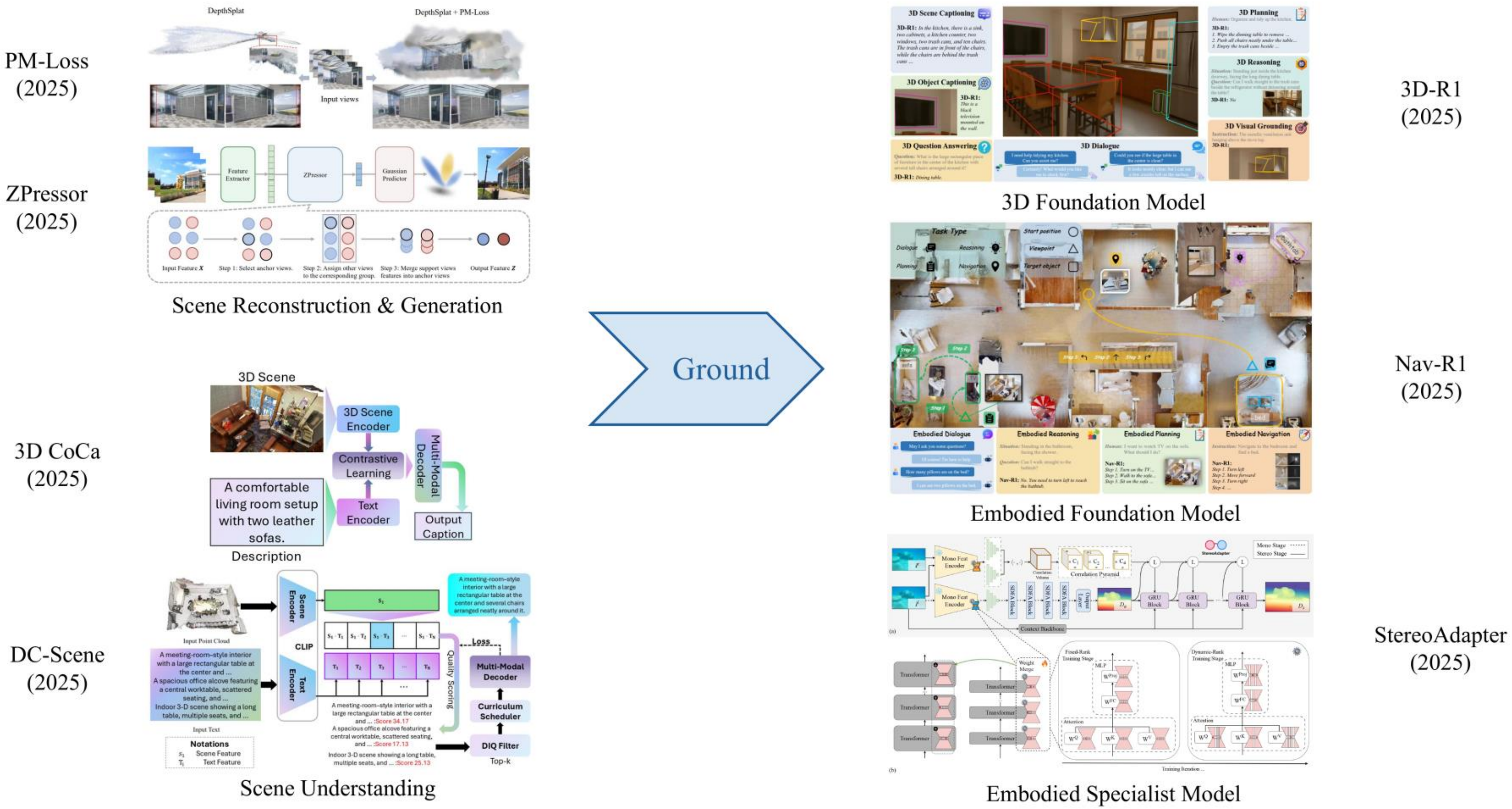
Talk @ Peking University, Sep 19, 2025

Some Quotes

"Nowadays, we are more interested in generating a full understanding of the scene from our cameras and from our video, so that we can, for instance, enable a robot to navigate through a room—not just seeing what objects are there and recognizing them, but working out where they are in relation to one another and being able to plan paths through (the environment)."

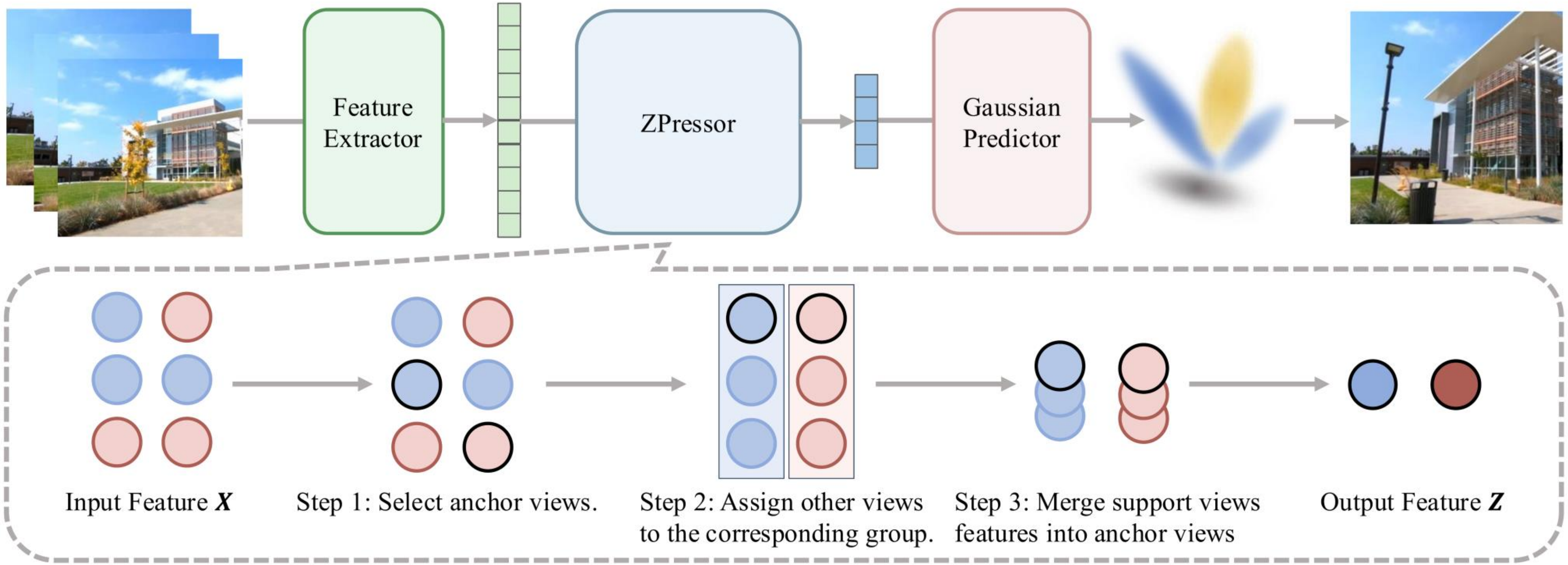
— *Ian Reid*

From Benchmarks to Real World



Recent works attempt to ground 3D foundation models, which are usually evaluated in benchmarks or simulations, to the real world.

Efficient 3D Reconstruction: ZPressor (2025)



ZPressor is an efficient feed-forward 3D scene reconstruction model with bottleneck-aware compression.

Weijie Wang, Yuedong Chen, Zeyu Zhang et al. *ZPressor: Bottleneck-Aware Compression for Scalable Feed-Forward 3DGS* (NeurIPS 2025)

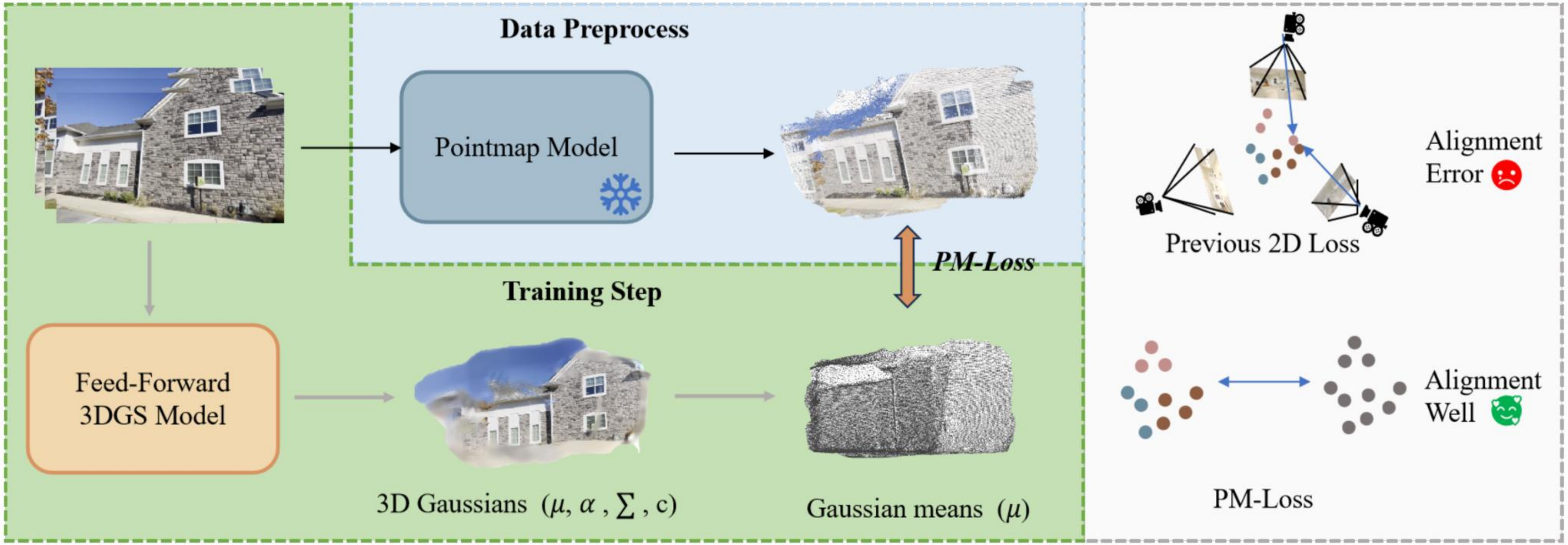
Results of ZPressor (2025)

Visualization on DL3DV (36 Input Views)

a62c330f5403e2e41a82a74c4e865b705c5706843b992fae2fe2e538b122d984

63798f5c6fbfcb4eb686268248b8ecbc8d87d920b2bcce967eeaedfd3b3b6d82

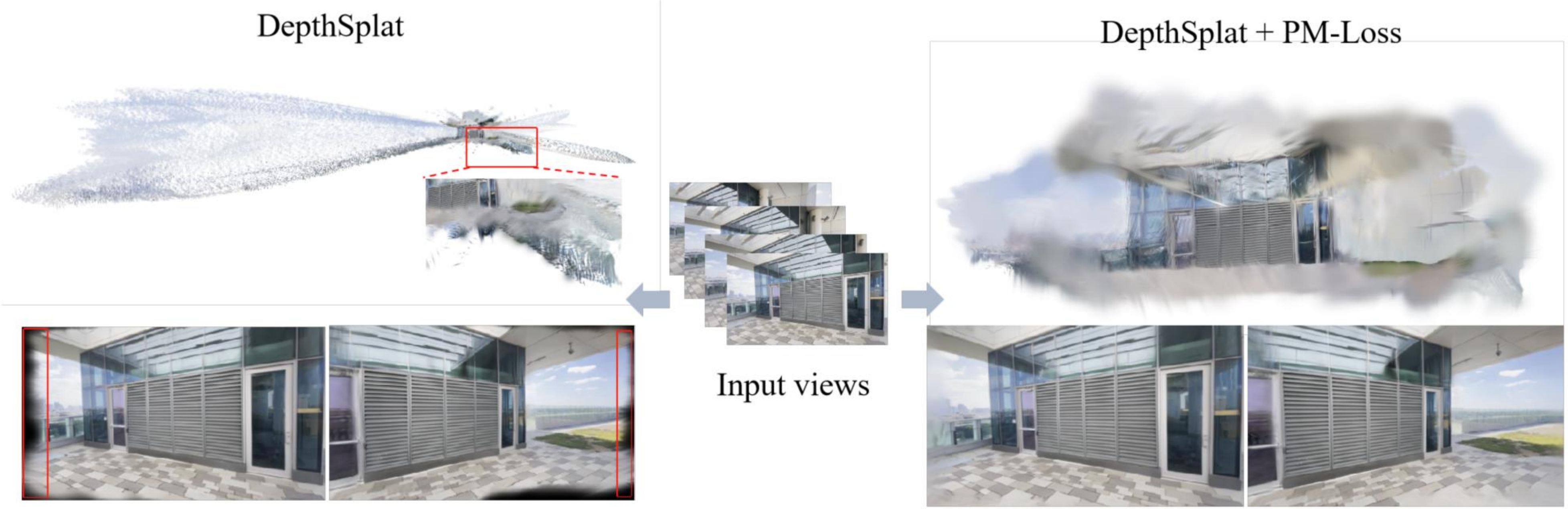
Geometric Prior Matters: PM-Loss (2025)



PM-Loss is a novel regularization loss based on a learned point map for feed-forward 3DGS, leading to smoother 3D geometry and better rendering.

Duochao Shi, Weijie Wang, Yuedong Chen, Zeyu Zhang et al. *Revisiting Depth Representations for Feed-Forward 3D Gaussian Splatting* (2025)

Results of PM-Loss (2025)



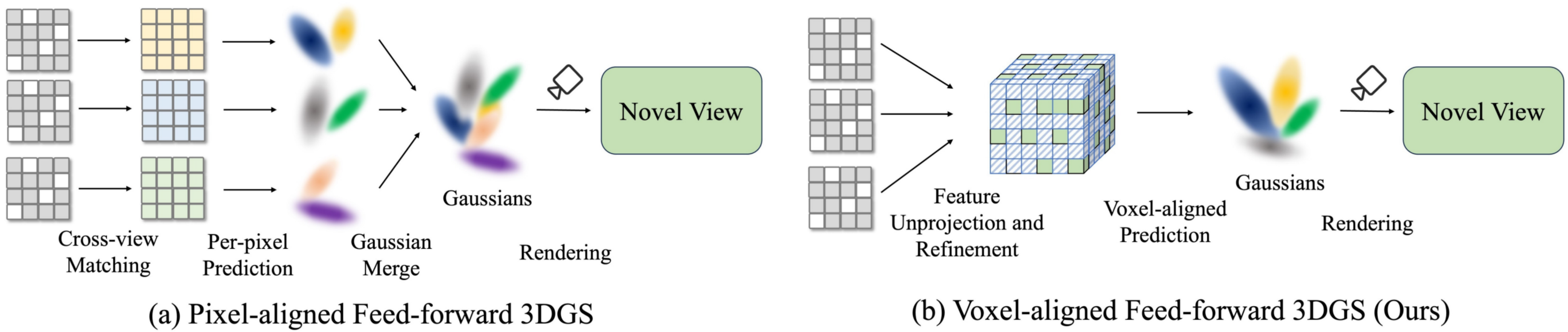
However, depth discontinuities at object boundaries often lead to fragmented or sparse point clouds, degrading rendering quality—a well-known limitation of depth-based representations. To tackle this issue, we introduce **PM-Loss**, a novel regularization loss based on a pointmap predicted by a pre-trained transformer (Chamfer distance). Although the pointmap itself may be less accurate than the depth map, it effectively enforces geometric smoothness, especially around object boundaries.

Results of PM-Loss (2025)

Depthsplat

Depthsplat + PM-Loss

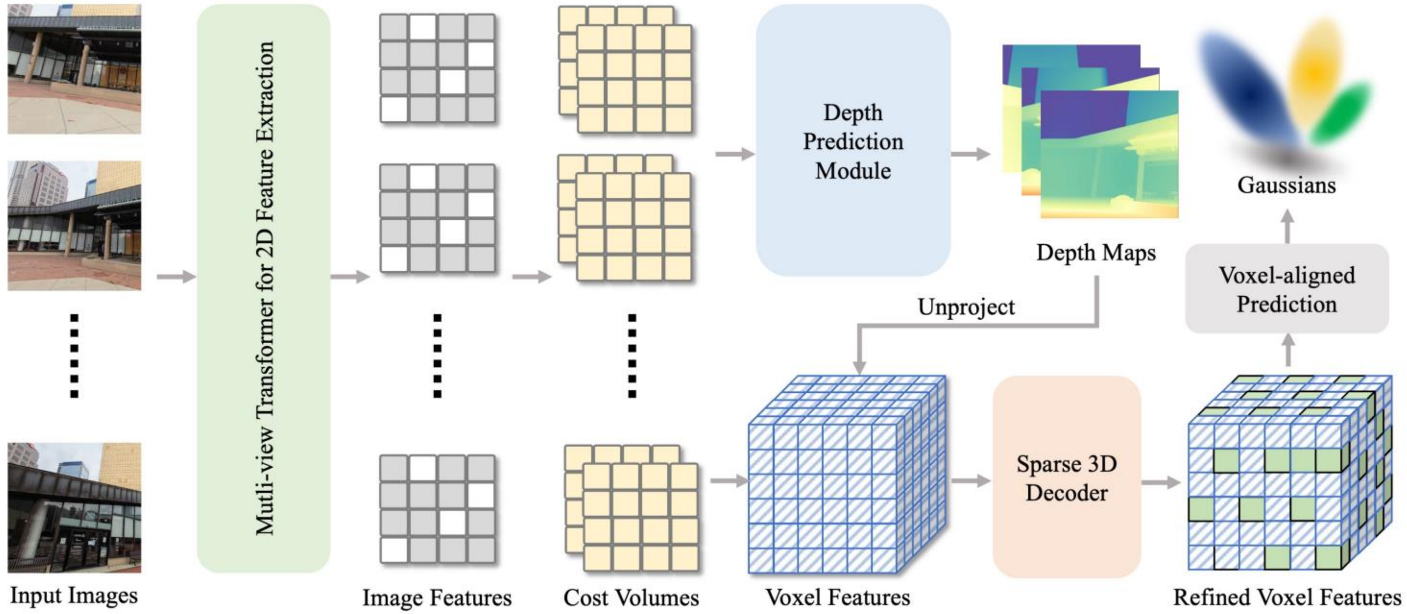
Voxel-Aligned Matters: VolSplat (2025)



Pixel-aligned feed-forward 3DGS methods suffer from two primary limitations: 1) 2D feature matching struggles to effectively resolve the multi-view alignment problem, and 2) the Gaussian density is constrained and cannot be adaptively controlled according to scene complexity.

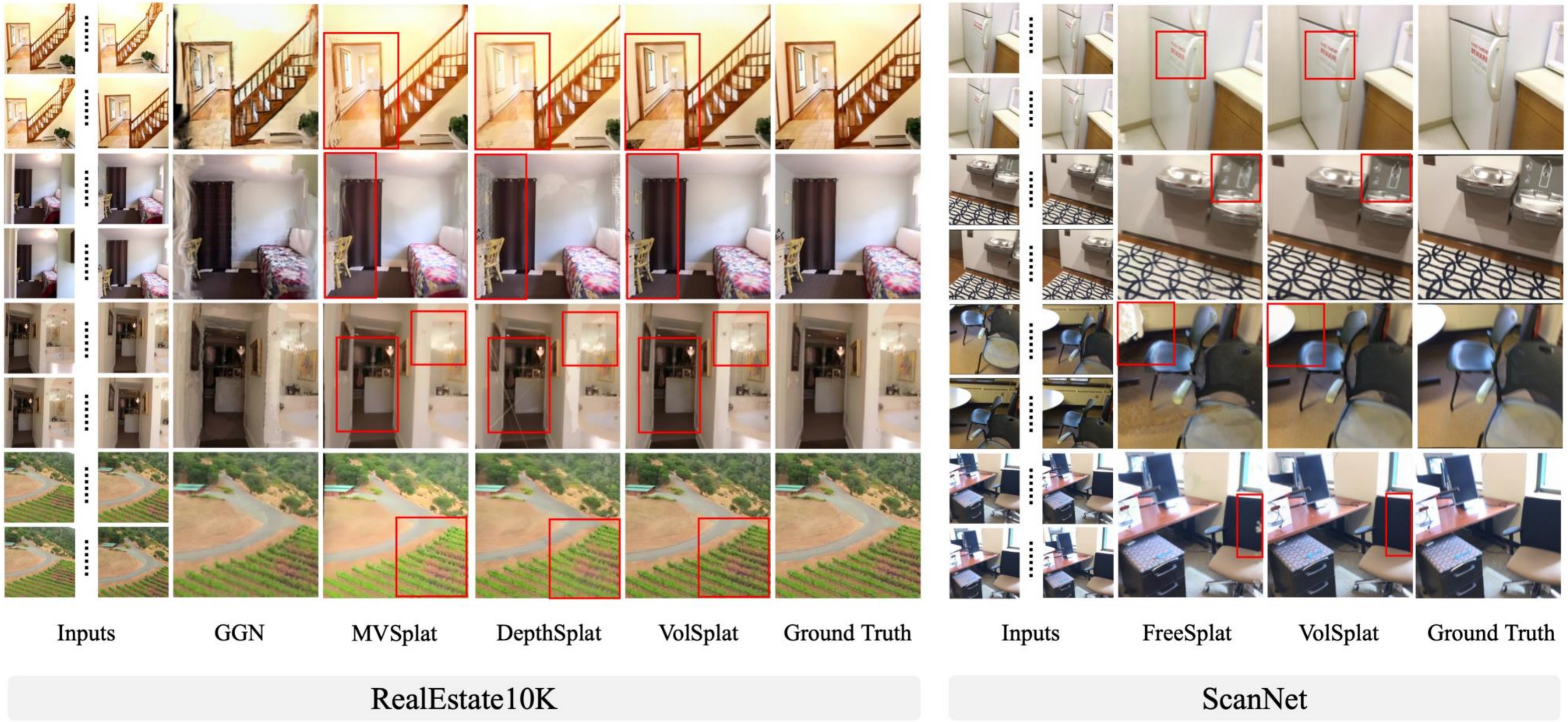
Weijie Wang, Yeqing Chen, Zeyu Zhang et al. *VolSplat: Rethinking Feed-Forward 3D Gaussian Splatting with Voxel-Aligned Prediction* (2025)

Voxel-Aligned Matters: VolSplat (2025)



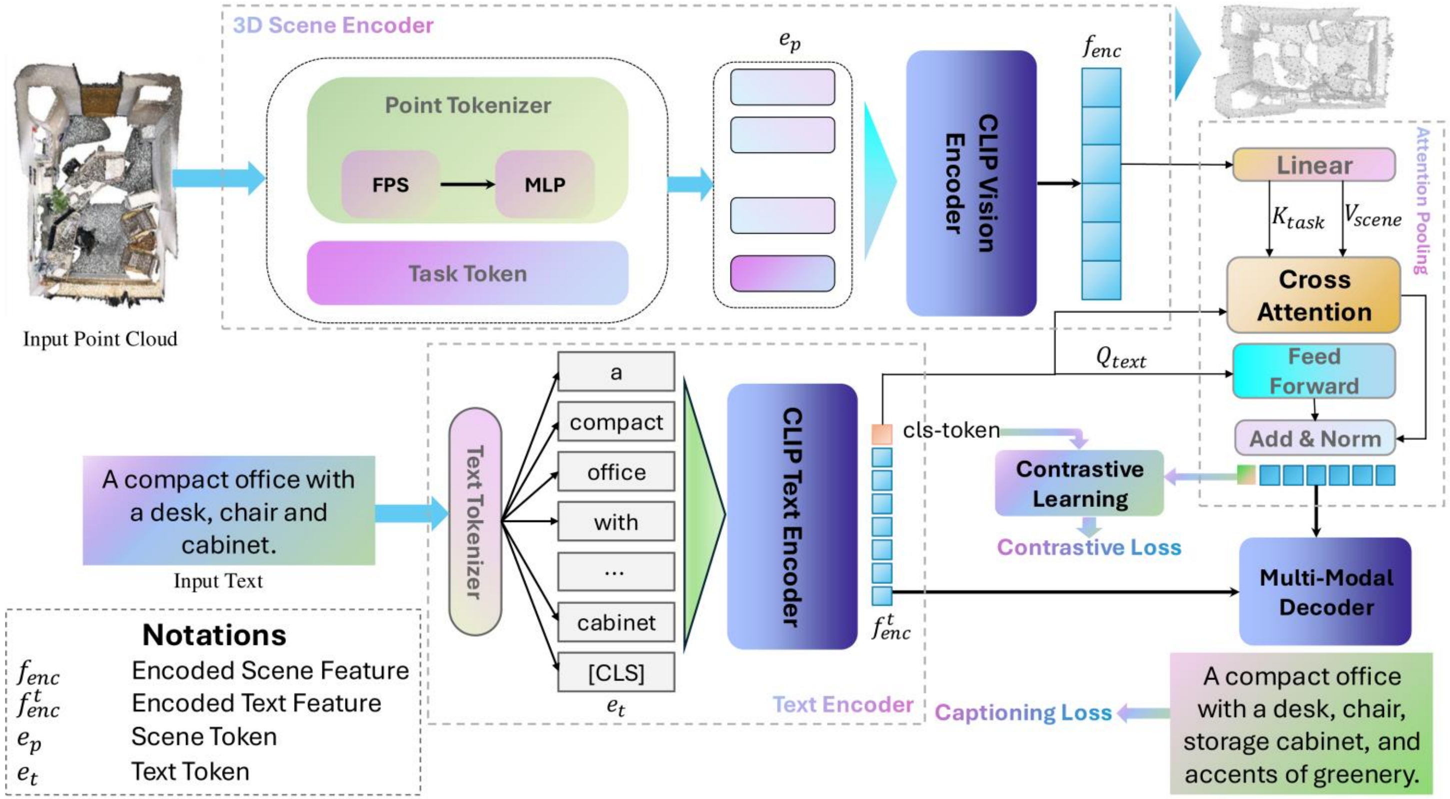
Given multi-view images as input, we first extract 2D features for each image using a Transformer-based network and construct per-view cost volumes with plane sweeping. Depth Prediction Module then estimates a depth map for each view, which is used to unproject the 2D features into 3D space to form a voxel feature grid. Subsequently, we employ a sparse 3D decoder to refine these features in 3D space and predict the parameters of a 3D Gaussian for each occupied voxel. Finally, novel views are rendered from the predicted 3D Gaussians.

Results: VolSplat (2025)



The results on the left are from RealEstate10K, and the results on the right are from ScanNet.

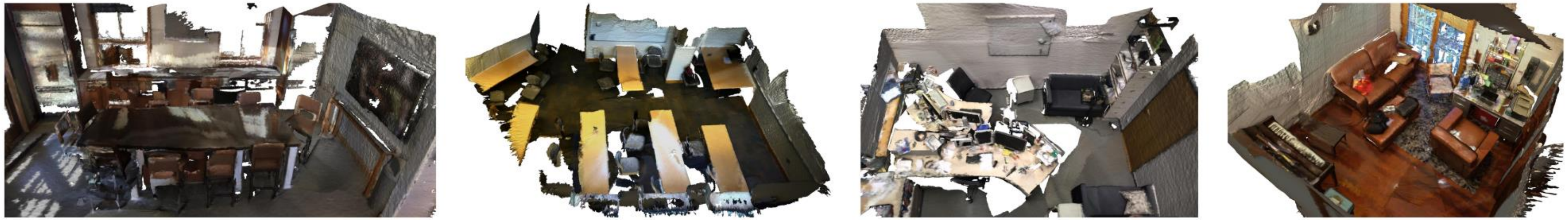
3D Representation Learning: 3D CoCa (2025)



3D CoCa leverages 3D multimodal representation learning to tackle scene understanding through large-scale contrastive pretraining.

Ting Huang, Zeyu Zhang et al. *3D CoCa: Contrastive Learners are 3D Captioners* (2025)

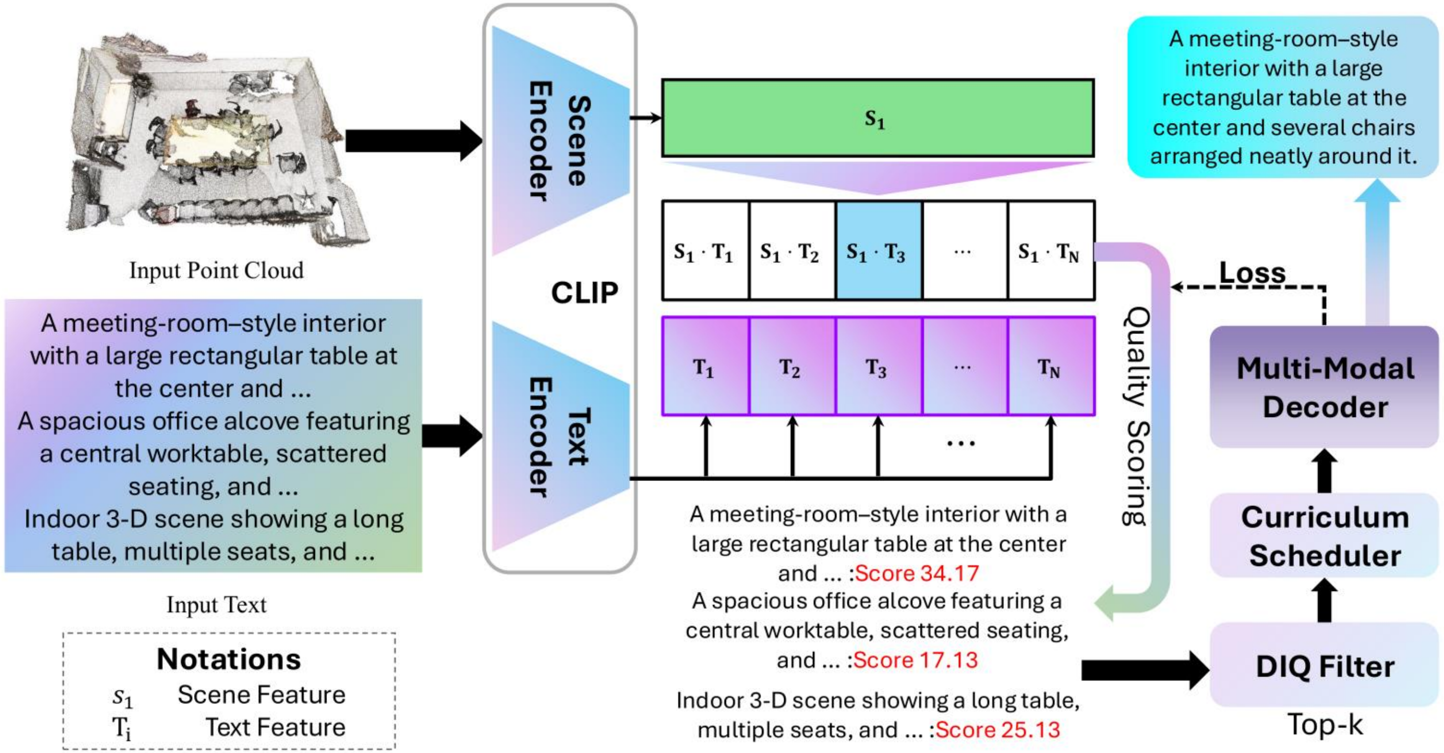
Results of 3D CoCa (2025)



Vote2Cap-DETR++: A room with a large wooden dining table and multiple chairs.	**Vote2Cap-DETR++**: A room with several rectangular tables and various items on them.	**Vote2Cap-DETR++**: A room with a few tables, cluttered items on top, and several chairs nearby.	**Vote2Cap-DETR++**: A living room with two sofas and a small side table.
Ours: A spacious dining area featuring a long wooden table surrounded by several chairs, with a painting on the wall.	**Ours**: An open space designed for work or study, with multiple tables and chairs arranged to form a collective workspace, and ample floor space around them.	**Ours**: A messy workspace, with various documents or tools scattered on the tables and a few chairs and electronic devices placed around.	**Ours**: A cozy lounge area featuring two brown sofas and a coffee table, with a rug on the floor and some decorative items nearby.
GT: In a bright dining room, a long wooden table is flanked by neatly arranged chairs. Light filters in through the window, and a decorative painting adorns the wall.	**GT**: A spacious indoor setting with several parallel tables and chairs, offering walking and working areas on all sides. The layout resembles a classroom.	**GT**: An office area, where tabletops are covered with multiple items and documents. Chairs and computer accessories are set around the room.	**GT**: A comfortable living room setup with two leather sofas, a small coffee table, and a rug on the floor. The corner have a musical instrument and ornaments.

A visual comparison on the ScanRefer dataset showcasing indoor scenes described by Vote2Cap-DETR++, 3D CoCa (Ours), and the ground truth (GT).

3D Data-Centric Learning: DC-Scene (2025)



Point clouds and captions are encoded, scored with 3D CLIP, and filtered by the Dual-Indicator Quality (DIQ) module to select top-k candidates. A Curriculum Scheduler trains the Multi-Modal Decoder, while a feedback loop updates CLIP scores with caption loss, forming a data-centric learning cycle.

Ting Huang, Zeyu Zhang et al. *DC-Scene: Data-Centric Learning for 3D Scene Understanding* (2025)

Results of DC-Scene (2025)

Baseline(full data): a small kitchen with cabinets, a sink, and a white appliance on the right.

DC-Scene(Top-75%): a kitchen where wooden cabinets frame a metal sink beneath a wall picture, while a white washer-dryer sits to the right of the light-tiled floor that opens into a carpeted hallway.

GT: A compact galley kitchen with wooden upper and lower cabinets, a stainless-steel sink centered along the back work-top, and a white washer-dryer unit standing on the right side of the tiled floor.

Baseline(full data): a bedroom with two beds, a desk and some clutter on the floor.

DC-Scene(Top-75%): a cramped dormitory room with parallel single beds, a back-wall desk piled high with textbooks, and clothing and an open teal suitcase strewn over the dark-blue carpet.

GT: A student dorm room containing two single beds along opposite walls, a wooden study desk cluttered with books and electronics, and clothes plus an open turquoise suitcase scattered across the blue carpet.

Baseline(full data): a small bedroom with a bed, green carpet, and a bathroom to the right.

DC-Scene(Top-75%): a bedroom featuring a bed topped with a bright blue blanket, a wicker hamper near the footboard, and an ensuite bathroom on the right where a basin and shower are visible through the open doorway.

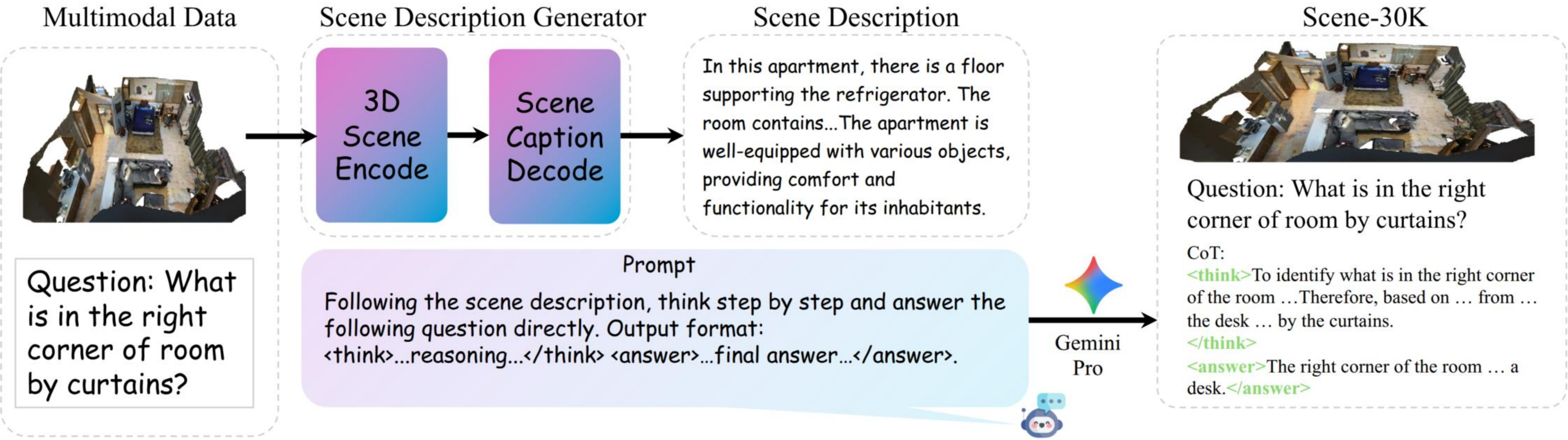
GT: A small bedroom with a light-wood single bed covered by a blue throw, green carpet flooring, a wicker laundry basket at the foot of the bed, and an adjoining bathroom on the right showing a white sink and shower stall.

For three validation scenes from the ScanRefer dataset, we present the rendered point cloud mesh (top row), followed by captions generated by three sources: the full-data baseline model (in pink), our **DC-Scene** model trained on the top-75% DIQ samples (in red), and the human-annotated ground truth (in green).

What's next for 3D foundation models?

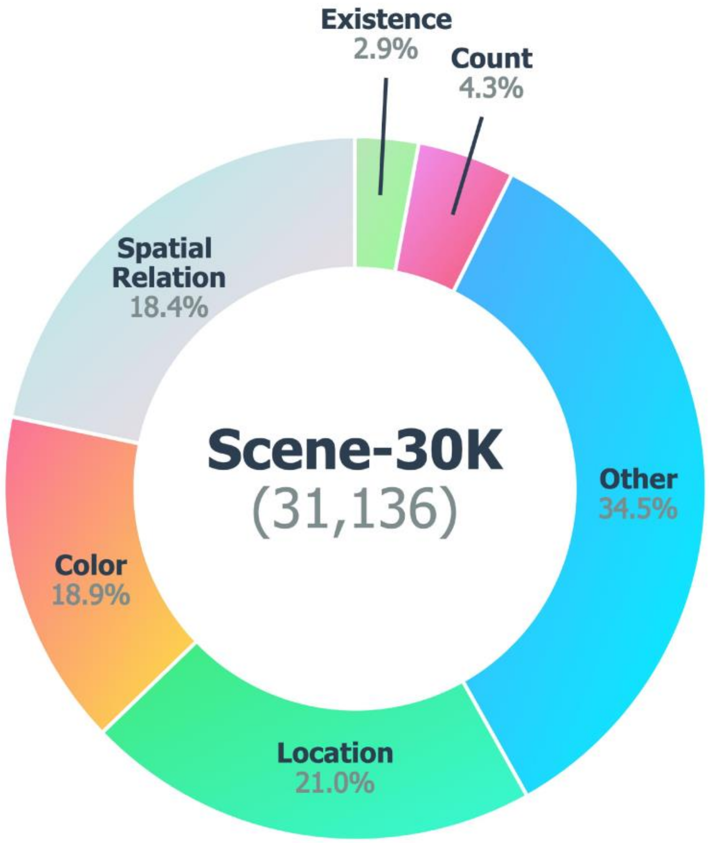
- How can we achieve zero-shot generalizability across different tasks given the domain knowledge gap between them?
- How can we adjust a foundation model after conventional supervised post-training when the outcomes are unsatisfactory on specific tasks?
- And most importantly, how can we ground our foundation model in the physical world?

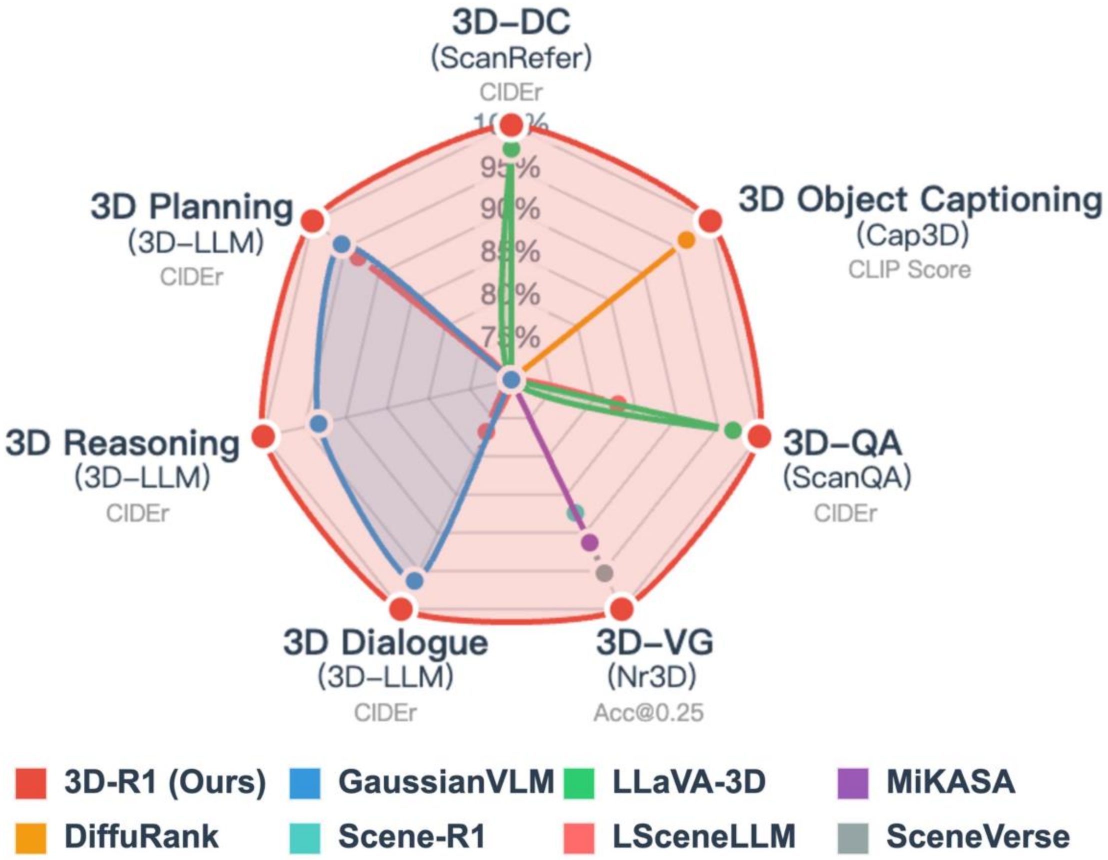
Synthetic Data Helps Enhance Generalizability: 3D-R1



CoT Data Engine. The point cloud of a scene is first sent to scene dscription generator to get a description of the scene. Then based on the description, we apply Gemini-Pro to synthetic CoT data.

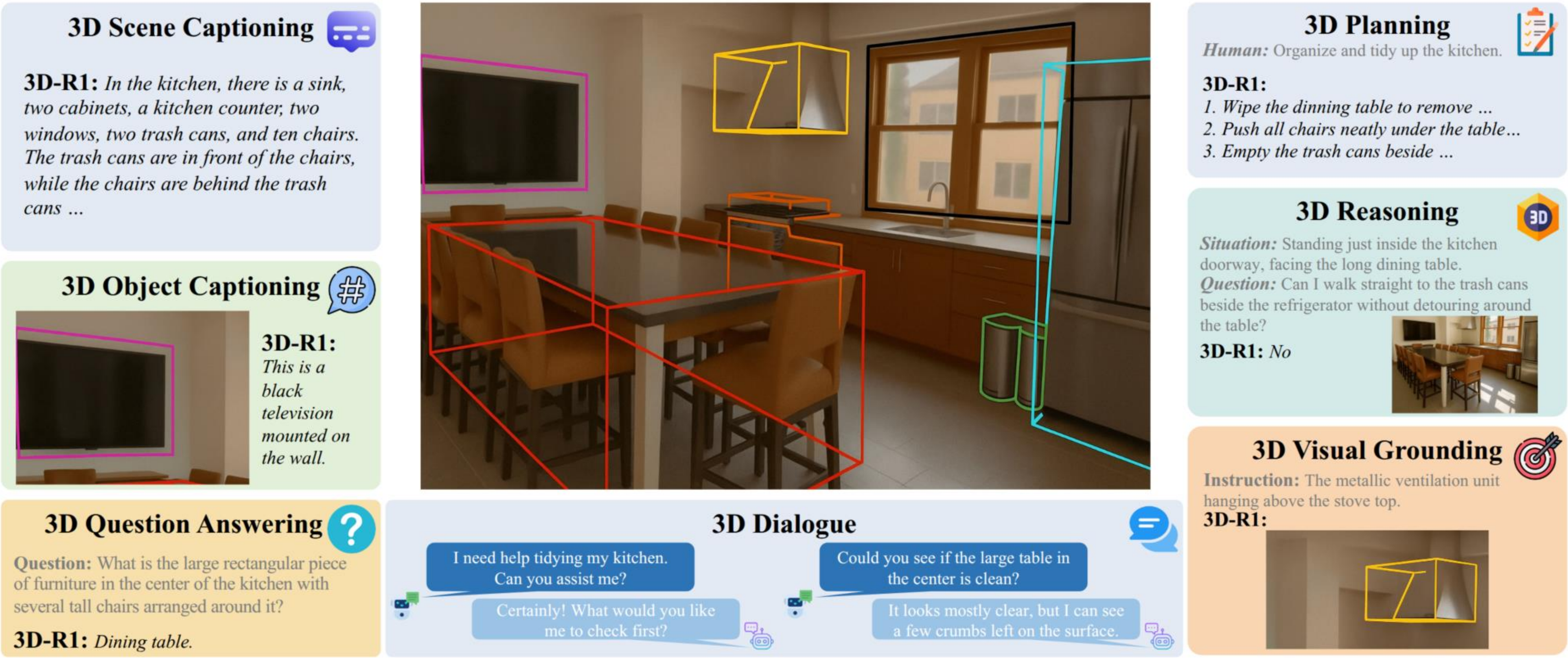
Scene-30K in 3D-R1





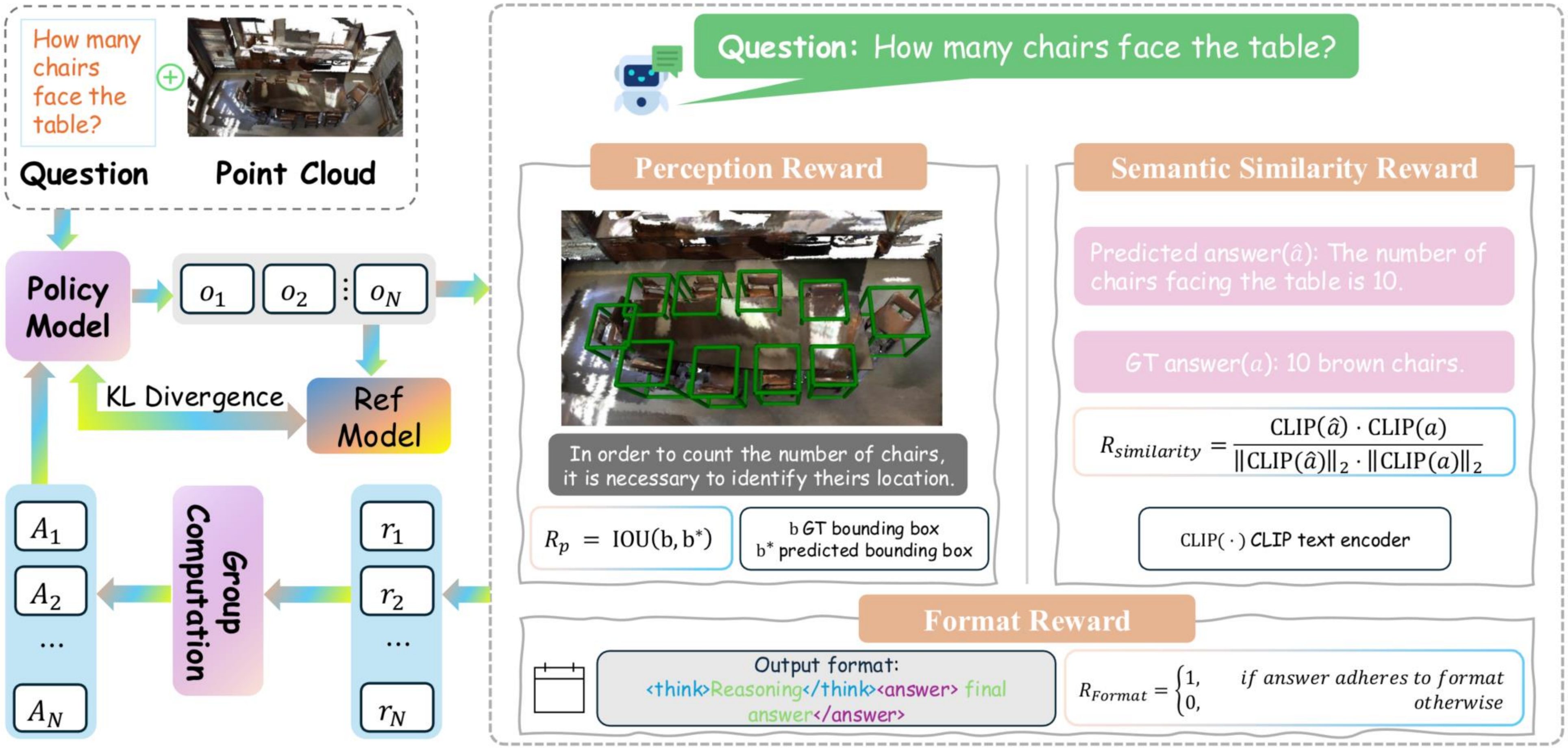
Scene-30K contains diverse scene categories and question types. **3D-R1** demonstrates strong performance across various tasks.

Generalizability: 3D-R1



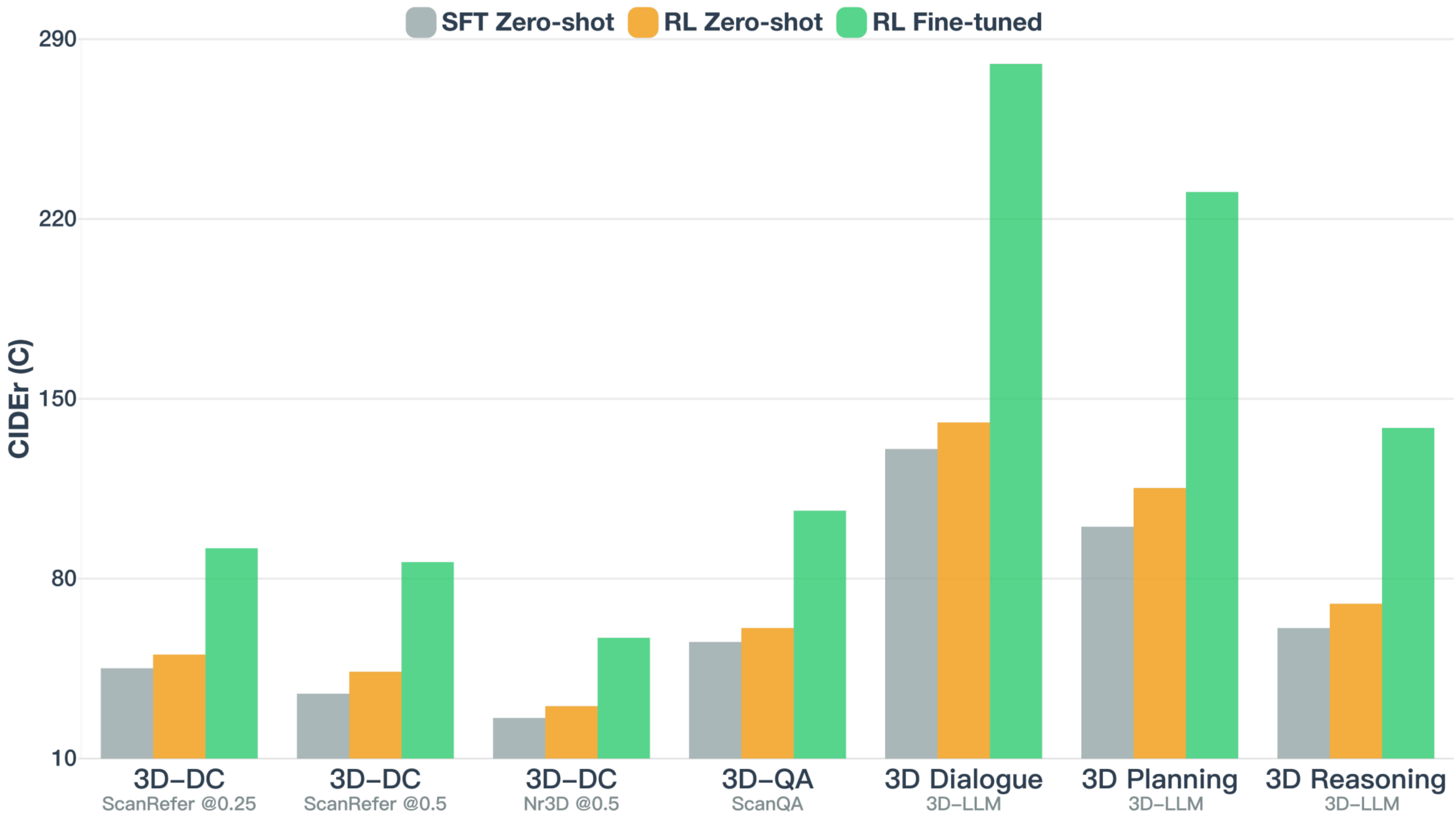
3D-R1 is a generalist model capable of handling various downstream tasks and applications in a zero-shot manner with incredible generalizability, significantly reducing the need for expensive adaptation.

Adjust Output: Reinforcement Learning with Verifiable Rewards (RLVR)



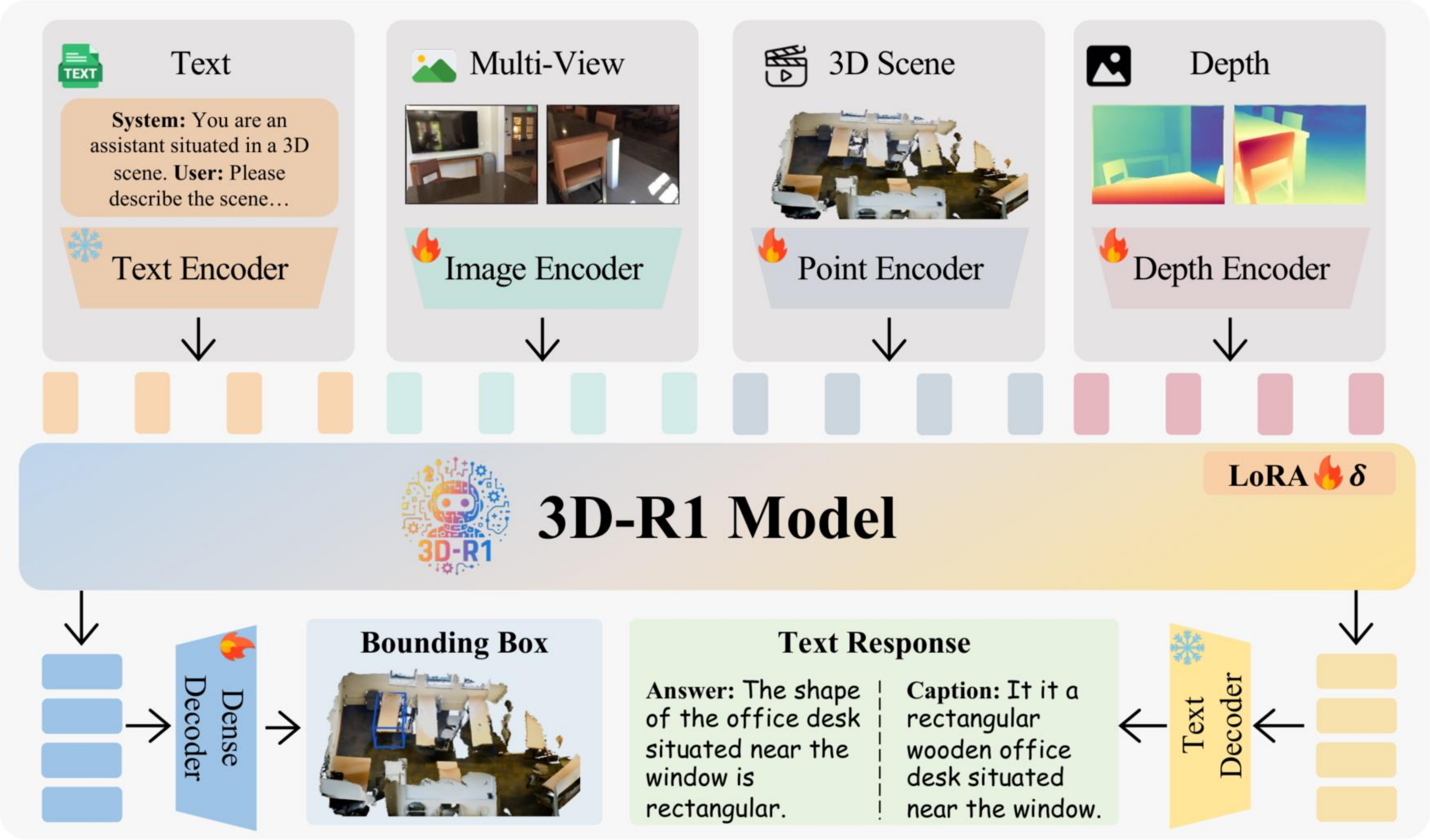
The policy model generates N outputs from a point cloud and question. Then perception IoU, semantic CLIP-similarity, and format-adherence rewards are computed, grouped, and combined with a KL term to a frozen reference model to update the policy.

Enhanced Reasoning: 3D-R1



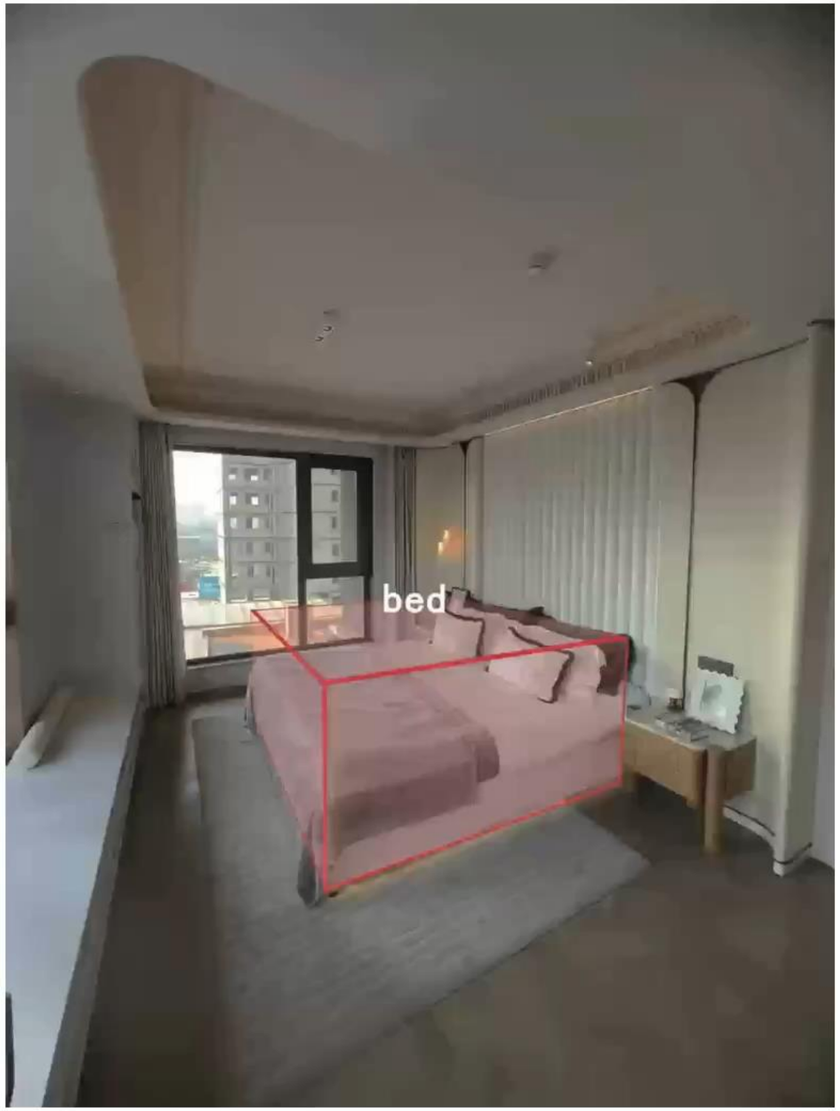
3D-R1 exhibits remarkable generalizability with enhanced reasoning capabilities.

Foundation Model: 3D-R1



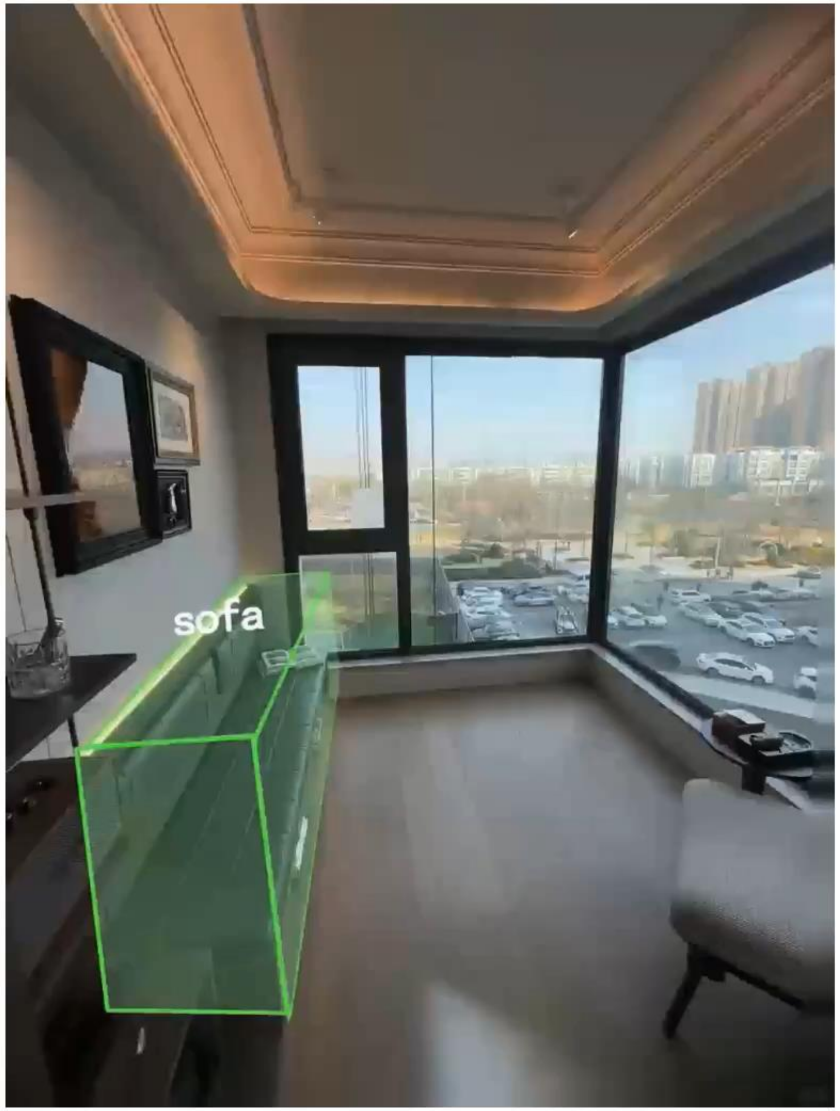
3D-R1 is an open-source generalist model that enhances the reasoning of 3D VLMs for unified scene understanding.

3D Scene Dense Captioning (3D-DC)



3D-DC

3D Object Captioning

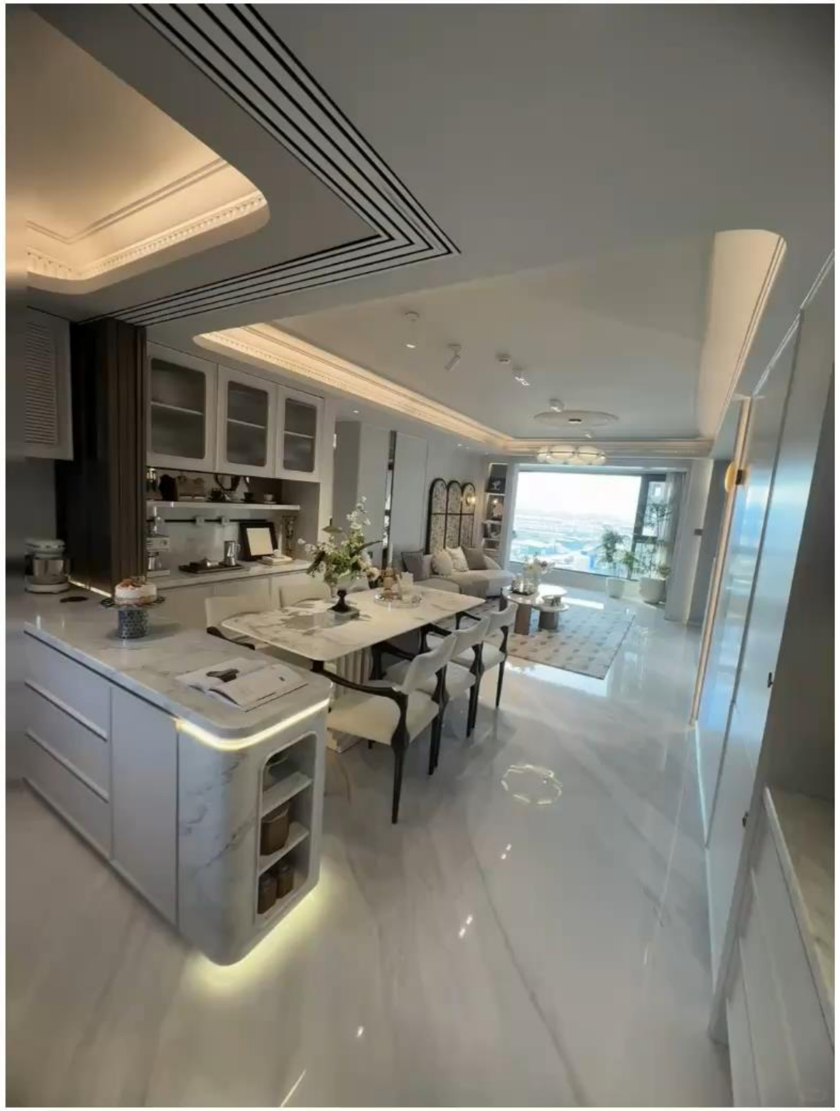


3D Object Captioning

3D Visual Grounding (3D-VG)

3D-VG

3D Question Answering (3D-QA)



3D-QA

3D Dialogue

3D Dialogue

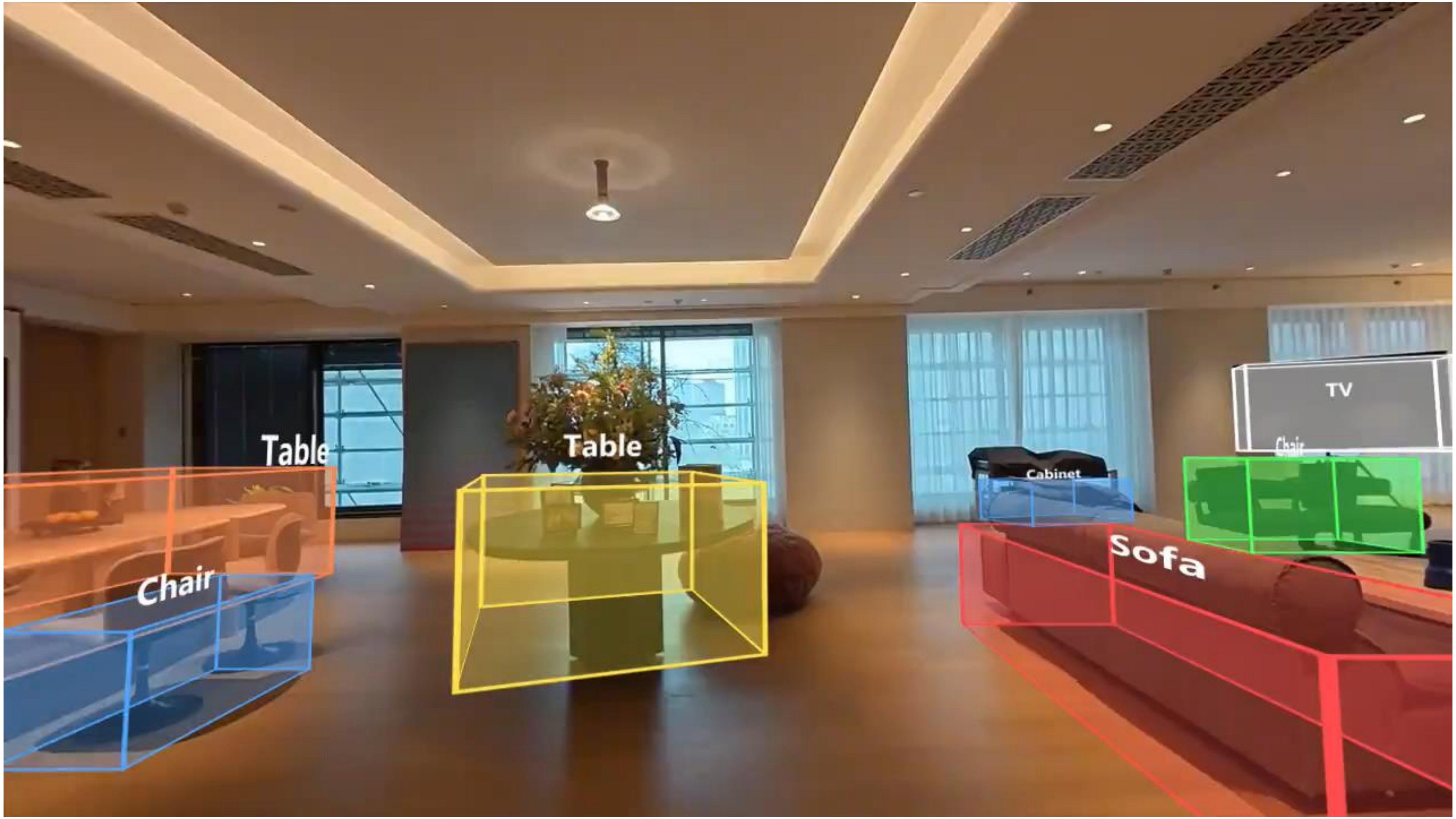
3D Reasoning

3D Reasoning

3D Planning

3D Planning

Zero-Shot Results



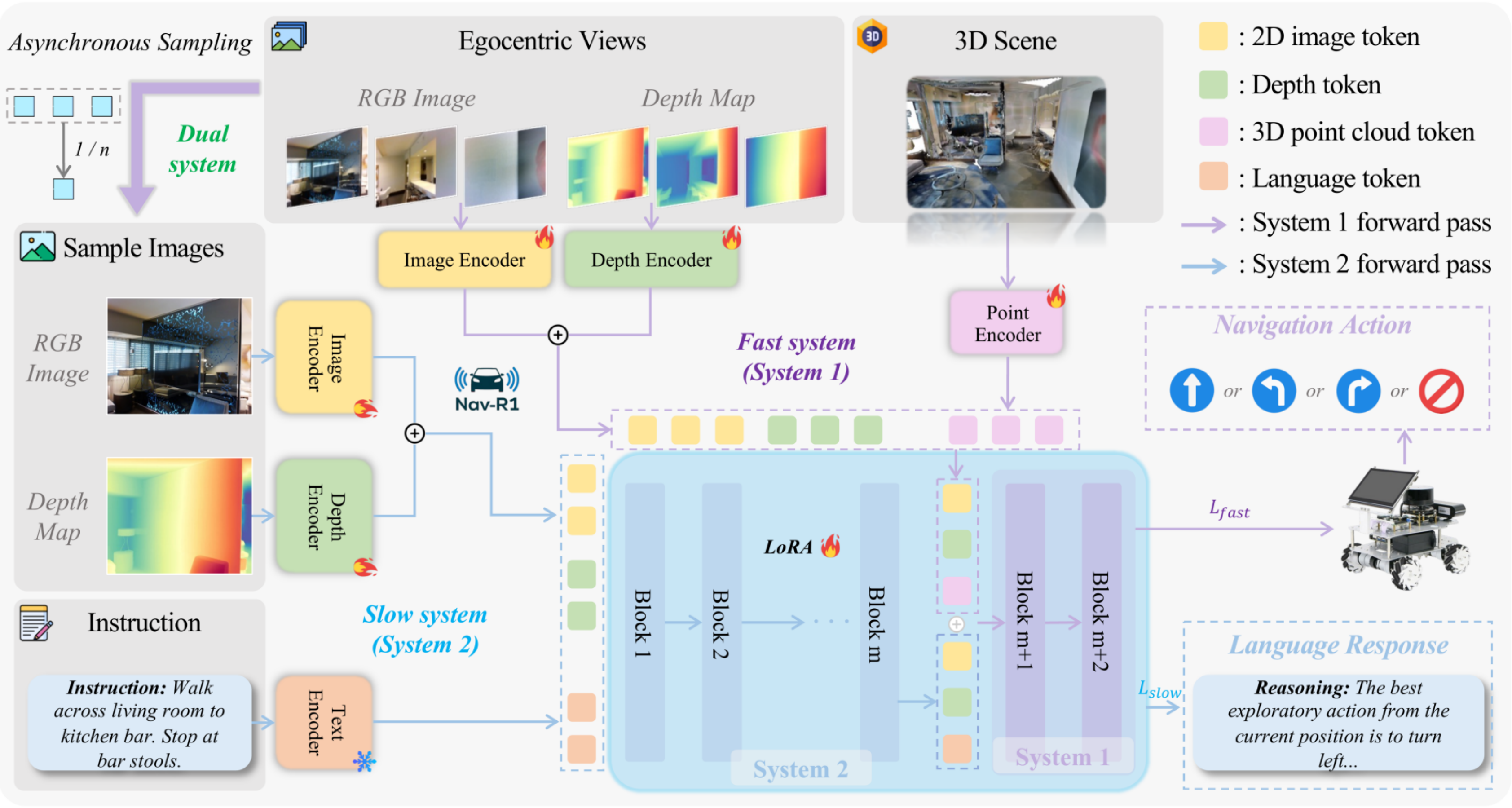
System and Memory: Nav-R1

What if we ground a 3D foundation model in embodied scenes? How can its reasoning approach human-level intelligence? This is inspired by psychology.

"The division of labor between System 1 (fast) and System 2 (slow) is highly efficient: it minimizes effort and optimizes performance."

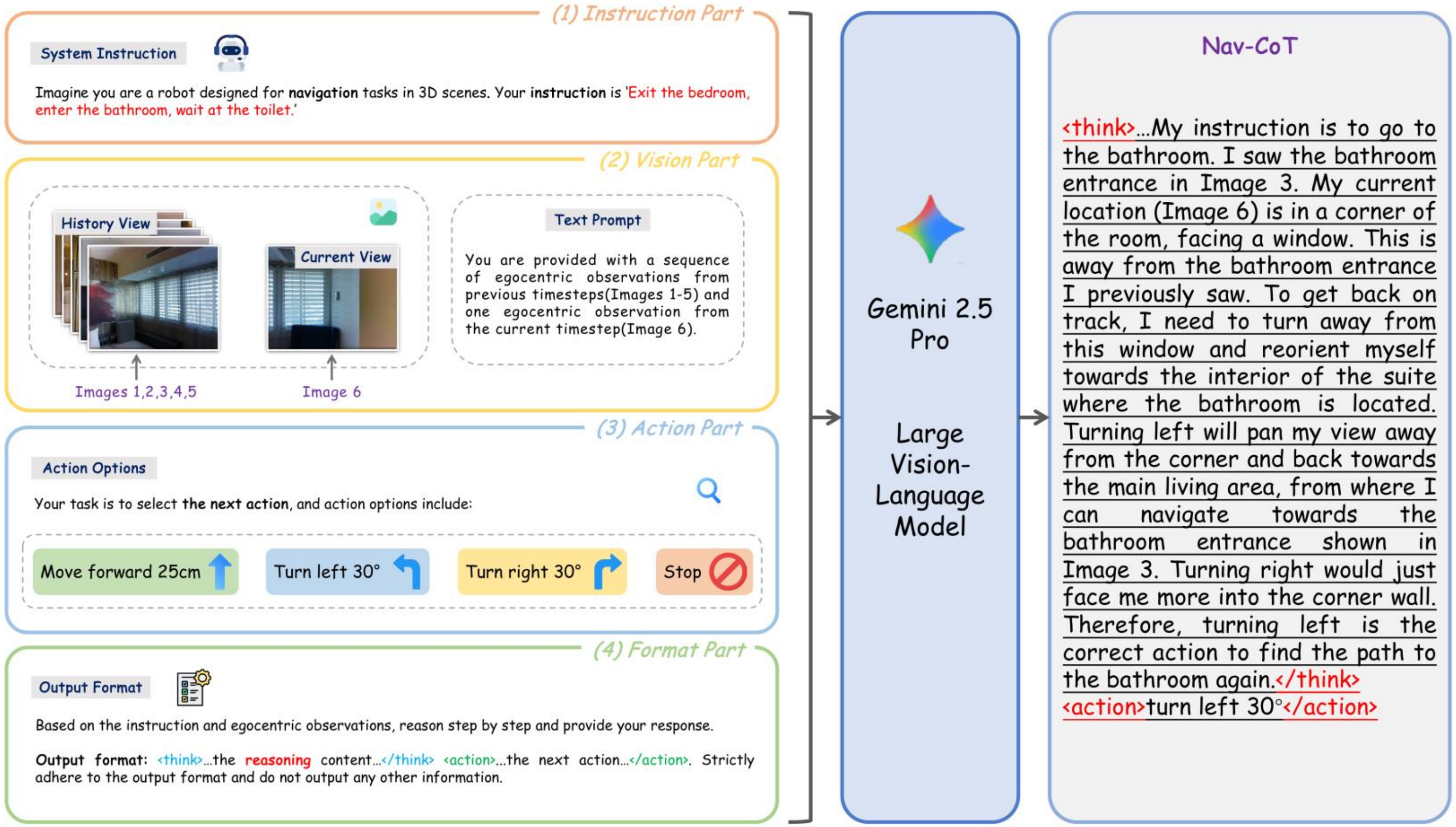
— Daniel Kahneman (Nobel Prize in Economics)

Fast-in-Slow: Nav-R1



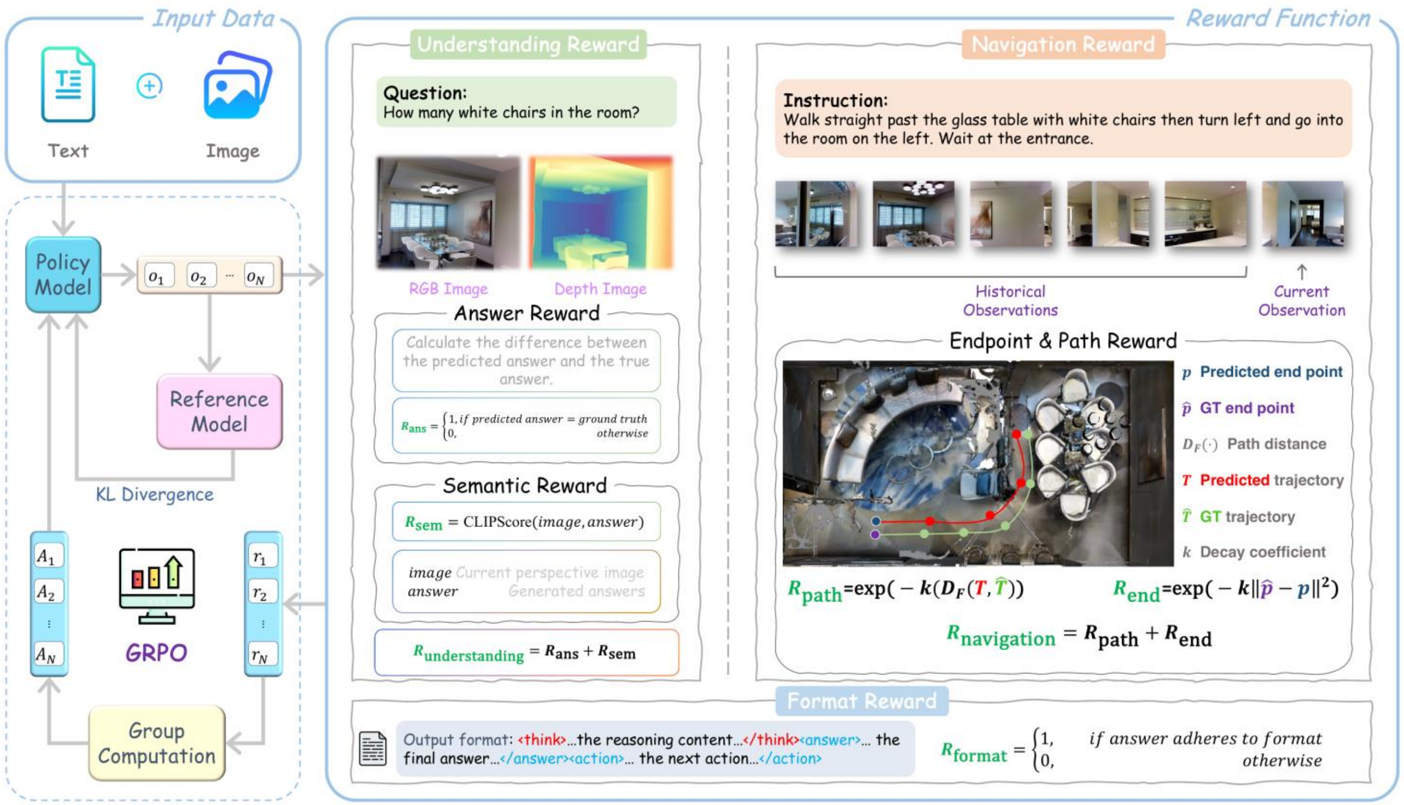
Nav-R1 features a Fast-in-Slow design that ensures rapid decision-making within long-horizon planning..

Synthetic Data: Nav-CoT-110K



We construct the **Nav-CoT-110K** dataset by defining navigation instructions, integrating egocentric visual inputs, providing action options and specifying the output format. These components are fed into Gemini 2.5 Pro, which generates step-by-step reasoning and action decisions aligned with navigation goals.

Adjust Output: RLVR



The pipeline of RL Policy. The policy model generates N outputs from text-image input. Then understanding reward (answer correctness and semantic alignment), navigation reward (path fidelity and endpoint accuracy), and format reward (structure adherence) are computed, grouped, and combined with a KL term to a frozen reference model to update the policy.

Navigation Foundation Model: Nav-R1

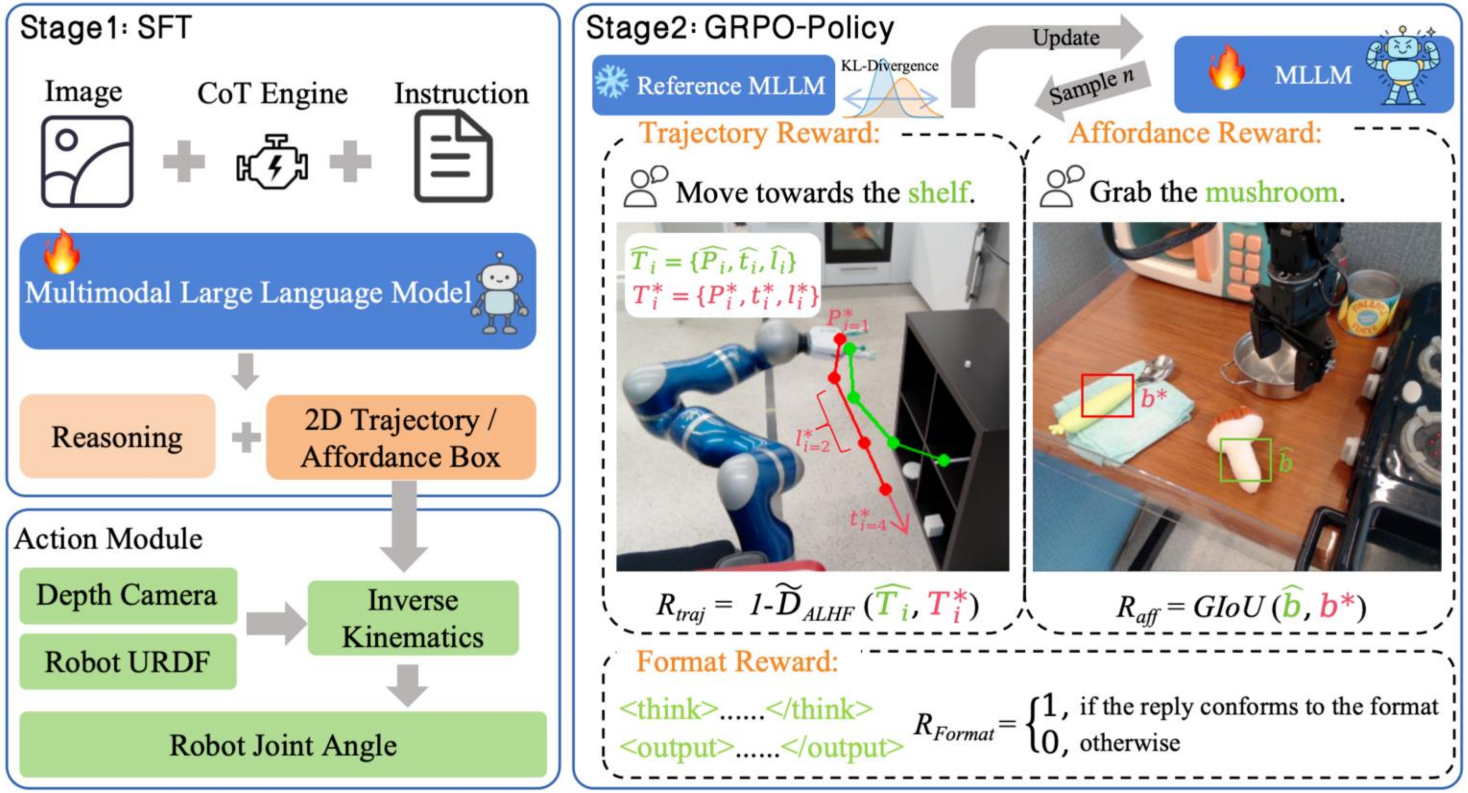
Nav-R1 is an embodied foundation model that integrates dialogue, reasoning, planning, and navigation capabilities to enable intelligent interaction and task execution in 3D environments.

Results: Nav-R1

Nav-R1: Reasoning and Navigation in Embodied Scenes

Qingxiang Liu, Ting Huang, Zeyu Zhang, Hao Tang

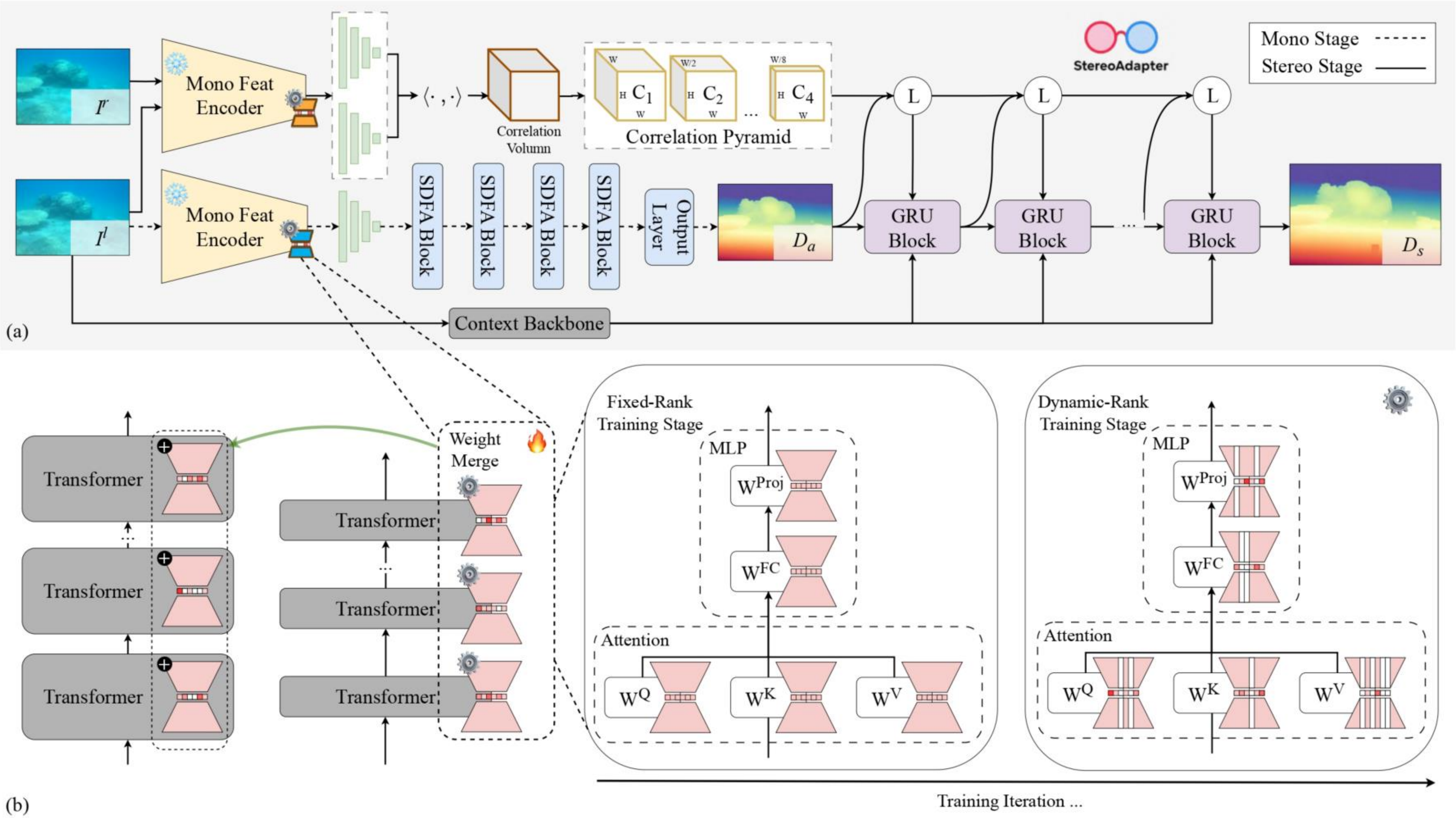
Similar Idea for Arm Robots: VLA-R1



Training has two stages: **Stage 1** uses SFT with CoT supervision to learn reasoning over images and instructions; **Stage 2** refines reasoning and actions via RL with verifiable rewards (GRPO). **During inference**, a control stack converts outputs into joint-level robot commands.

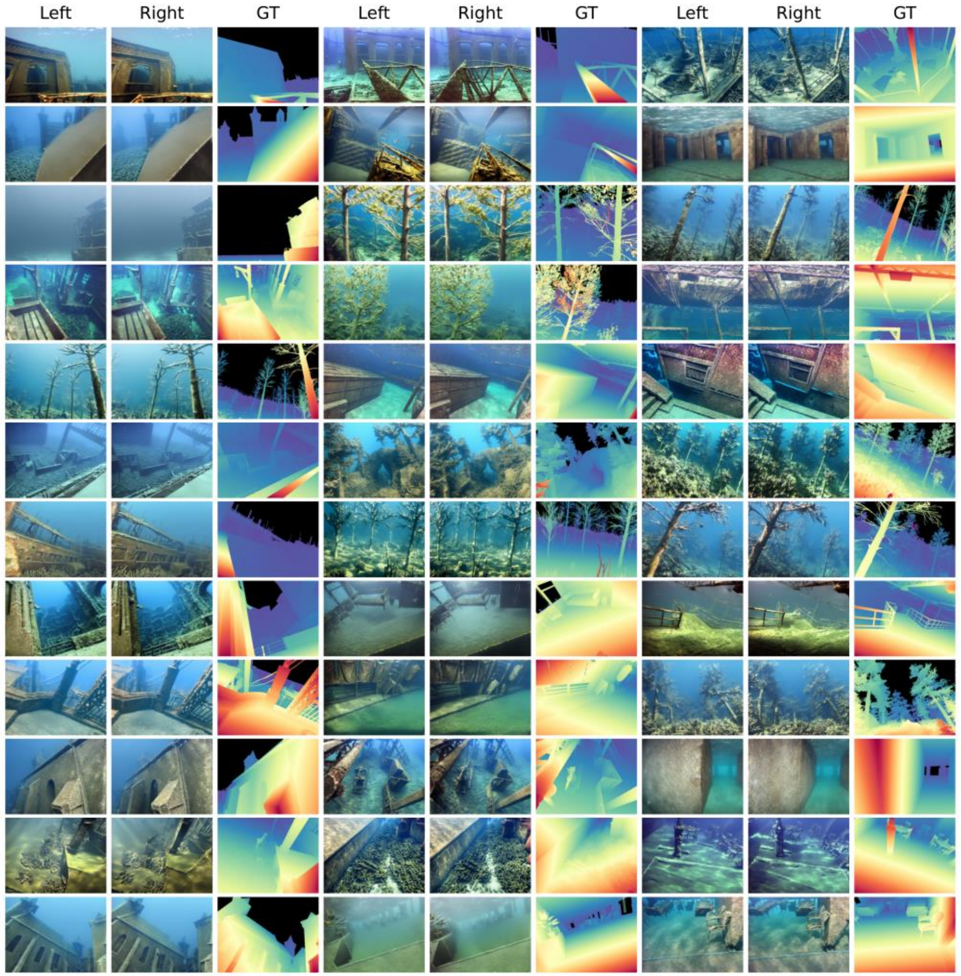
Results: VLA-R1

Bridging the Domain Gap in Post-Training: StereoAdapter



StereoAdapter is a self-supervised adaptive model that allows robust underwater depth estimation.

Synthetic Data: UW-StereoDepth-40K



Data synthesis. Unreal Engine 5 rendering for UW-StereoDepth-40K dataset.

Results: StereoAdapter

StereoAdapter

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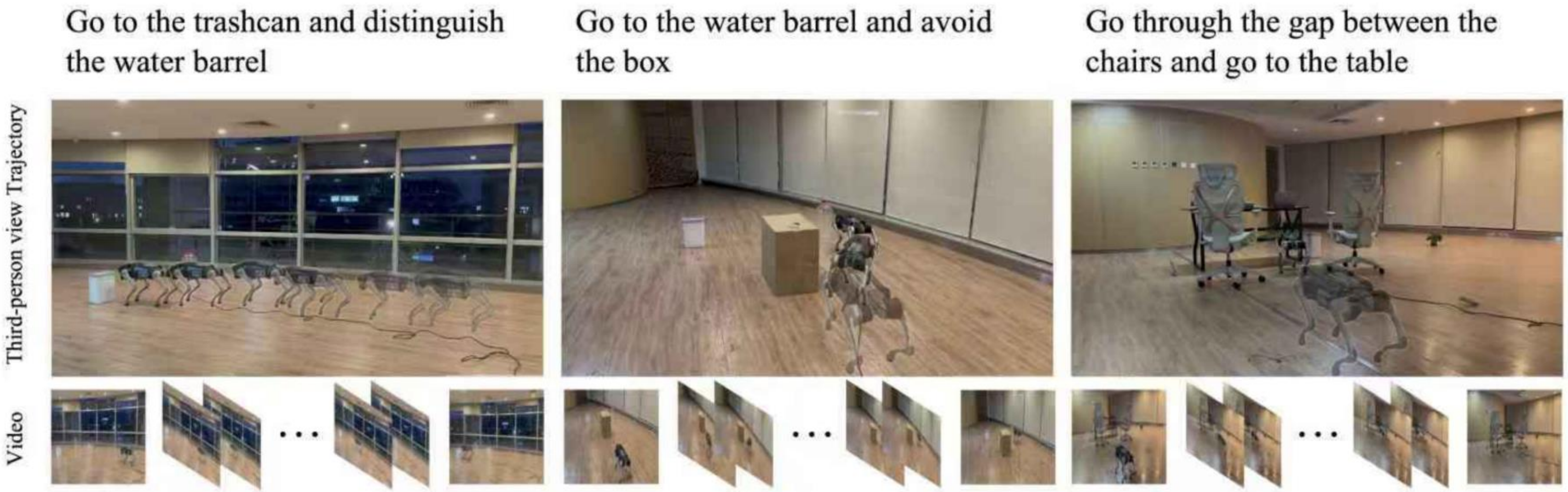
StereoAdapter: Adapting Stereo Depth Estimation to Underwater Scenes

Zhengri Wu, Yiran Wang, Yu Wen, Zeyu Zhang, Biao Wu, Hao Tang

Works in Progress

- Vision–Language–Action models for mobile robots such as robot dogs, UAVs, and humanoid robots.
- Real-time 3D Reconstruction for Mobile Robots
- Video World Models



Our mobile robot's VLA model follows user instructions to perform scene understanding, navigation, and action.

Takeaways

- Do not abuse reinforcement learning for post-training; use RL only to adjust the foundation model's output.
- Synthetic data and data-driven methods are the key to achieving scalability and generalizability.
- Work on unimodal LLMs that perform next-token prediction will not achieve advanced machine intelligence. If you are interested in human-level intelligence, do not rely solely on LLMs; instead, enhance spatial awareness in visual foundation models.

End

Thank you.