



FI 2026

Future Innovation tech eXpo Conference

자율주행을 위한 Physical AI 기술

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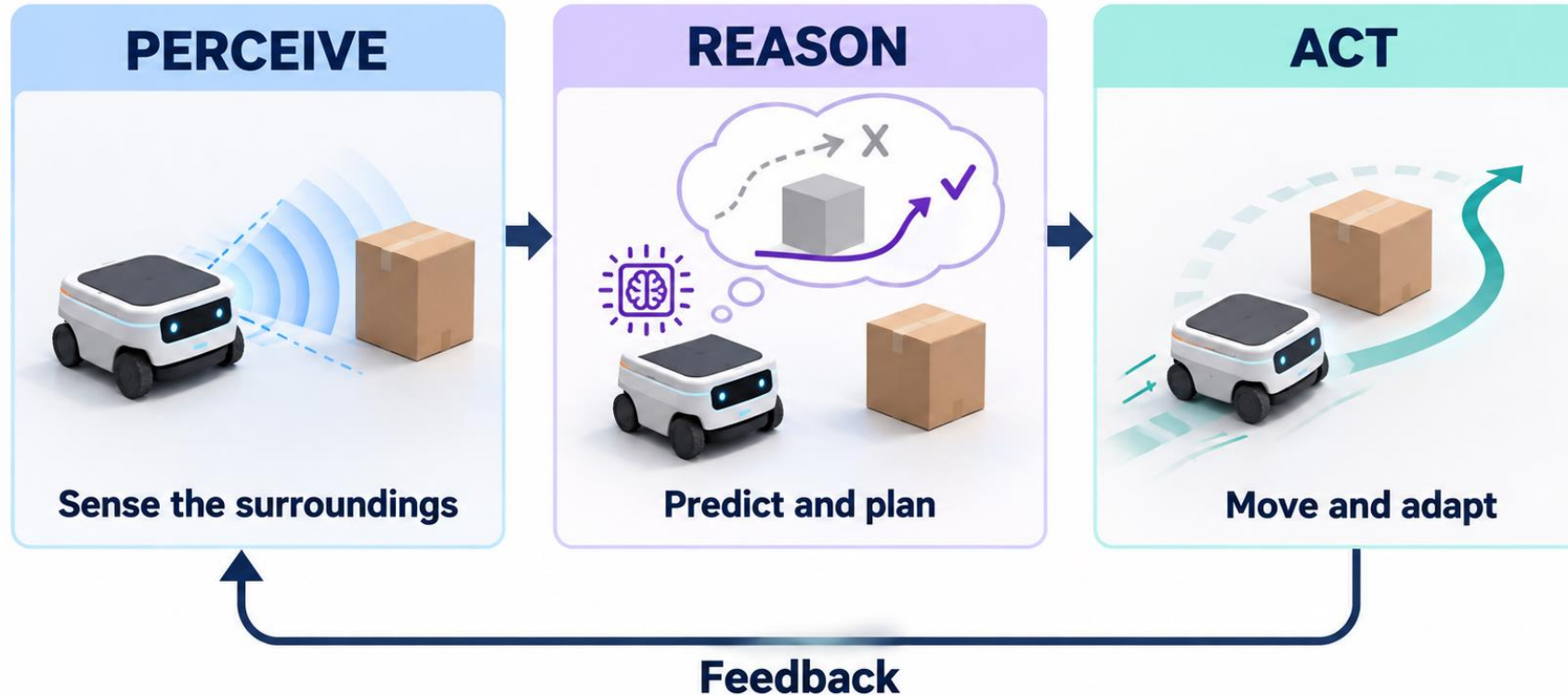
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Physical AI

- Physical AI enables machines to perceive, reason about, and act in the physical world.



Physical AI for Autonomous Driving

- Advances in Physical AI are pushing autonomous driving closer to commercial readiness

Tesla FSD v14 release in Korea



<https://www.youtube.com/watch?v=QgzHTPheRO4&t=89s>

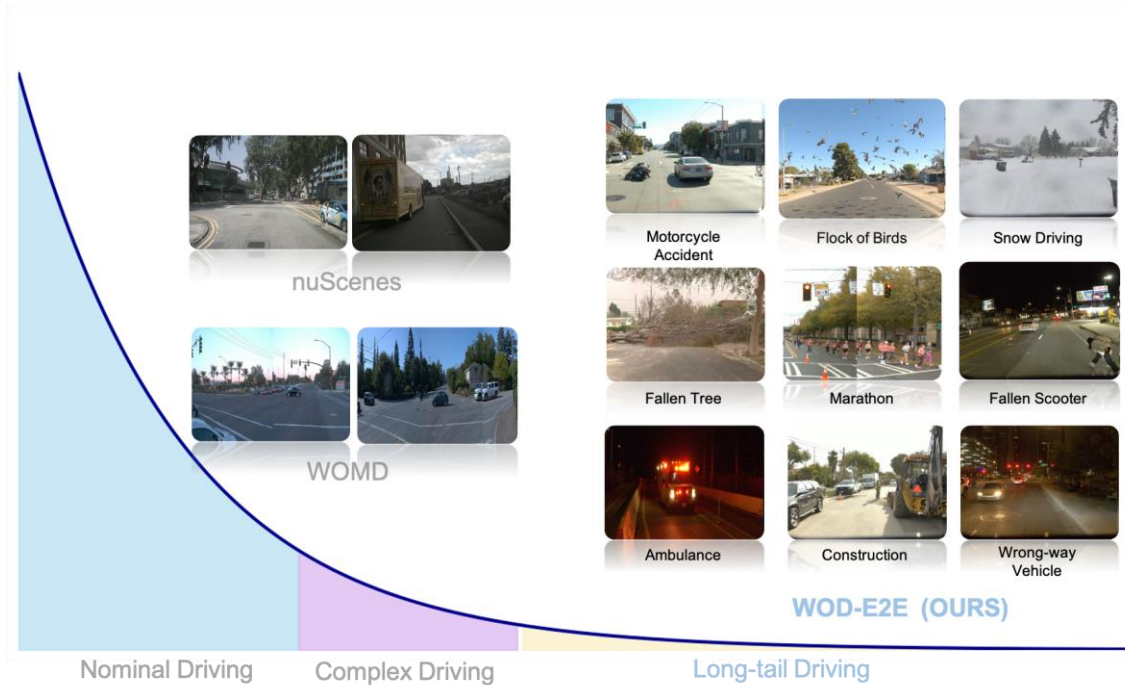
Autonomous Driving Problem

- Autonomous driving can be formulated as learning a mapping from high-dimensional inputs to a two-dimensional action space.



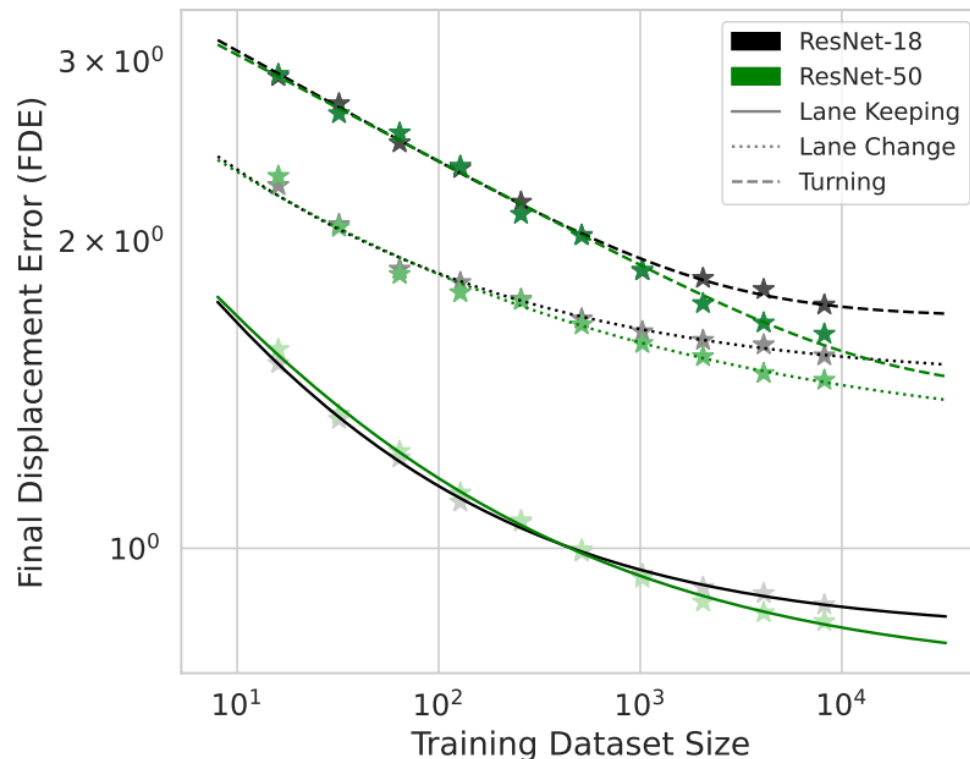
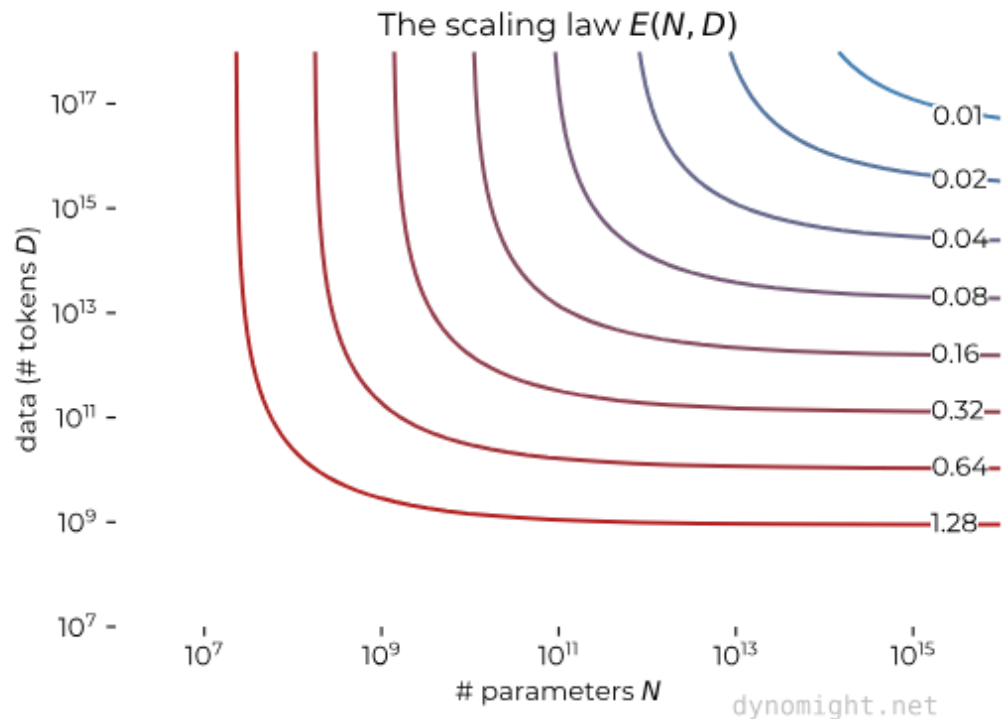
Autonomous Driving Challenges

- Autonomous vehicles must operate safely in complex edge scenarios.
- These edge cases are rare in training datasets.



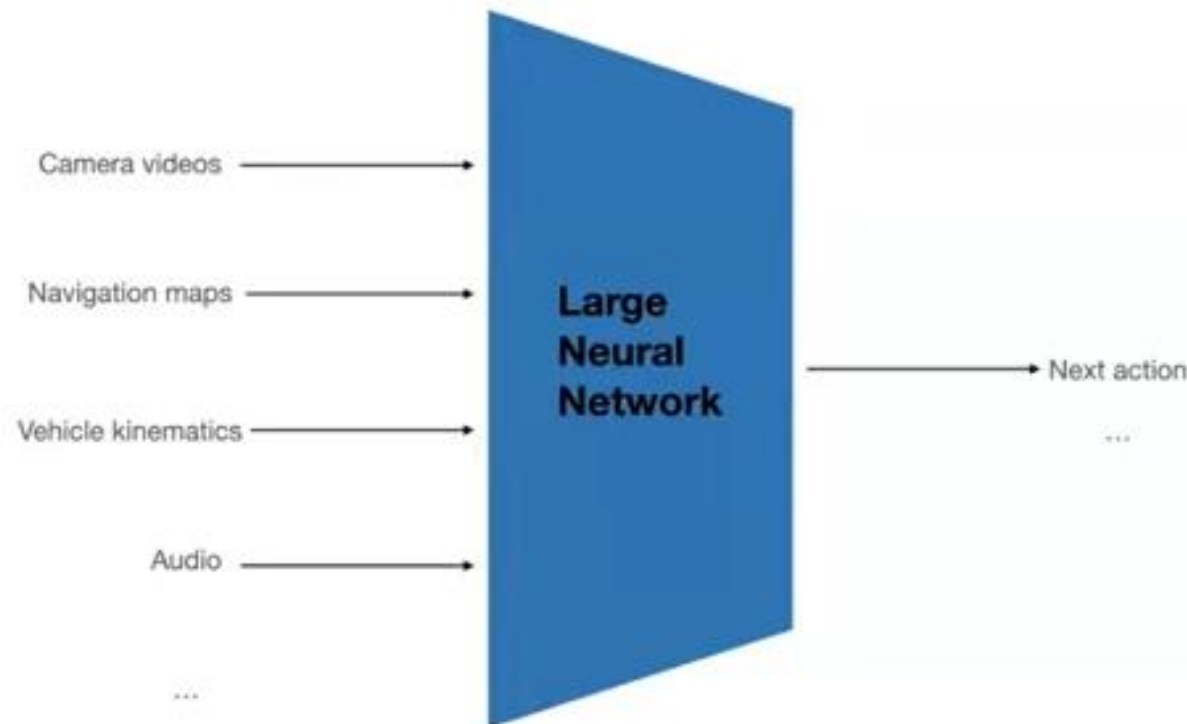
Scaling law

- Model improves as model size, training data, and compute increase.
- Scaling improves generalization abilities.
- Scaling law applies to autonomous driving!



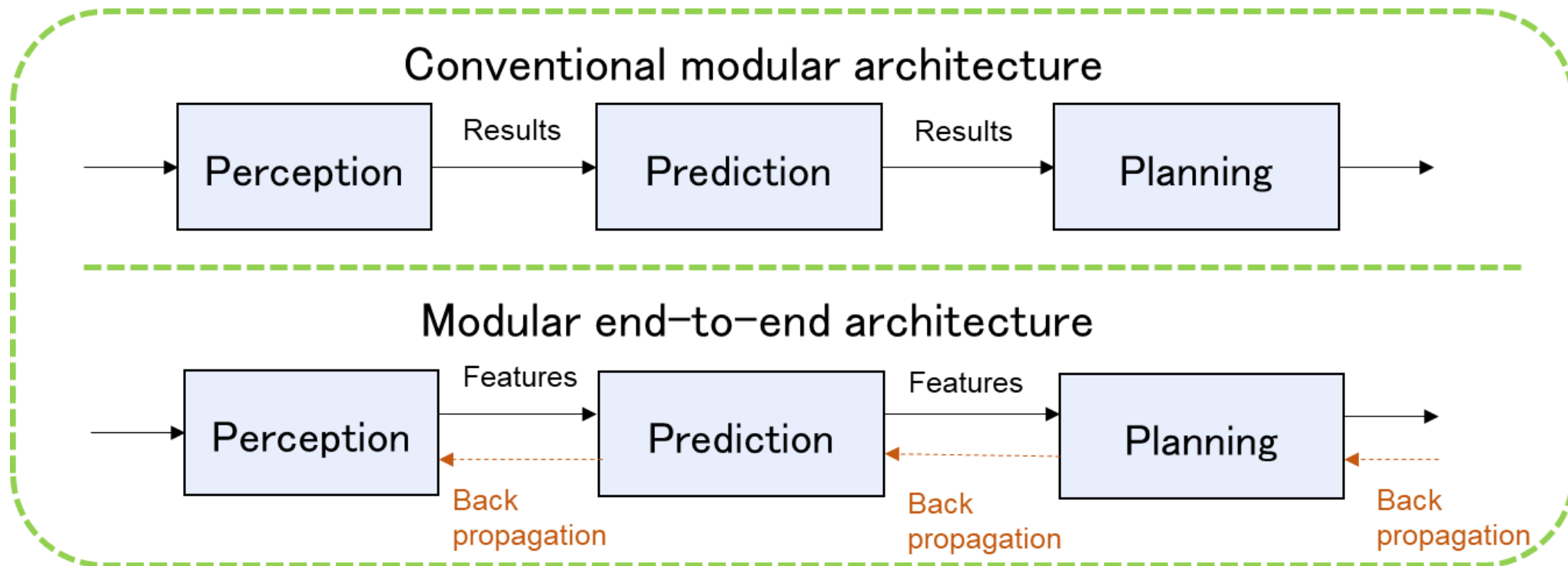
Autonomous Driving Foundation Models

- A general model trained on large-scale data that can generalize across diverse environments and tasks.



End-to-End (E2E) Autonomy

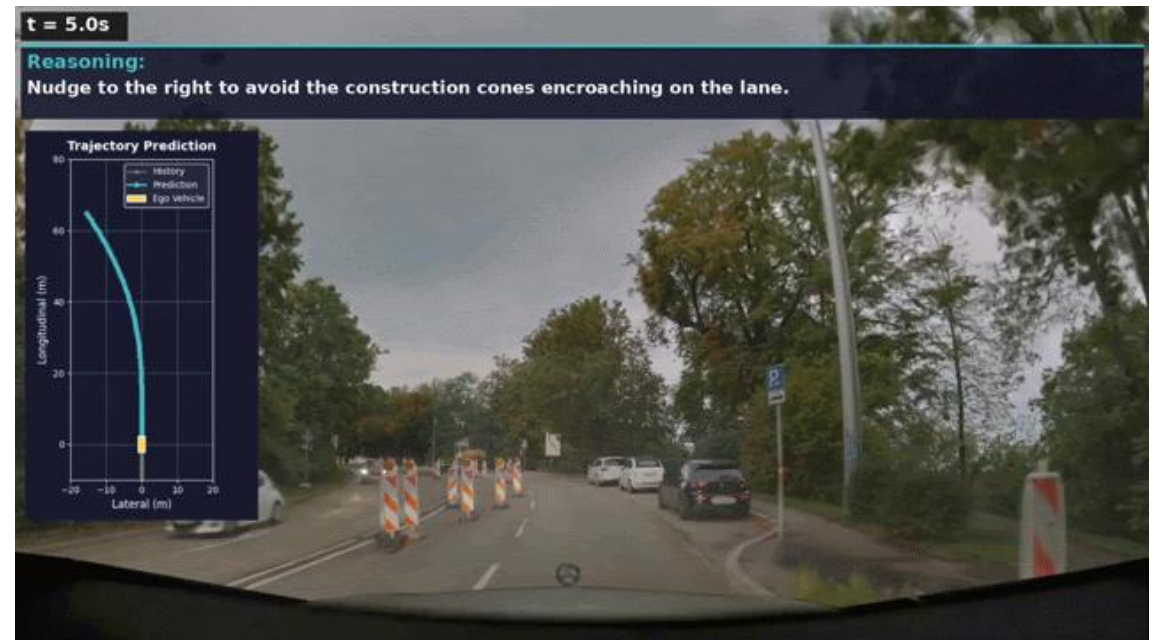
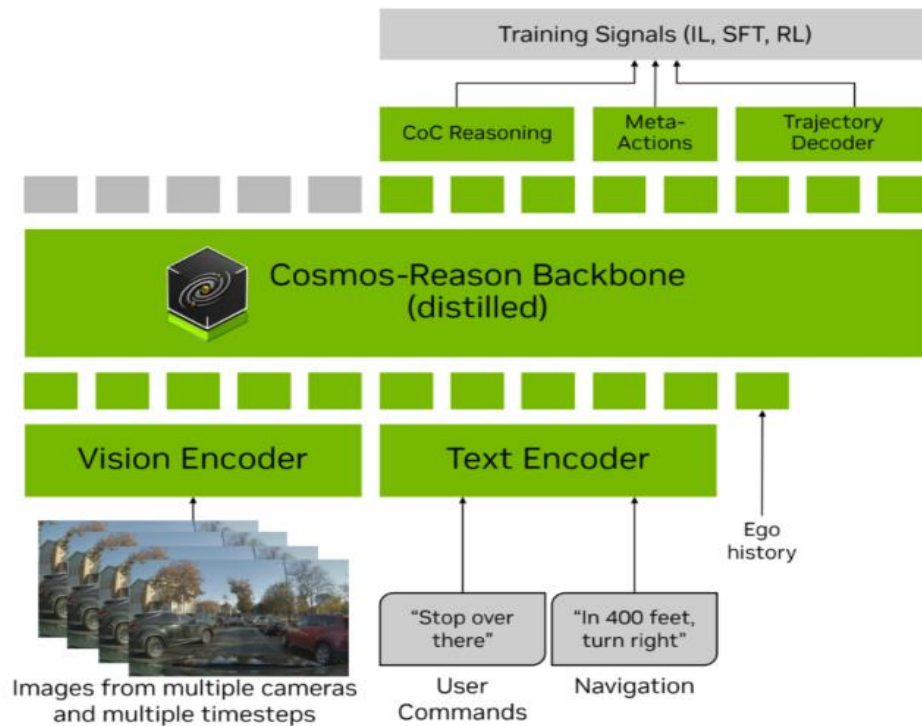
- Learn an E2E mapping from sensor observations to action
- Robust to perception errors
- Suitable for large-scale training



Vision-Language-Action (VLA) Models

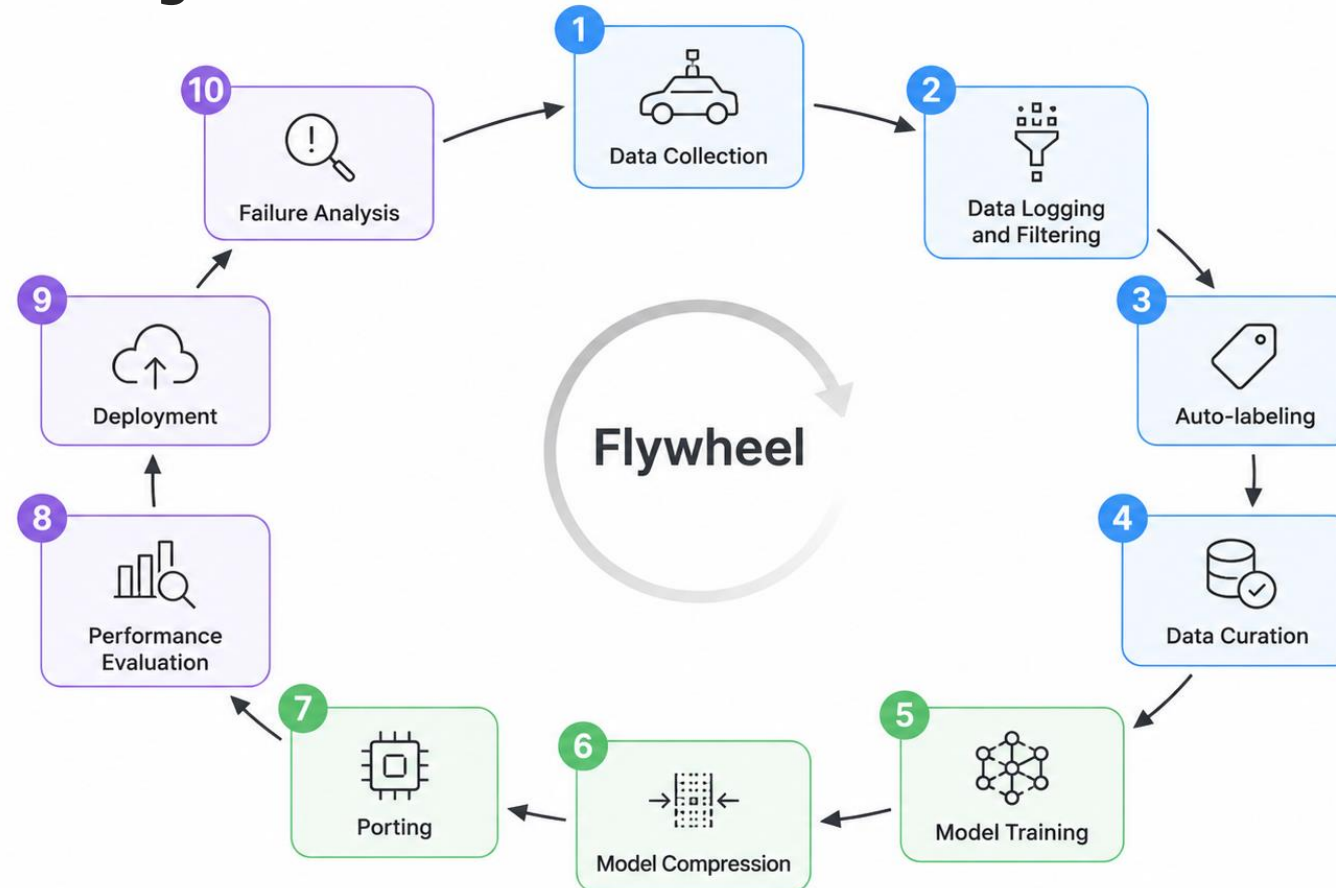
- Learn knowledge, common sense, and physical laws from large-scale web data
- Reasoning improves robustness to edge cases
- Improved explainability

NVIDIA 에서 공개한 Alpamayo-R1 프레임워크



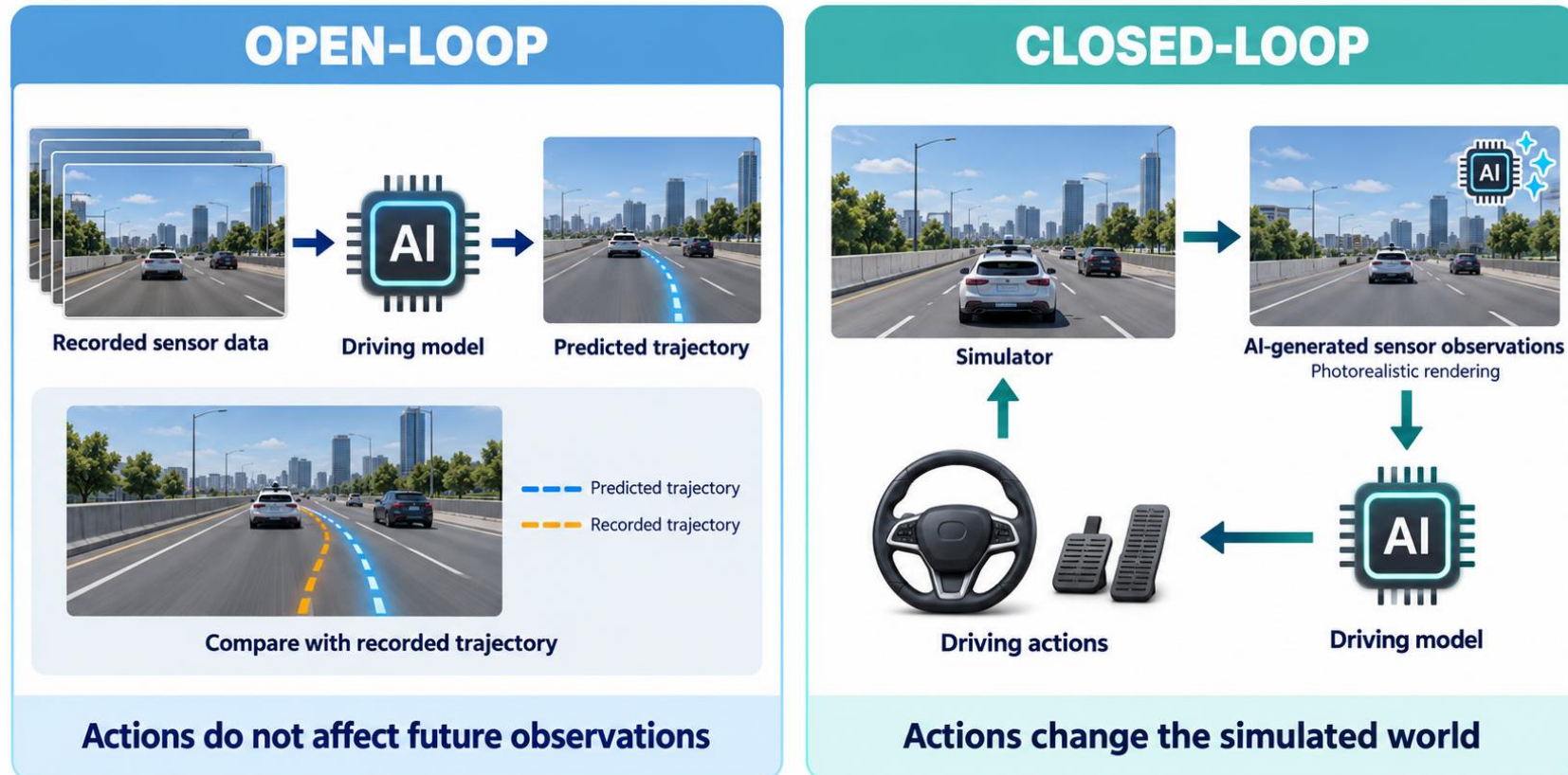
Data Flywheel

- Model continuously improves through data processing cycle
- Used to realize scaling law



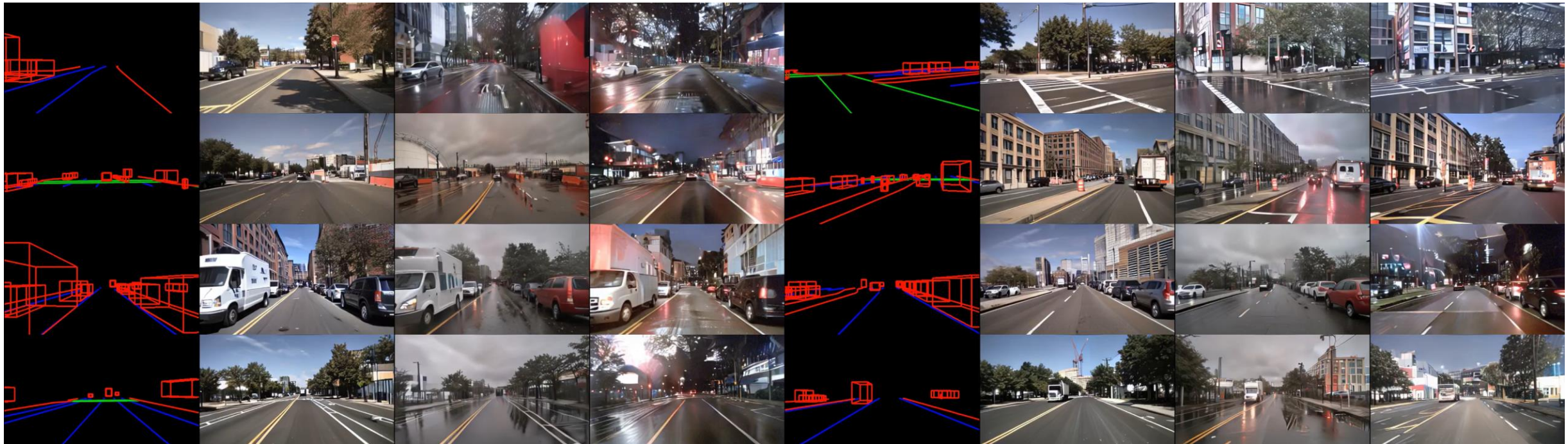
Closed-loop Evaluation

- Open-loop vs. Closed-loop evaluation



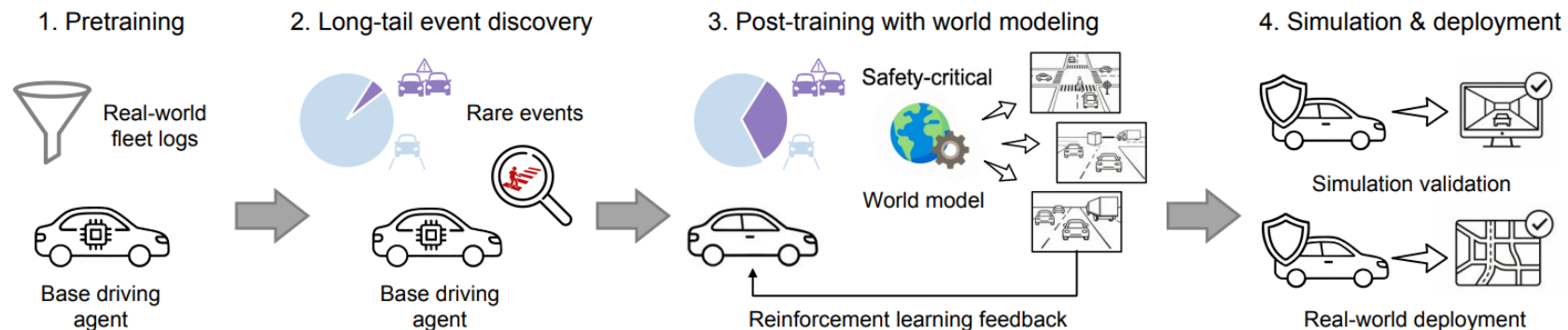
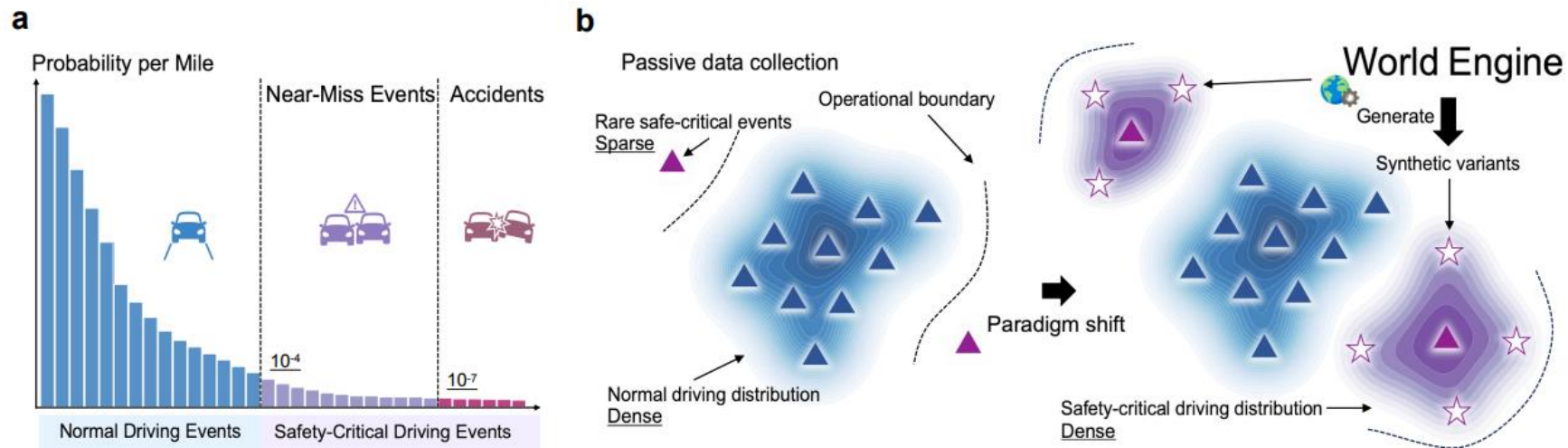
Closed-loop Simulations

- AI is used to build realistic closed-loop simulation environments.
- Neural rendering (3DGS) or diffusion models are used.



Safety-Critical Scenario Generation

- Safety-critical or fail-case scenario generation
- Post-training via Reinforcement learning



OpenDriveLab
에서 제시한 Wo
rld Engine

EAD: Korean E2E Foundation Model

- EAD (Evolutionary Autonomous Driving) Models
 - Provides an open-source reference foundation models for Korea's autonomous driving industry.
 - Evolves through incremental improvements (v1.0 to v1.1)
 - SafeDrive, a safety reasoning model presented as a Highlight at CVPR 2026.

SafeDrive: Fine-Grained Safety Reasoning for End-to-End Driving in a Sparse World

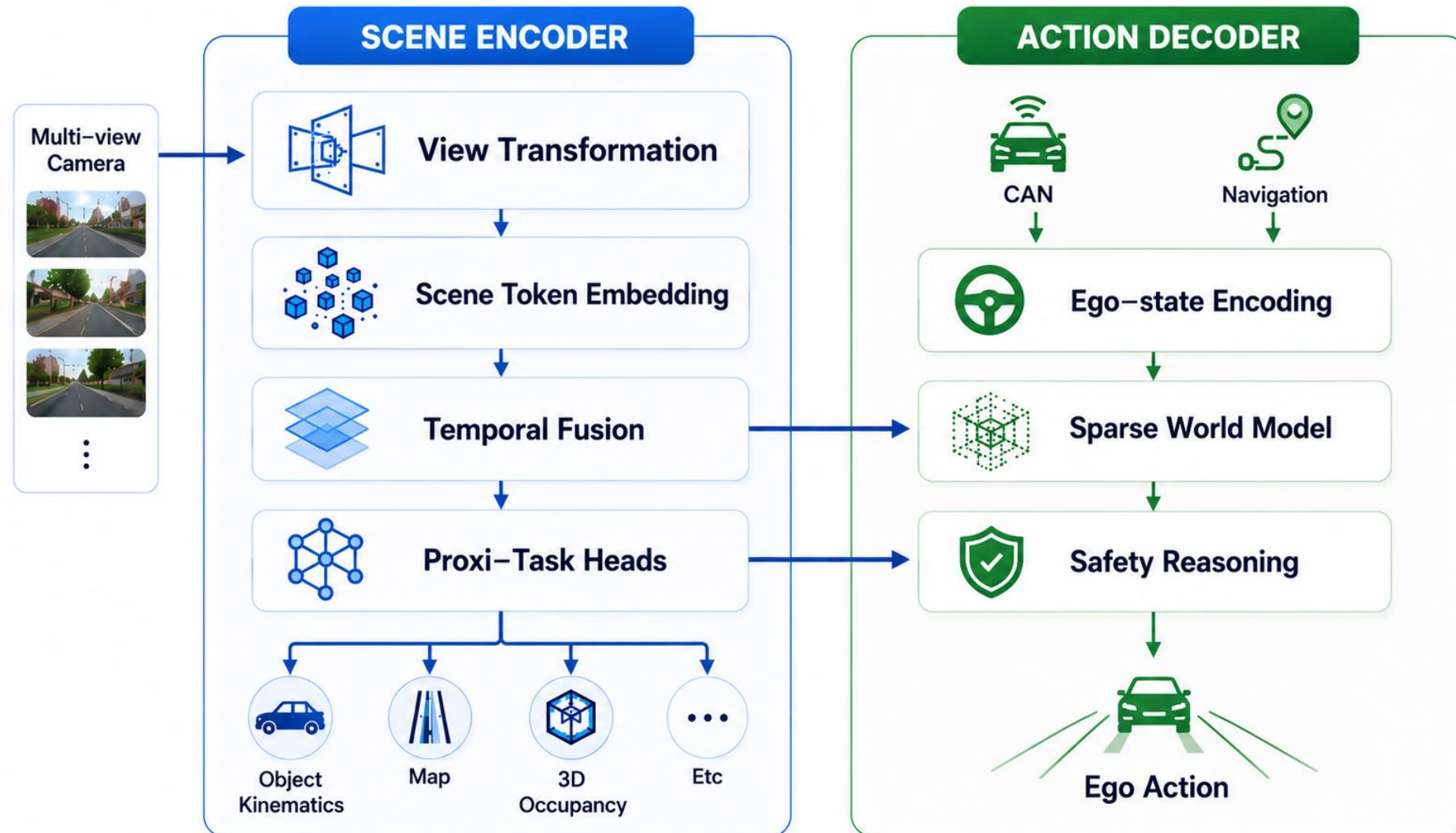
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<https://spa-junghokim.github.io/SafeDrive-Page/>



EAD Architecture



EAD Performance

Method	Venue	PDMS	NC	DAC	EP	TTC	C
DiffusionDrive	CVPR 2025	88.1	98.2	96.2	82.2	94.7	100.0
WoTE	ICCV 2025	88.3	98.5	96.8	81.9	94.9	99.9
SeerDrive	NeurIPS 2025	88.9	98.4	97.0	83.2	94.9	99.9
DriveSuprim	AAAI 2026	89.9	97.8	97.3	86.7	93.6	100.0
SafeDrive	CVPR 2026	91.6	99.5	99.0	84.3	97.2	100.0
SparseDriveV2	ECCV 2026	92.0	98.5	98.4	88.6	95.0	99.9
EAD v1.0	Ours	89.4	98.9	97.1	83.1	95.9	100.0
EAD v1.1	Ours	92.5	99.0	98.2	89.2	95.6	100.0

EAD Computation Latency

RTX 3090 PyTorch FP32

EAD v1.0
80.1 86.2 36 **202.4 ms**

EAD v1.1
60 60.9 26.3 **147.2 ms**

Jetson AGX Thor Nota optimised

EAD v1.0
23.3 73.1 16.9 **113.3 ms**

EAD v1.1
1 21.4 16.8 6 **45 ms**

Pre-process Encoder Perception Planning

Encoder

3090
80.1 → 60.0 **1.3×**
Thor · Nota
23.3 → 21.4 **1.08×**

Perception

3090
86.2 → 60.9 **1.4×**
Thor · Nota
73.1 → 16.8 **4.35×**

Planning

3090
36.0 → 26.3 **1.4×**
Thor · Nota
16.9 → 6 **1.87×**

Total

3090
202.4 → 147.2 **1.4×**
Thor · Nota
113.3 → 45 **2.5×**

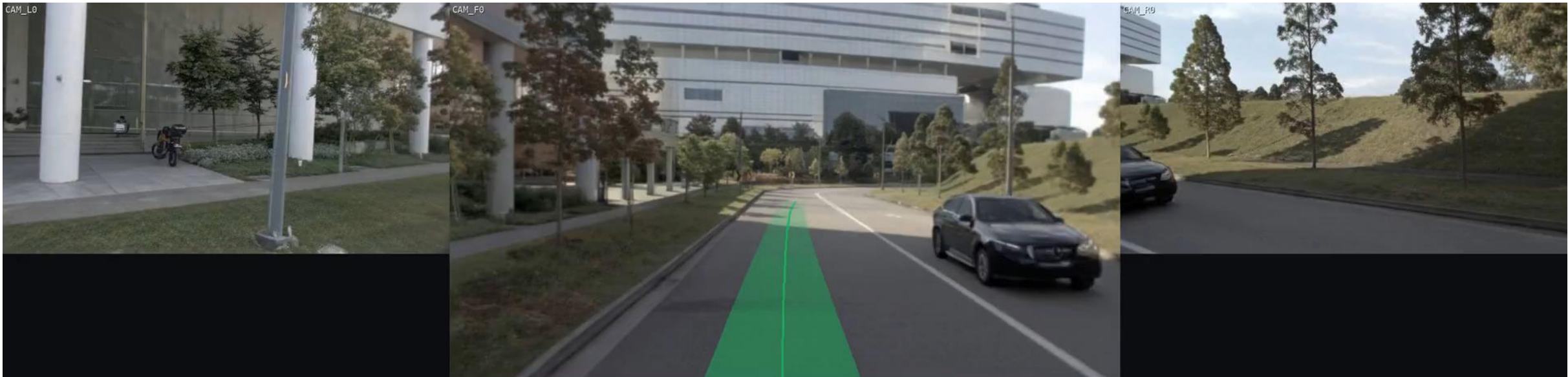
Closed-loop Evaluation of EAD

- Closed-loop test of EAD V1.1



Closed-loop Evaluation of EAD

- Closed-loop test of EAD V1.1



Conclusions

- Develop E2E and VLA driving foundation models
- Establish **Data Flywheel** for data scaling.
- Develop **world simulation** to overcome real-world data limitations.
- Evaluate autonomous driving stacks through **closed-loop simulation**.
- Generate **safety-critical scenarios** to expand training data.
- **EAD reference model** to strengthen Korea's Physical AI competitiveness.