

OpenDriveLab



上海人工智能实验室
Shanghai Artificial Intelligence Laboratory

ELM: Embodied Understanding of Driving Scenes

(A 60 min Talk)

Online

August 2024

Yunsong Zhou, Shanghai Jiao Tong University / Shanghai AI Lab

Outline

- **Introduction to End-to-end Autonomous Driving**
 - Modular vs End-to-end
 - Industry Applications
 - Research Roadmap
- **Challenges**
- **Mainstream Lineup of Work**
 - Embodied Understanding of Driving Scenarios

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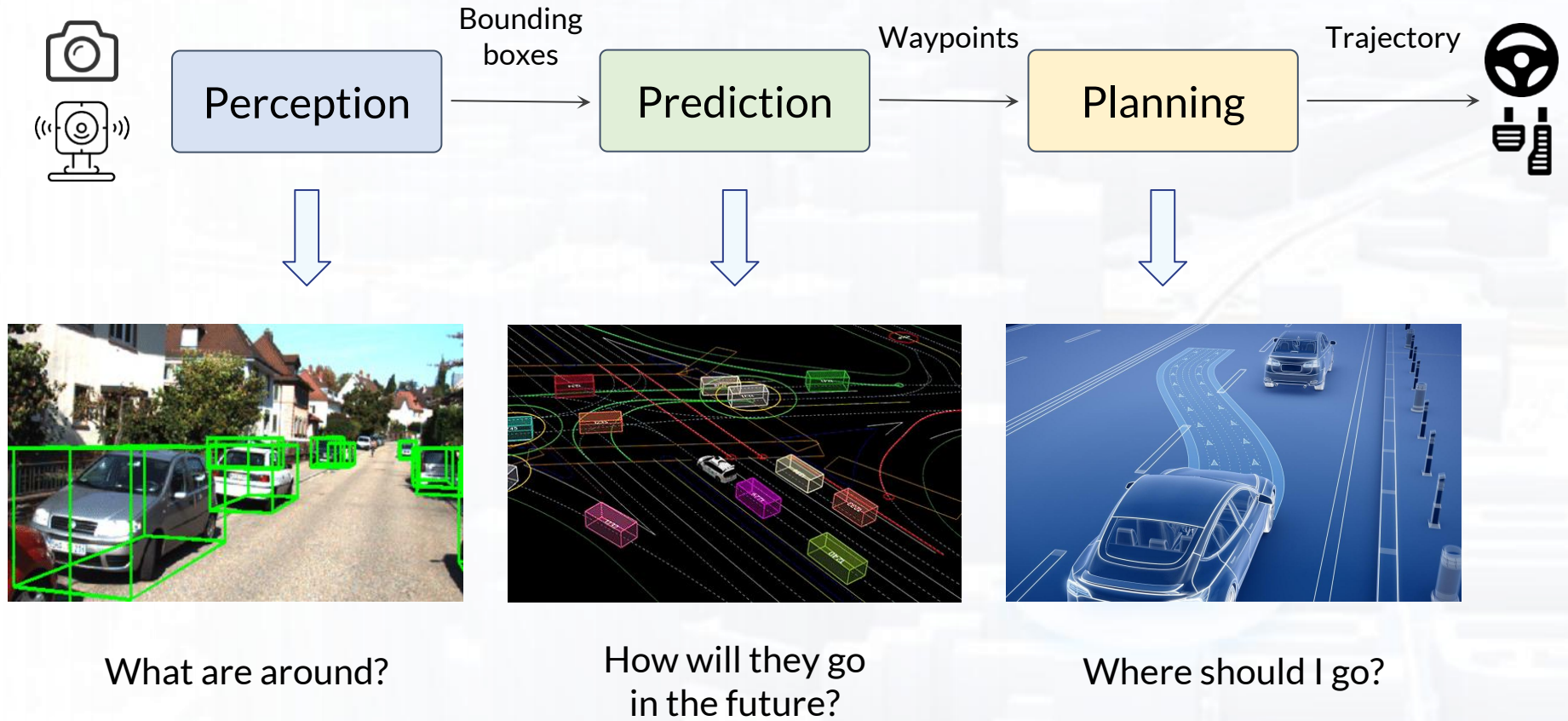
Introduction

End-to-end Autonomous Driving

Problem setting | Autonomous Driving (AD) Tasks



Challenge | Various weathers, illuminations, and scenarios



Motivation | Why End-to-end (E2E) Autonomous Driving?

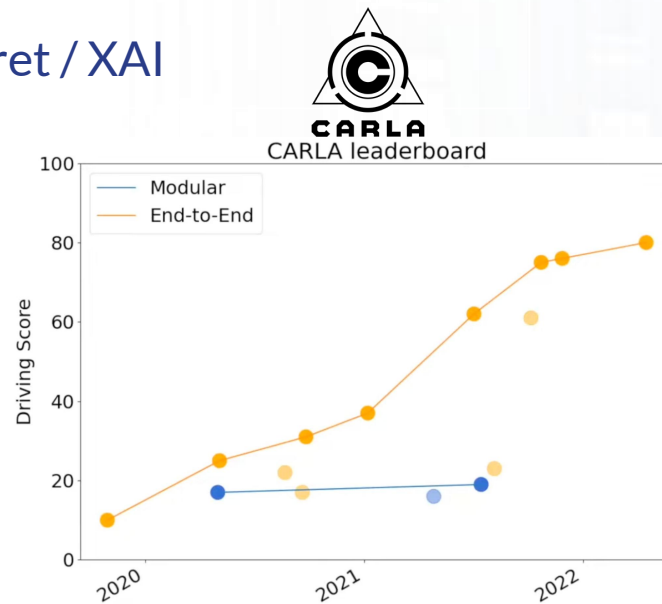


Disadvantages

- Closed-loop evaluation only available in simulator / onboard test
- Lack of real-world data
- Hard to interpret / XAI

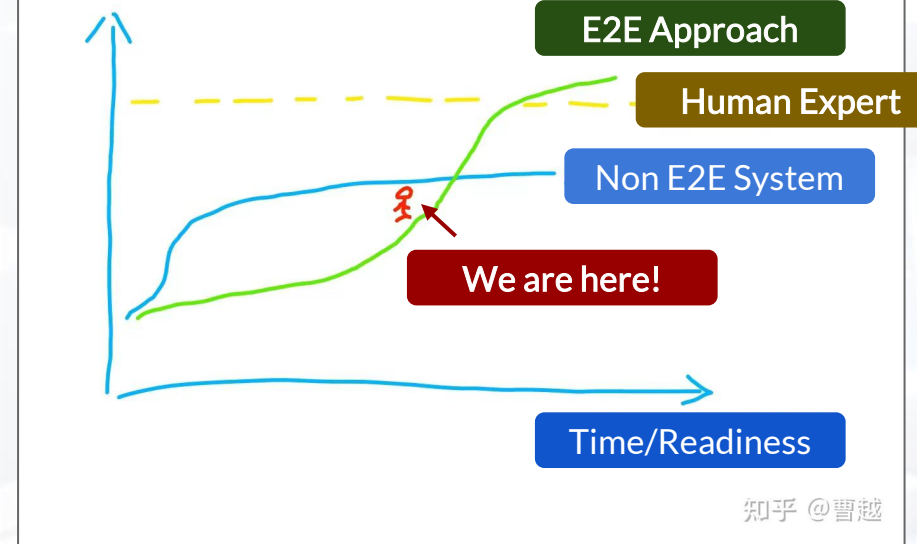
E2E vs Non-E2E

Performance



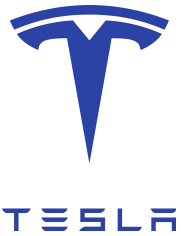
Credit to Andreas Geiger @ CVPR Workshop 2023

<https://leaderboard.carla.org/>



Credit to Dr. Yue Cao @ Zhihu

Trending | End-to-end AD (E2EAD)



E2E Vehicle

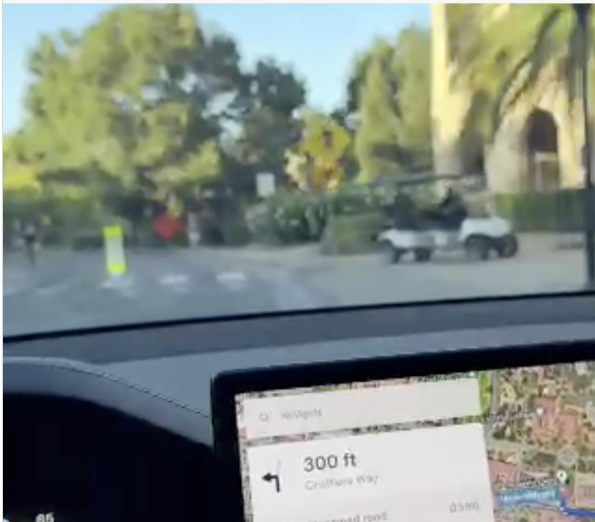


...
v12 is reserved for when FSD is **end-to-end AI**, from images in to steering, brakes & acceleration out.

Ashok Elluswamy
@aelluswamy

This end to end neural network approach will result in the safest, the most competent, the most comfortable, the most efficient, and overall, the best self-driving system ever produced. It's going to be very hard to beat it with anything else!

Elon Musk
@elonmusk · Aug 26
twitter.com/i/broadcasts/1...



*No hard-code.
Completely learning on its own.
End-to-end, video to neural network to controls.
Don't need map data at all, only coordinates!
No cellular connection needed.*

My Opinion

- Probably e2e as a backup module
- Massive high-quality data prevail
- Mapless is promising and feasible

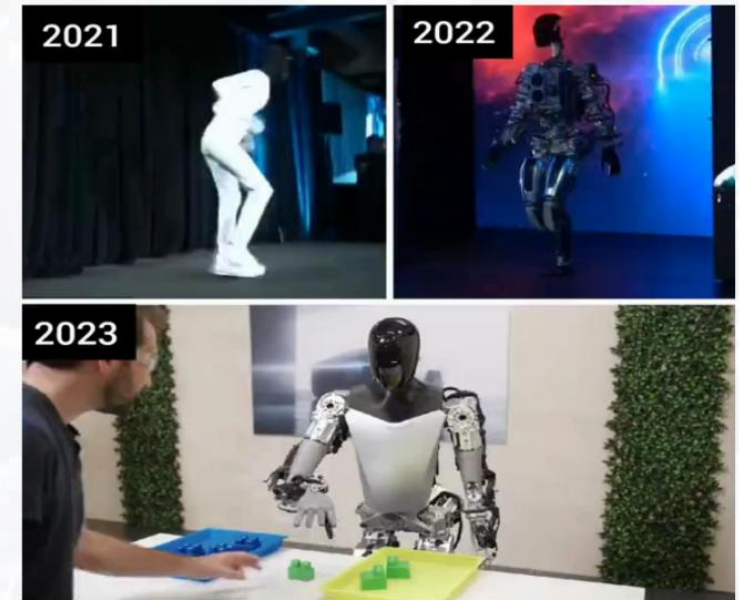
Industry

E2E Robot



Tesla Optimus
@Tesla_Optimus · Sep 24
Optimus can now sort objects autonomously

Its neural network is trained fully **end-to-end**: video in, controls out.



NEWS

Tesla FSD Beta v12.12 rolls out to customers

The End-to-End Approach in Autonomous Driving

Two types of end-to-end implementation:

Next-Generation Automated Driving: the Power of End-to-End AI

多模块走向端到端融合，“轻”车更熟路

端到端感知决策大模型
小米自研 全球首次应用于量产车



TESLA

- *Tesla website*



mobileye
An Intel Company

- *Mobileye at CES 2024*



WAYVE

- *Wayve website*



DEEPRUTE.AI

- *DeepRoute (元戎启行) at GTC 2024*



- *Mi (小米) Automobile Technological Event 2024*

研究背景与现状 - 端到端

AGI (L5)
Drive Anywhere/Anytime

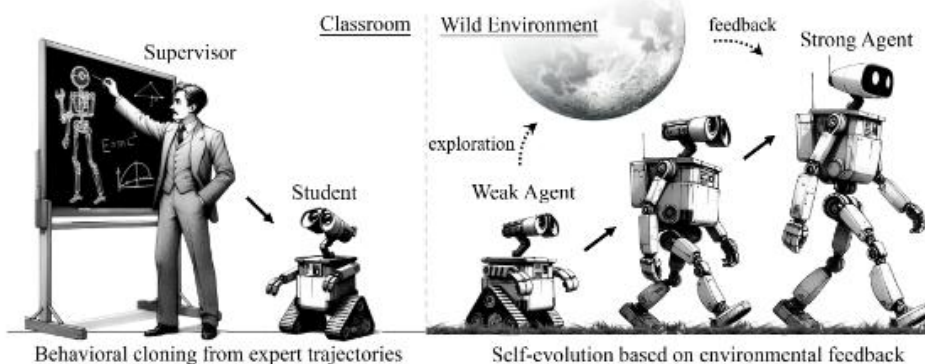
泛化、智能、安全

80% 自动驾驶问题
已被解决 (L2)



加数据?
如何采?
如何训?

通用的端到端具身智能体进化方法

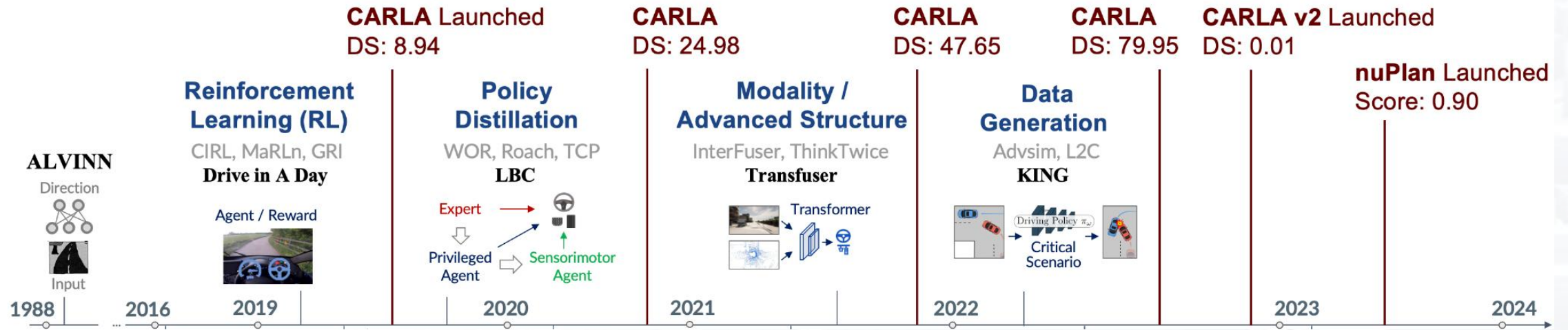


剩余10%
Corner case in Daily Life
靠规则永远写不完 (L3/L4)

Bad Cases in Tesla FSD v12.3 Test drive before CVPR'24



Roadmap | End-to-end Autonomous Driving



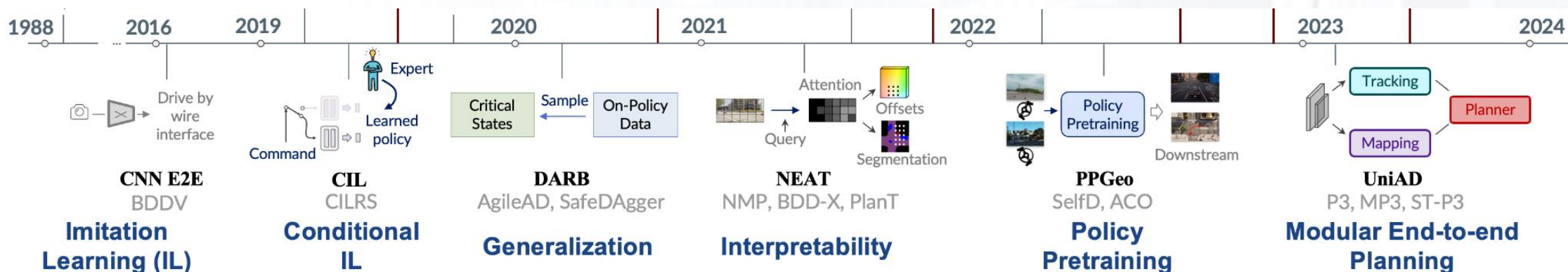
Summary (1/2)

- Carla leaderboard gets much improved over the years. With new mapping / routes (Carla v2) and nuPlan benchmark, this field got so much to do.
- RL method is prevalent in the beginning (since it's natural)
- Input modality and more advanced structure boosts the performance

Roadmap | End-to-end Autonomous Driving

Summary (2/2)

- The First Neural Net based method dates back to 2016 using Imitation Learning
- Learned policy from Experts (IL), with data augmentation, could prevail in performance
- Interpretability, with explicit design in the network stands out recently
- End-to-end design comes to obsess many merits in previous attempt






Analogy to General Domains in CV/NLP/Robotics

General Large Models

Domain	Method Abbreviation	Institute / Time	Data Scale	Public?
NLP (LLM)	GPT-4	 OpenAI / 2023.3	13T tokens	✗
	LLaMA 2	 Meta / 2023.7	2T tokens	☑
Vision	ViT-22B	 Google / 2023.2	4B images	✗
Vision Language (LLM backend)	BLIP-2	 Salesforce / 2023.1	129M images-text pairs	☑

Industrial Large Models (Application)

Autonomous Driving nuScenes: 4.5h	DriveAGI (GenAD)	 OpenDriveLab / 2023.11	2000 h videos (public)	☑
	GAIA-1	 Wayve / 2023.6	4700 h videos	✗
	World Model Demo	 Tesla / 2023.6	Unknown (Large-scale)	✗
Robotics (LLM backend)	PaLM-E	 Google / 2023.3	Unknown (Large-scale)	✗
	RT-2	 DeepMind / 2023.7	1B img-text pairs / 13 robots / 17 months	✗

If taken seriously for AD: lots of compute (at least 200 A100s) + massive amount of data (at least 10k hours of diverse, high-quality data)

Trending in E2EAD | Driving + Language



Go straight at an intersection then turn left.
There are **construction cones** on the road.

HAD – human-to-vehicle driving advice, highlighting key objects.

Explainable Driving Behavior

BDD-X – one-sentence explanation of driving behavior.



Action description: **Action justification:**

(1) *The car is driving as there is nothing to impede it.*



Trending in E2EAD | Driving + Language

Dataset	Source Dataset	# Frames	Avg. captions / QA per annotated frame	Total captions / QA in Perception	Total captions / QA in Prediction	Total captions / QA in Planning	Logic among captions/QA pairs
nuScenes-QA [47]	nuScenes	34,149	13.5	460k**	✗	✗	None
nuPrompt [66]	nuScenes	34,149	1.0	35k*	✗	✗	None
HAD [31]	HDD	25,549	1.8	25k	✗	20k	None
BDD-X [30]	BDD	26,228	1	26k	✗	✗	None
DRAMA [40]	DRAMA	17,785	5.8	85k	✗	17k	Chain
Rank2Tell [51]	Rank2Tell	5,800	-	-	✗	-	Chain
DriveLM-nuScenes	nuScenes	4,871	91.4	144k*	153k	146k	Graph
DriveLM-CARLA	CARLA	183,373	20.5	2.46M**	578k**	714k**	Graph

Table 1. Comparison of DriveLM-nuScenes & -CARLA with Existing Datasets. * indicates semi-rule-based labeling (w/ human annotators), ** indicates fully-rule-based (no human annotators), and - means publicly unavailable. DriveLM-Data significant advances annotation quantity, comprehensiveness (covering perception, prediction and planning), and logic (chain to graph).

Explainable Driving Behavior

BDD-X — one-sentence explanation of driving behavior.



HAD — human-to-vehicle driving advice, highlighting key objects.

2019

Planning

2022

Prediction



DRAMA — caption about important objects and future decision.

DriveLM — perception-prediction-planning driving description with graph VQA.

2023

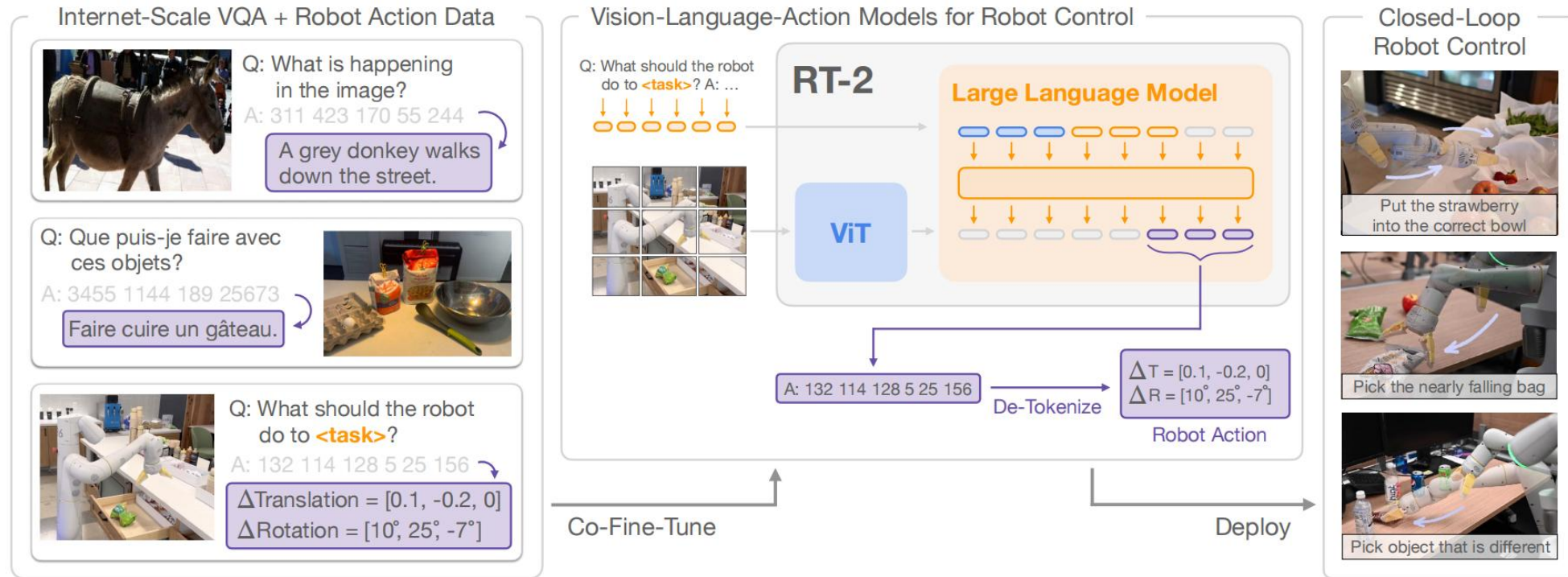
Full-stack

LINGO-1 — commentary for explaining driving behaviours.



For now, language into driving is marginal (trivial). Serves only as a “commentator”. We haven’t verified (or seen) the effectiveness.

Insight | VLM in Robotics / Embodied AI



- How vision-language models trained on Internet-scale data can be incorporated directly into **end-to-end robotic control**
- Goal: to **boost generalization** and enable emergent semantic reasoning

- Robotic tasks naturally fits into language at dissecting tasks step by step using language (prompt).
- Is it the **right way** to open the language tool box as does in Robotics for Autonomous Driving?

Key ingredient(s): huge amount of data (not public) + language prompt to dissect tasks

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Grand Challenge 2024

CVPR 2023 AD Challenge - Recap

<https://opendrivelab.com/AD23Challenge.html>

Overview

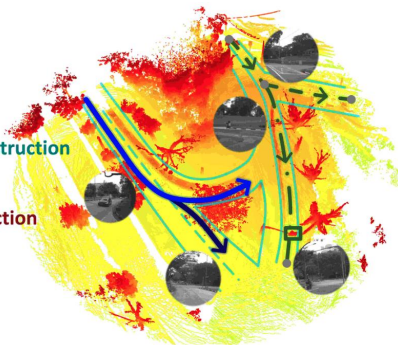
Tracks

Track 1
OpenLane Topology

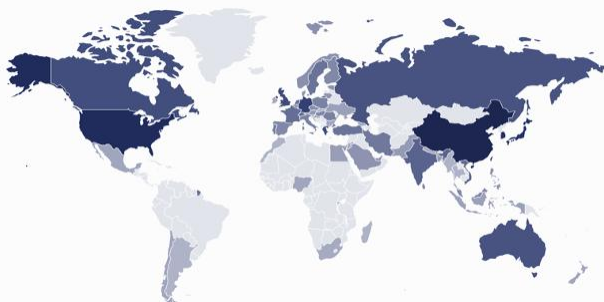
Track 2
Online HD Map Construction

Track 3
3D Occupancy Prediction

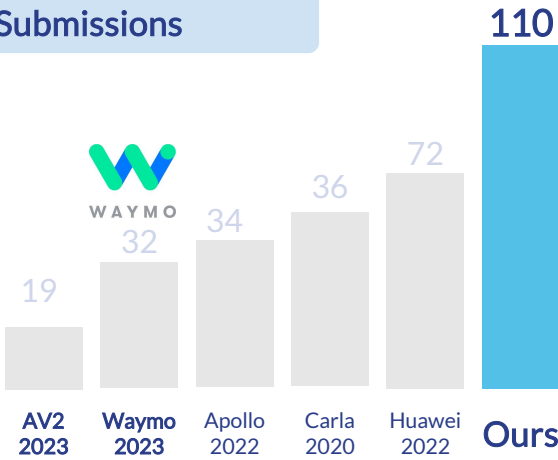
Track 4
nuPlan Planning



Internationalization



Submissions



Teams



> 2.3k
Submissions

> 15
Countries / Regions

> 68k
Website / Social Media Views

Competing Teams



Attention from All Sides

NVIDIA Research Award at CVPR
New work introduces sta
June 15, 2023 by CALISA COLE

Bosch Center for Artificial Intelligence (BCAI)
54,190 人关注
+ 关注
浏览完整页面

42dot
Team 42dot Wins 2nd Place in the Autonomous Driving Challenge at CVPR 2023

International Teams Advance AV Research at CVPR 2023
nuPlan Challenge

Challenges of Mass Production of Autonomous Driving in China
And the Recent Progress from Xpeng Motors in 2023

什么样的方案，夺得了CVPR自动驾驶挑战赛冠军？

机器之心 2023-06-19 19:21 发表于北京

36Kr 旷视刷榜了什么自动驾驶比赛？
旷视研究院参加的这个比赛，是CVPR 2023专门面向自动驾驶感知决策系统设立的挑战赛。

CVPR 2024 Autonomous Grand Challenge

120,000 USD Bonus!

<https://opendrivelab.com/challenge2024/>

Timeline

2023.12

Contest tracks open for comments

2024.02

Track Announcement

2024.03

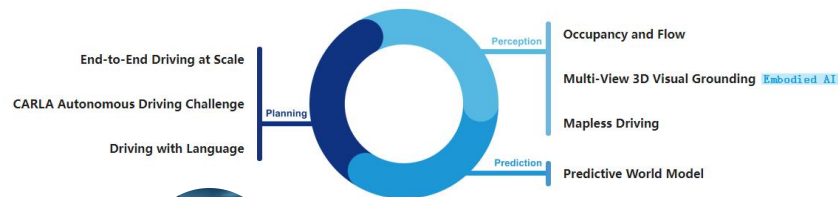
Challenge Starts
Dataset / Evaluation Metrics Public

2024.06

Workshop @ Seattle

Competition ends
Announcement of winning teams

Seven Brand-new Tracks



End-to-End Driving at Scale

Predictive World Model



Occupancy and Flow

Multi-View 3D Visual Grounding



CARLA AD Challenge

Driving with Language



Mapless Driving

Cooperation from All Sides

OpenCV Lab

OpenRobot Lab



Hugging Face



Motional



NVIDIA



Meituan
Autonomous Delivery

EBERHARD KARLS
UNIVERSITÄT
TUBINGEN



WAYVE



机器之心
Synced



OpenDriveLab



上海人工智能实验室
Shanghai Artificial Intelligence Laboratory



ELM: Embodied Understanding of Driving Scenarios



Embodied Understanding of Driving Scenarios

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Hang Qiu⁴ Hongzi Zhu^{2†} Minyi Guo² Yu Qiao¹ Hongyang Li^{1†}

¹ OpenDriveLab, Shanghai AI Lab ² Shanghai Jiao Tong University

³ Fudan University ⁴ University of California, Riverside

Credits:

[https://github.com/OpenDriveLab/EL](https://github.com/OpenDriveLab/ELM)

[M](https://github.com/OpenDriveLab/ELM),

<https://arxiv.org/abs/2403.04593>

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星合联盟
STAR LEAGUE

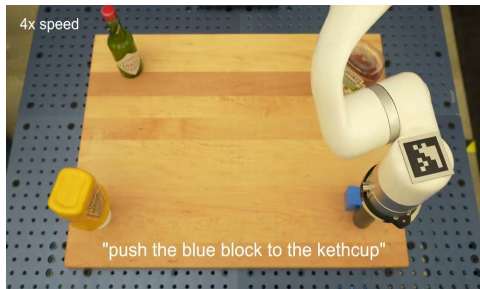
Introduction



ELM - Introduction

Embodied Understanding

Interacting with environments & reasoning via common sense



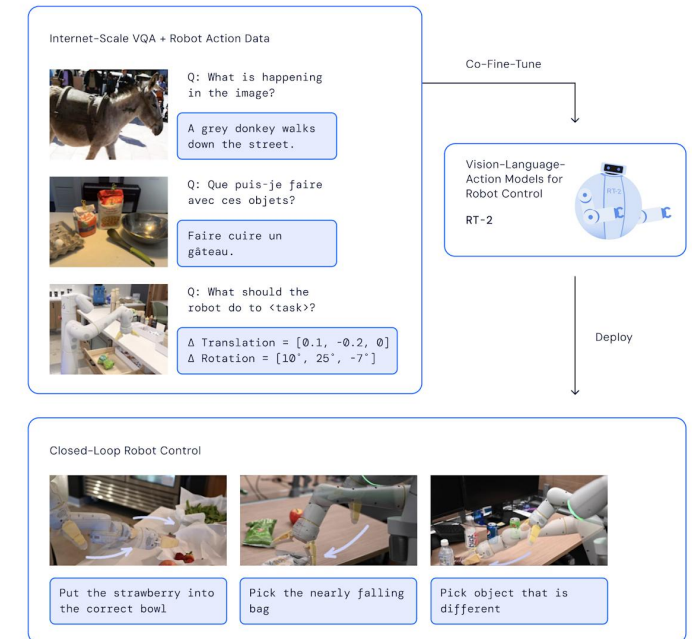
“

This makes transfer of internet scale knowledge to robots more direct, and may provide a more scalable class of approaches in the future.

”



Credits:
Google DeepMind, RT-2, RT-X,
PaLM-E





ELM - Introduction

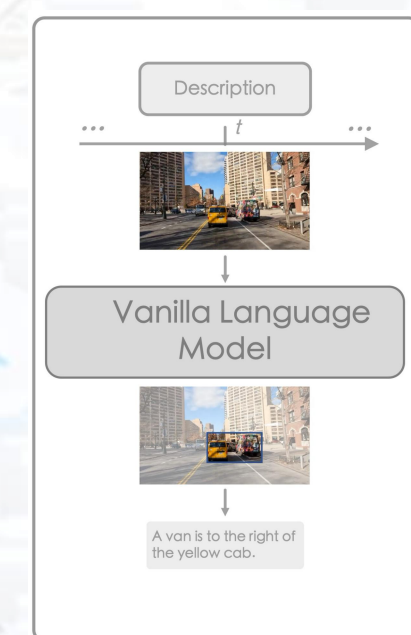
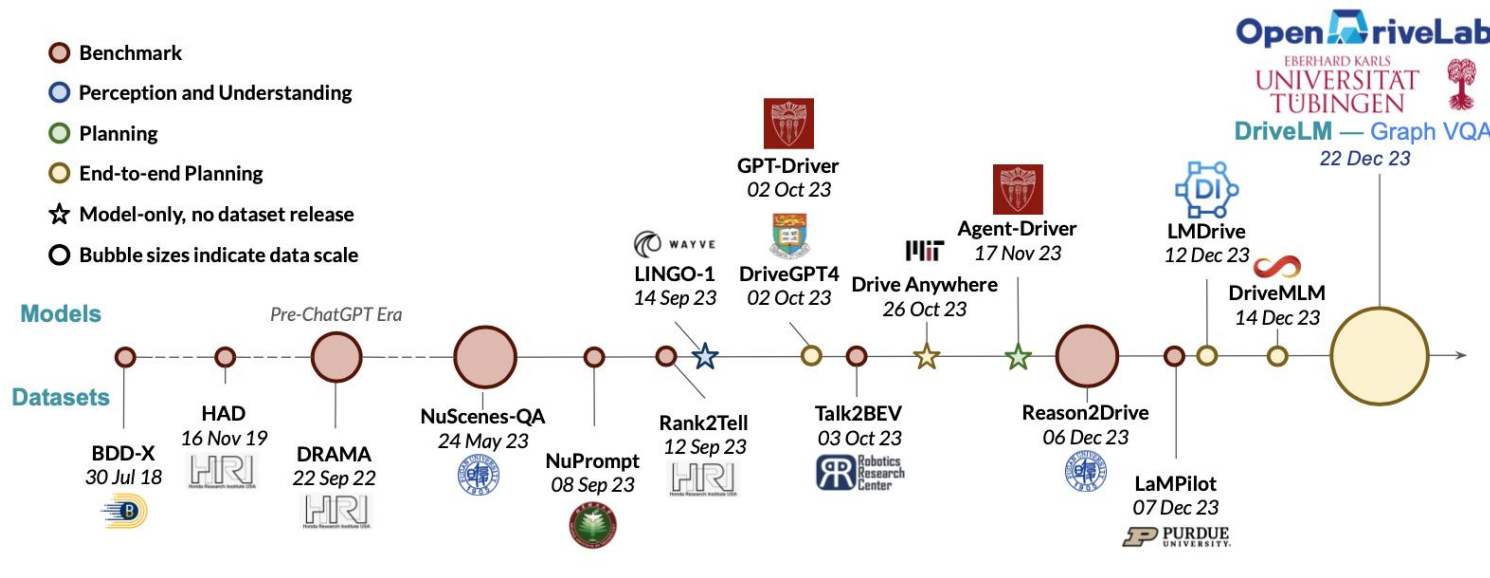
Embodied Understanding

Interacting with environments & reasoning via common sense

Vision Language Models

Only focus on 2D domain, *i.e.*, description

Credits: DriveLM; Open-sourced Data Ecosystem in Autonomous Driving



ELM - Introduction

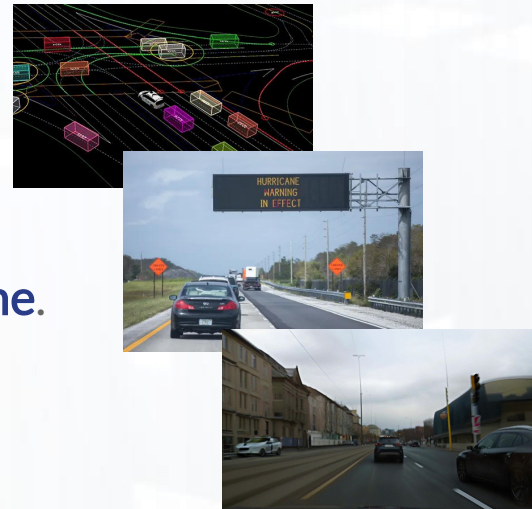
Embodied Understanding

Interacting with environments & **reasoning** via common sense

- Task: embodied understanding of driving scenarios.
- Capabilities: description, **localization**, **memorization**, **forecasting**.
- Model: **ELM** with long-horizon **space** and **time**.
- Benchmark: A spectrum of tasks in an embodiment setting.

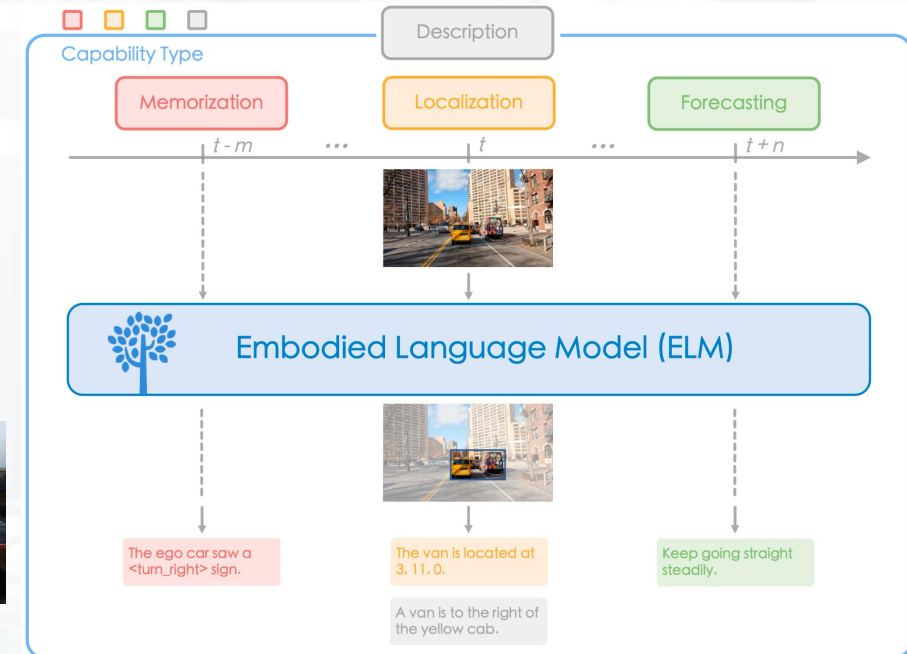
Vision Language Models

Only focus on 2D domain, *i.e.*, **description**



Embodied Language Model

Expanding vanilla VLMs to driving scenes



ELM - Introduction

Embodied Understanding

Interacting with environments & **reasoning** via common sense

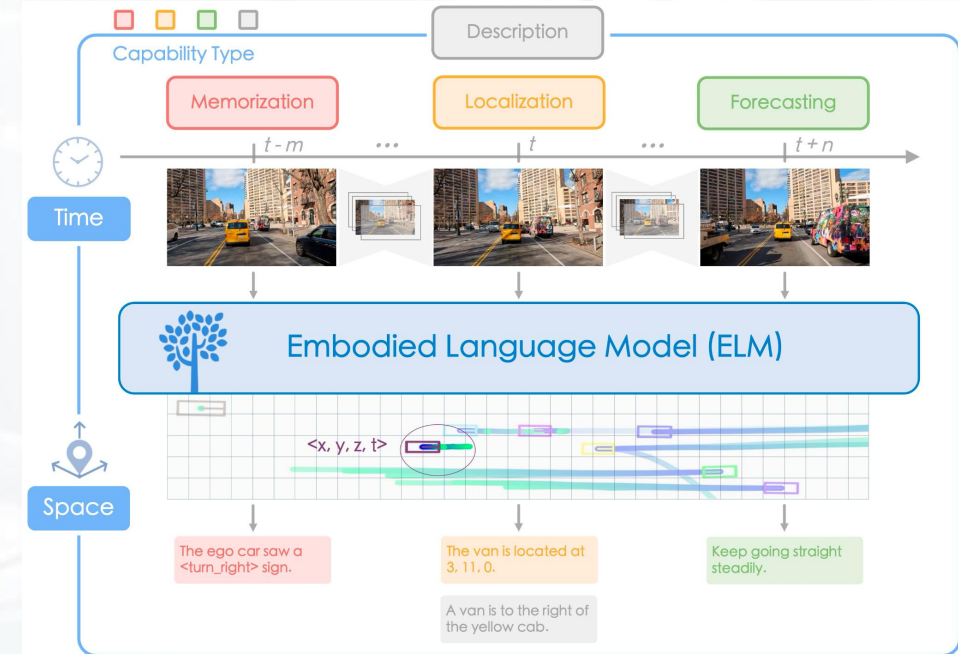
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Vision Language Models

Only focus on 2D domain, *i.e.*, **description**

Embodied Language Model

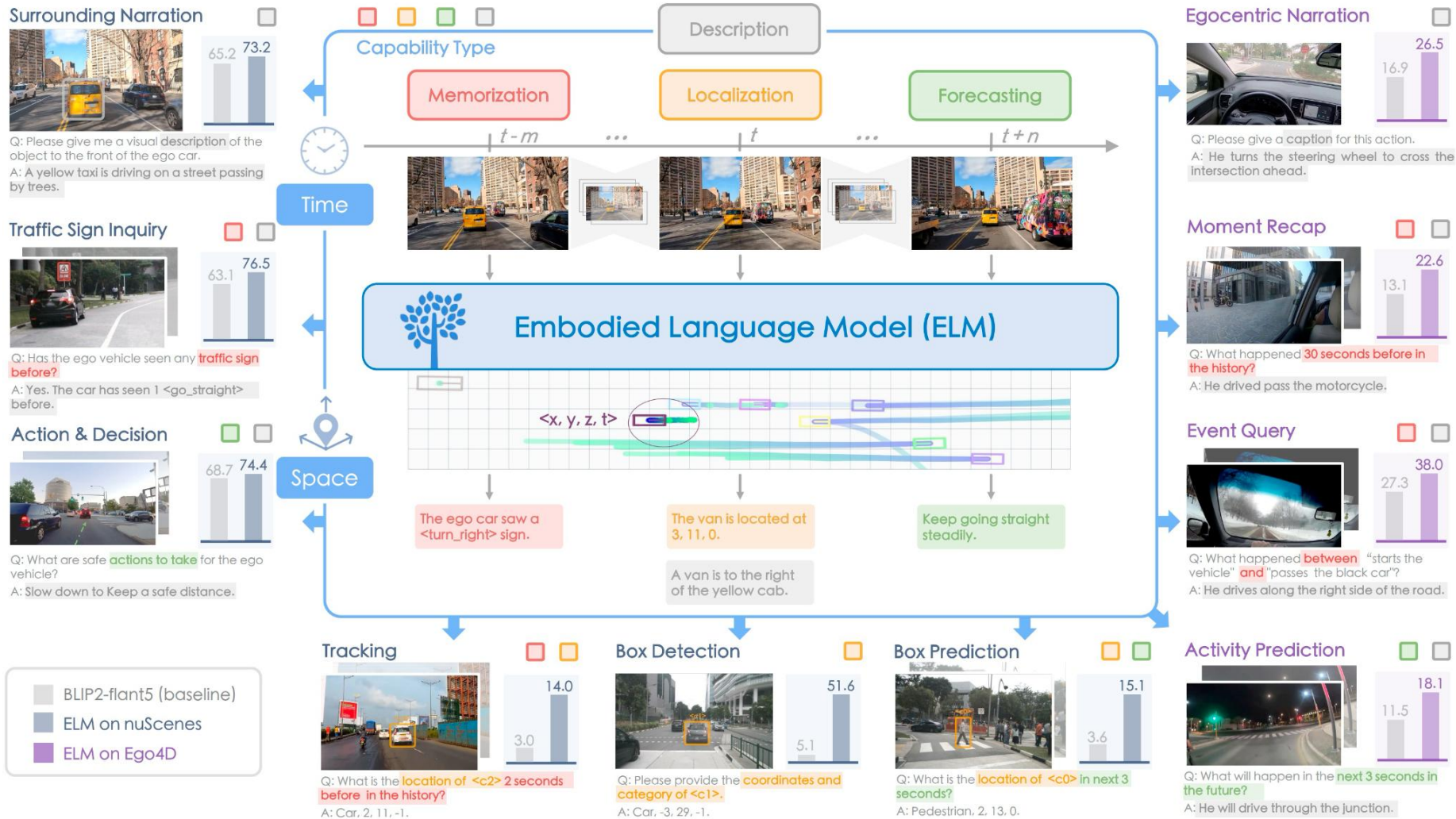
Expanding Vanilla VLMs to **Driving Scenes**





Embodied Understanding

At A Glance

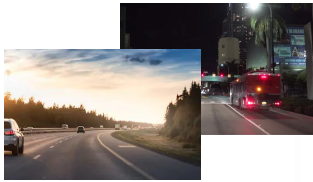
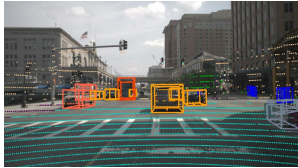


We expand a wide spectrum of **new tasks** to fully leverage large language models in an embodiment setting

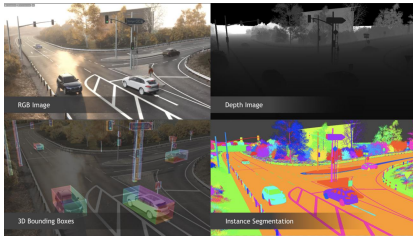
ELM - The Big Picture

Data-centric Pipeline

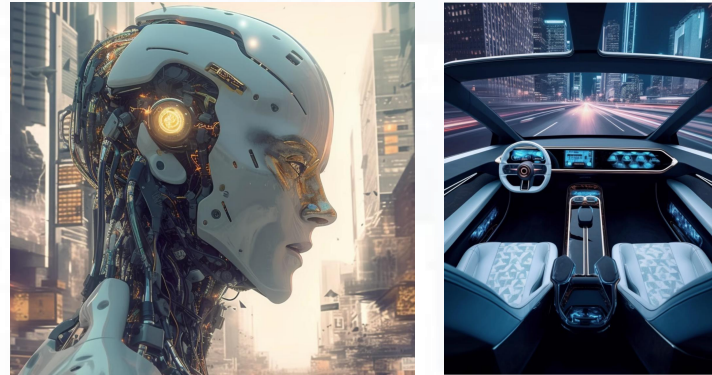
Data Collection



Data Generation



Pre-training DriveCore



Universal Foundation Model for autonomous driving

How to formulate?
What's the objective goal?
Space and time?

Benchmark

Autonomous Driving (nuScenes)



Robotics (Ego4D)

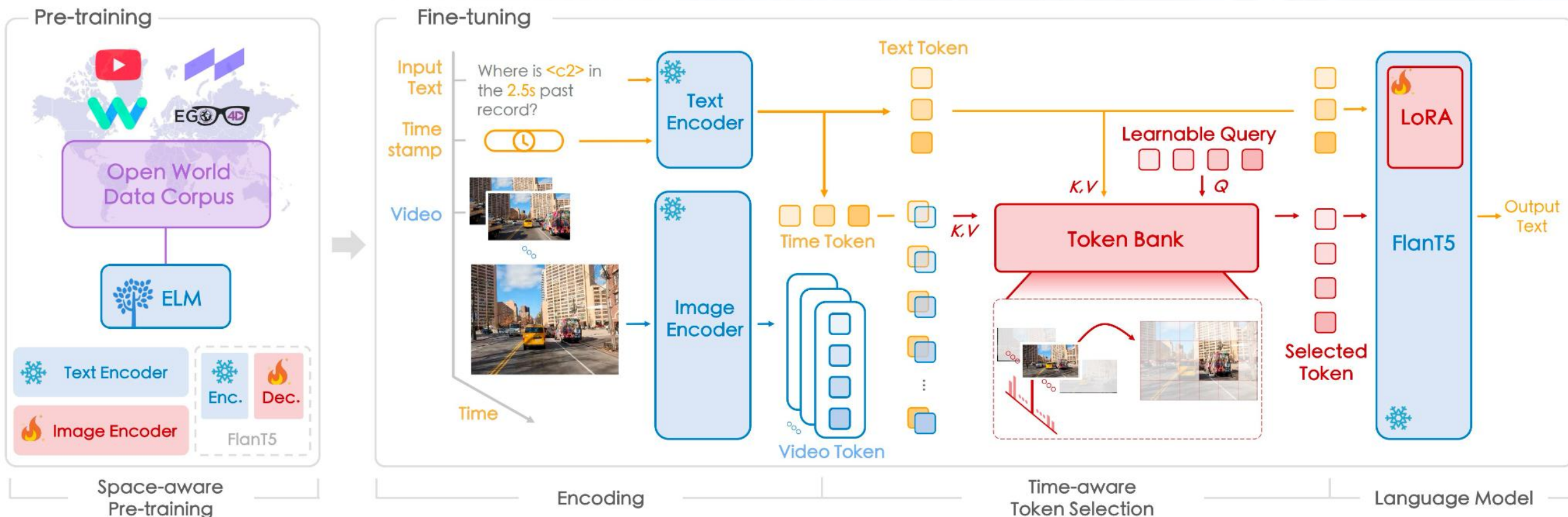


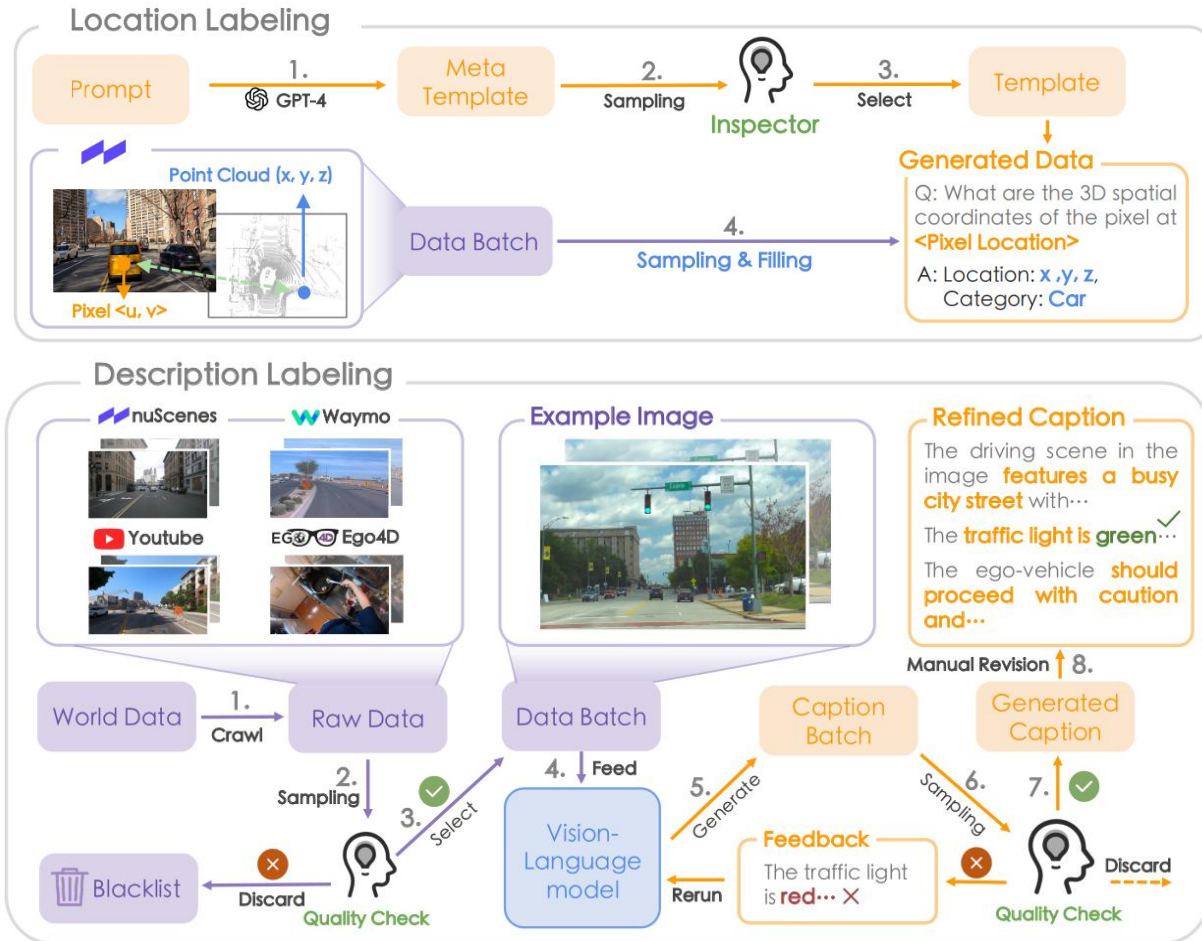
Partial photo by courtesy of online resources.



Embodied Understanding

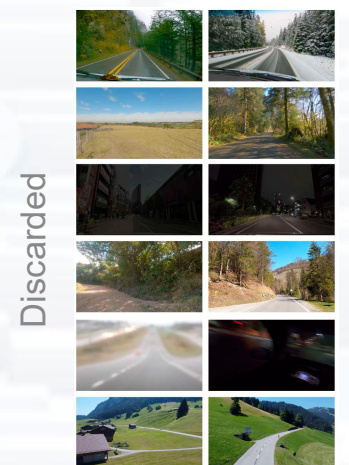
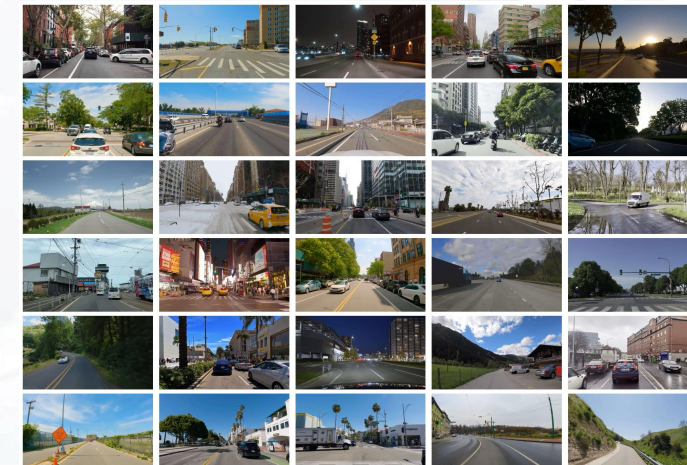
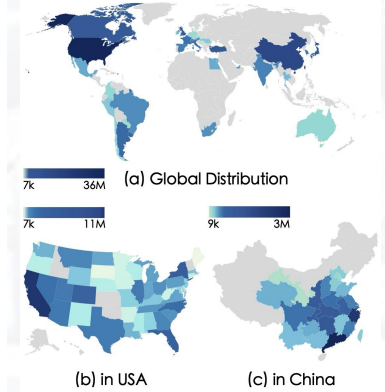
Pipeline

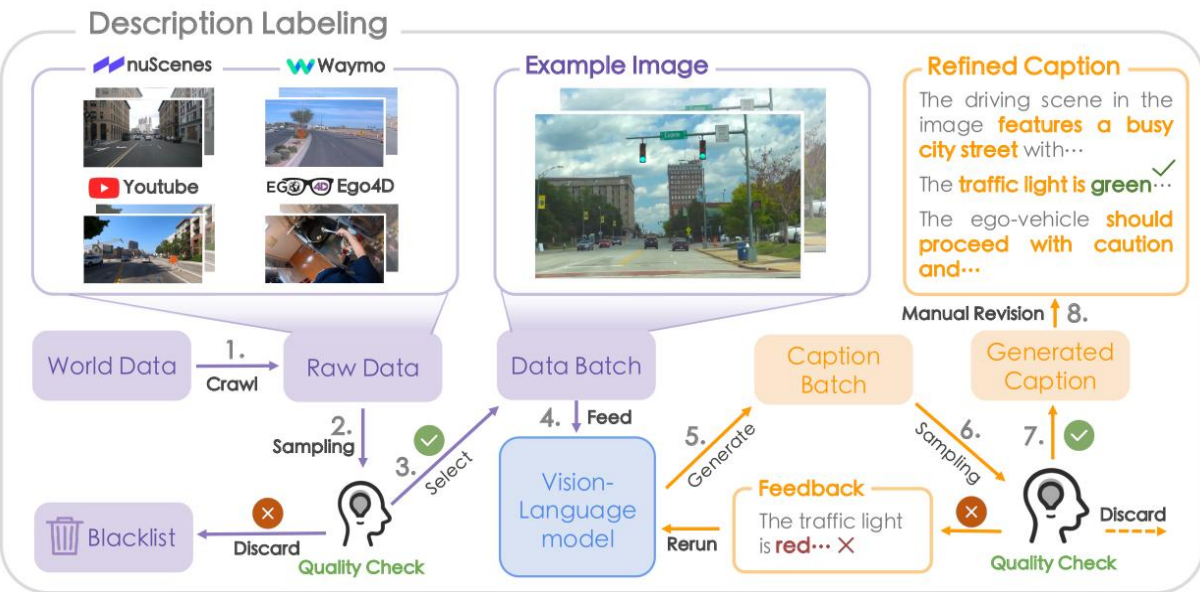
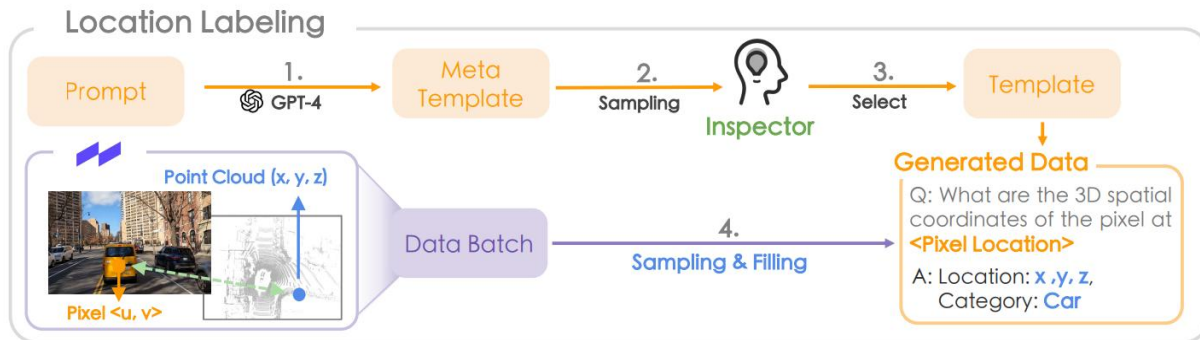




Data Status

Method	Pre-train Data	#	Time	City	Anno
LLaVA [48]	COCO [47]	150K	-	-	Des
VideoChat [44]	Self-Collected	18K	-	-	Des
Vid-ChatGPT [56]	ActivityNet-200 [6]	100K	-	-	Des
nuScenes-QA [61]	nuScenes [7]	460K	5.5	2	Des
DriveGPT4 [82]	BDD-X [38]	28K	77	4	Des
LLM-driver [11]	Self-Collected	160K	-	-	Des
ELM (Ours)	nuScenes [7]	7.4M	5.5	2	Des, Loc
	Waymo [70]	450K	6.4	3	Des
	YouTube	1.1M	1474	700	Des
	Ego4D [25]	300K	1638	74	Des





Examples of Description Labels



Raw: The scene is a busy city street with a red traffic light, a McDonald's restaurant, and a crosswalk. The traffic elements include traffic lights, cars, and pedestrians. The ego-vehicle is **traveling in the left lane**, and the traffic light is red...

Refined: The scene is a busy city street with a red traffic light, a McDonald's restaurant, and a crosswalk. The traffic elements include traffic lights, cars, and pedestrians. The ego-vehicle is **traveling in the right lane**, and the traffic light is red...

Q: How should the ego-vehicle drive at this point?



A: The ego-vehicle should follow the traffic light's instructions and **wait for the light to turn green before proceeding**.



Raw: The driving scene in the image features a car driving under a bridge, with a truck carrying a load of wood in the background. The car is **traveling in the left lane**, and it appears to be moving in the same direction as the truck.

Refined: The driving scene in the image features a car driving under a bridge, with a truck carrying a load of wood in the background. The car is **traveling in the middle lane**, and it appears to be moving in the same direction as the truck.

Q: Are there any potential dangers in the scenario?



A: The ego-vehicle should continue **driving through the intersection**, following the traffic light's instructions. It is important to **be cautious and attentive to the pedestrians** to ensure safety for all involved.

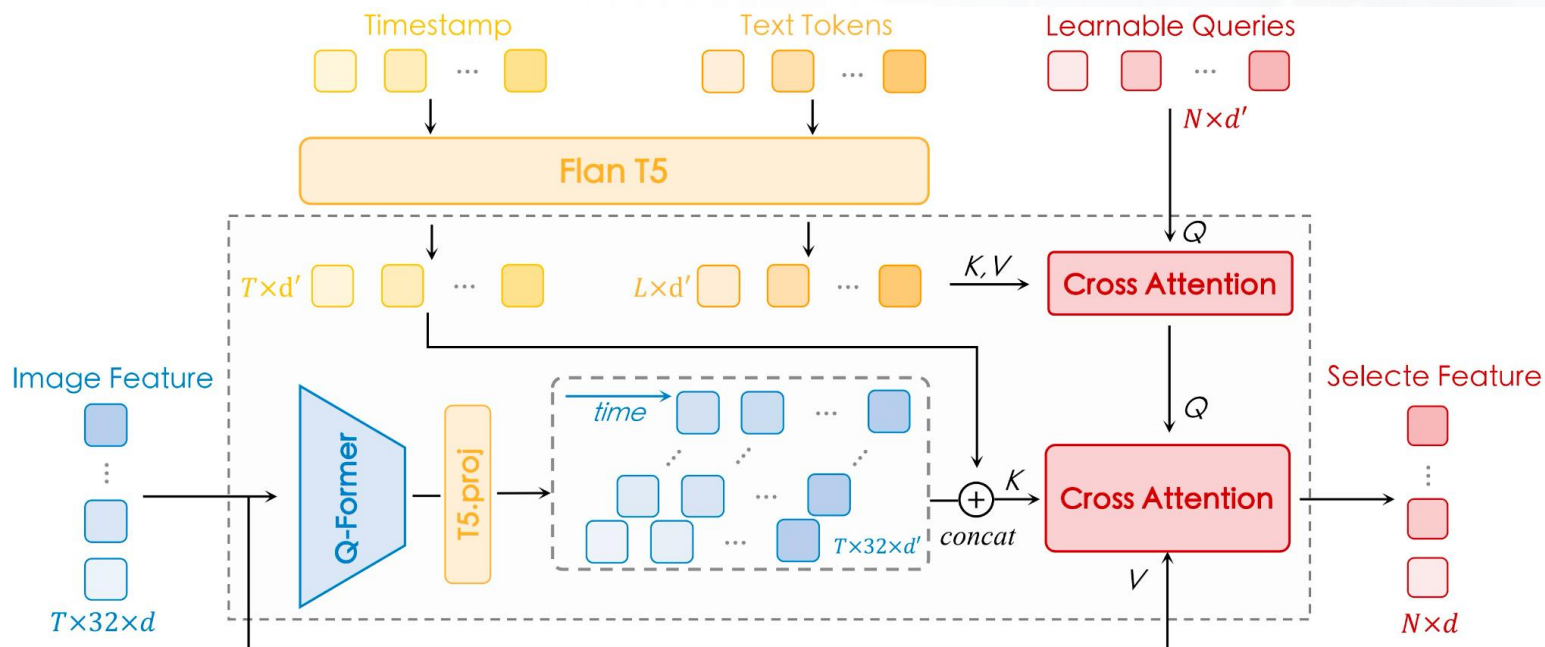


Embodied Understanding

Time-Aware Token Selection

- Utilize text prompts as guidance to select tokens wisely.
- Alignment among text, timestamps, and videos.

Examples of Selection



Q: What happened between 'C holds the handle of a frying pan' and 'C turns on the cooker with her right hand'?



GT: C moves the cover of a pot
Ours: C operates the cooker

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Experiments



Embodied Understanding

Benchmark

- Performing tasks for embodied understanding.

Tasks	Fine-tune Dataset	Description	Capability			Statistics		
			Localization	Memorization	Forecasting	S(m) / R(m)	T (s) / F	#
Surrounding Narration	nuScenes [7]	✓				30 / 5	0.5 / 1	142K
Traffic Sign Inquiry		✓		✓		30 / 1	3.5 / 7	20K
Action & Decision		✓			✓	30 / 5	3.5 / 7	301K
Box Detection				✓		50 / 1	0.5 / 1	232K
Tracking				✓		50 / 1	3.5 / 7	131K
Box Prediction				✓		50 / 1	3.5 / 7	133K
Egocentric Narration	Ego4D [25]	✓				20 / 3	3 / 1	357K
Moment Recap		✓		✓		20 / 3	60 / 20	70K
Event Query		✓		✓		20 / 3	60 / 20	70K
Activity Prediction		✓			✓	20 / 3	60 / 20	69K

End-to-end Planning



Q: What is the **status** of the cars that are **to the front of the ego car**?
 BLIP2-T5: **Three cars are parked.**
 Ours: Many cars are parked and **one is moving.**
 GT: Many cars are parked and many are moving.



Q: Has the ego vehicle seen any **traffic sign** before?
 BLIP2-T5: There is no traffic sign in the scene.
 Ours: The ego vehicle has seen 1 go_straight, and 1 turn_right before.
 GT: The ego vehicle has seen 1 go_straight, and 1 turn_right before.



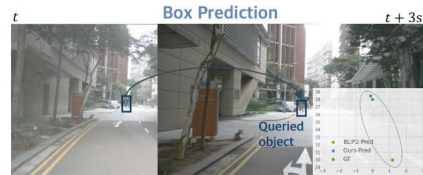
Q: Provide the 3D location of the **2D point <c, 856, 481>** in the image.
 BLIP2-T5: Location: [2.20, 8.85, -0.03], Car
 Ours: Location: [3, 12, 0], Car
 GT: Location: [3.38, 13.56, 0.003], Car



Q: What **actions** taken by the ego vehicle can lead to a collision with **<c, 817.5, 668.3>**?
 BLIP2-T5: **Sharp left turn.**
 Ours: Accelerate and go straight.
 GT: Accelerate and go straight.



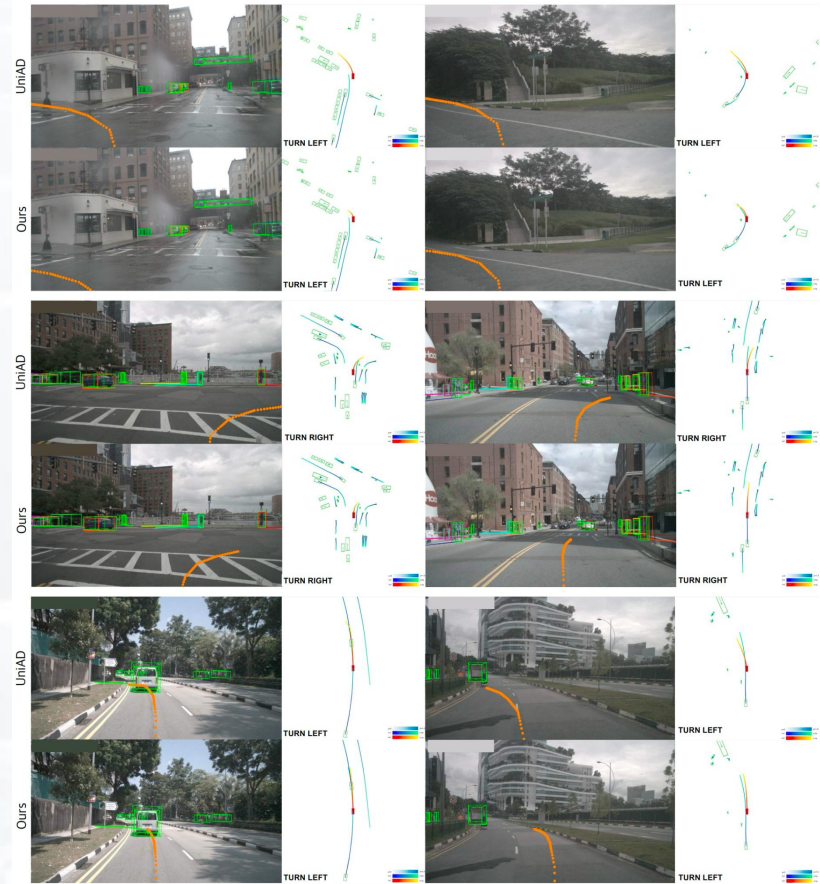
Q: What are the 3D spatial coordinates of the pixel at **<c, 1001.1, 544.6>** **2.0 seconds ago**?
 BLIP2-T5: Location: [-2.31, 19.62, -1.21], Barrier
 Ours: Location: [-1, 15, 0], Pedestrian
 GT: [-0.35, 15.32, -0.01], Pedestrian



Q: Determine the 3D location in the scene of the 2D pixel at **<c, 865.3, 505.9>** **3 seconds later**?
 BLIP2-T5: Location: [1.18, 29.96, 1.56], Car
 Ours: Location: [0, 38, 0], Pedestrian
 GT: Location: [-0.12, 38.45, 0.05], Pedestrian



Q: "What **happened 12.1 seconds before**?
 BLIP2-T5: C stirs the meat in the frying pan
 Ours: C moves the meat from the frypan to the plate
 GT: C moves the meat from the frypan to the plate





Q: What is the object **to the front of the ego car**?

BLIP2-T5: One bicycle **is parked**.
 Ours: One bicycle is without a rider.
 GT: One bicycle is without a rider.



Q: Has the ego vehicle seen any **traffic sign** before?

BLIP2-T5: Yes. The ego vehicle has seen 1 **turn_right** before.
 Ours: Yes. The ego vehicle has seen 1 **turn_left** before.
 GT: Yes. The ego vehicle has seen 1 **turn_left** before.



Q: Find the 3D position in the scene of the 2D pixel at **<c, 737.3, 472.7>**.

BLIP2-T5: Location: **[-0.2, 25.2, 1.3]**, truck
 Ours: Location: **[-2, 32, 1]**, bus
 GT: Location: **[-2.16, 34.06, 0.77]**, bus



Q: What is the future state of **<c3,826.7,521.7>**?

BLIP2-T5: **Still**.
 Ours: **Moving forward**.
 GT: **Moving forward**.



Q: Find the 3D world position of the 2D point **<c, 626.9, 558.3>** in the image. 1.5 seconds ago.

BLIP2-T5: Location: **[-0.87, 9.2, -0.3]**, Car
 Ours: Location: **[-1, 11, 0]**, Car
 GT: Location: **[-1.03, 11.17, -0.52]**, Car



Q: Calculate the 3D world location of the pixel with 2D coordinates **<c, 734.5, 673.2>**. 1.0 seconds later.

BLIP2-T5: Location: **[-0.2, 4.15, -1.3]**, Car
 Ours: Location: **[0, 8, 0]**, Car
 GT: **[-0.05, 8.00, -0.75]**, Car



Q: "What **happened 37.8 seconds before**?"

BLIP2-T5: **C pens the fridge**
 Ours: **C puts the water in the fridge**
 GT: **C puts the water in the fridge**



'C opens the water bottle'

Event Query

'C closes the water bottle'



Q: What happened between 'C opens the water bottle' and 'C closes water bottle'?

BLIP2-T5: C pours water from the water bottle

Ours: C drinks water

GT: C drinks water

'C picks up the drill'

'C puts the power drill on the wood'



Q: What happened between 'C picks up the drill' and 'C puts the power drill on the wood'?

BLIP2-T5: C picks the wood

Ours: C drills the wood

GT: C drills the wood

Egocentric Narration



Q: Give a caption.

BLIP2-T5: C moves the wires

Ours: C cuts black wire

GT: C cuts black wire

Event Forecasting

t

t + 0.7s



Q: What will happen in the next 0.7 seconds in the future?

BLIP2-T5: C drops the knife on the cutting board

Ours: C puts the slices of cabbage in the sieve

GT: C puts the slices of cabbage in the sieve with her left hand

t

t + 1.2s



Q: What will happen in the next 1.2 seconds in the future?

BLIP2-T5: C drops the knife on the cutting board

Ours: C cuts the onion with the knife

GT: C cuts the onion with the knife



Methods	Tracking		Box Detection		Box Prediction		Traffic Sign Inquiry			Surrounding Narration			Action & Decision		
	Pr@1	Pr@2	Pr@1	Pr@2	Pr@1	Pr@2	C	R	B	C	R	B	C	R	B
BLIP2-opt [27]	0.1	0.1	0.1	0.2	0.2	0.5	23.0	26.9	20.5	8.1	19.7	21.2	8.4	11.5	11.1
BLIP2-flant5 [27]	3.0	6.0	5.1	10.5	3.6	6.3	63.1	39.4	31.4	65.2	64.9	27.9	68.7	71.4	43.1
LLaMA-Ada. [17]	6.1	10.5	8.3	14.9	7.5	12.5	68.3	66.6	61.6	67.0	77.5	60.1	72.3	76.8	64.7
LLaVA [32]	5.5	9.3	28.5	31.2	6.1	10.2	51.1	58.5	50.8	64.9	64.6	41.2	64.4	62.4	57.9
Otter [26]	10.0	17.2	41.8	46.9	8.9	15.8	62.8	41.1	32.4	60.0	64.2	13.3	69.2	73.2	53.0
VideoChat [28]	0.4	0.9	0.1	0.3	0.1	0.2	25.3	21.9	11.7	21.7	29.2	12.2	29.6	33.2	13.1
Vid-ChatGPT [36]	0.1	0.6	0.1	1.0	0.3	1.2	49.6	57.1	48.6	61.0	69.6	37.2	53.6	58.5	43.5
ELM (Ours)	14.0	23.3	51.6	56.9	15.1	24.4	76.5	71.2	63.9	73.2	78.7	29.8	74.4	83.3	41.2

(a) **nuScenes**. We outperform the best previous methods on most metrics across the six tasks on nuScenes which validates the generality of our model.

Methods	Moment Recap			Event Query			Egocentric Narration			Activity Prediction			Methods	# param
	C	R	B	C	R	B	C	R	B	C	R	B		
BLIP2-opt [27]	1.2	8.9	6.8	7.8	28.4	14.7	5.2	19.8	10.7	2.7	18.7	9.6	BLIP2-opt	2.7B
BLIP2-flant5 [27]	13.1	31.9	12.5	27.3	33.0	16.6	16.9	33.5	15.4	11.5	31.2	11.3	BLIP2-flant5	2.7B
LLaMA-Ada. [17]	11.2	30.2	12.3	37.5	47.2	28.1	18.4	34.2	15.3	13.1	31.2	12.8	LLaMA-Ada.	7B
LLaVA [32]	9.6	28.3	12.1	39.8	44.6	29.9	6.5	28.2	11.6	8.4	28.0	13.0	LLaVA	7B
Otter [26]	11.4	29.6	10.5	27.1	38.3	19.1	14.1	31.4	13.9	11.1	29.4	10.3	Otter	7B
VideoChat [28]	13.2	32.5	13.8	34.5	42.2	26.4	20.7	35.0	17.6	12.1	32.4	14.1	VideoChat	7B
Vid-ChatGPT [36]	10.0	31.1	13.3	27.9	36.5	20.9	10.2	21.7	10.4	9.4	30.5	12.6	Vid-ChatGPT	7B
ELM (Ours)	22.6	36.7	19.4	38.0	43.1	27.6	26.5	37.7	16.9	18.1	34.1	17.0	ELM (Ours)	2.7B

(b) **Ego4D**. We extended the model to Ego4D dataset and verified the generality of our token bank module on four tasks. (c) **Adopted LLM params**.

OOD Evaluation

Method	ADE↓	FDE↓	Time(s)↓
Command Mean	7.98	11.41	-
UniAD-single [34]	4.16	9.31	0.56
Flamingo [3]	2.78	5.31	1.47
ELM	2.28	4.27	1.61

Q: What is the unusual about the driving scene?

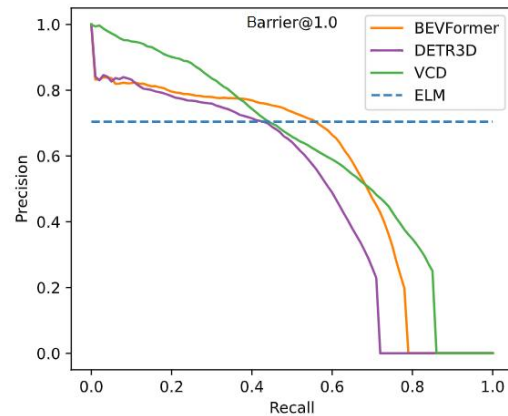
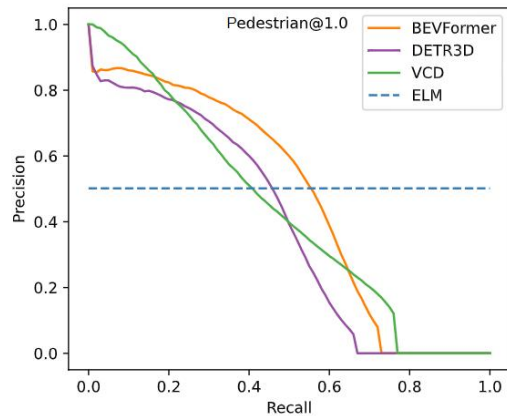
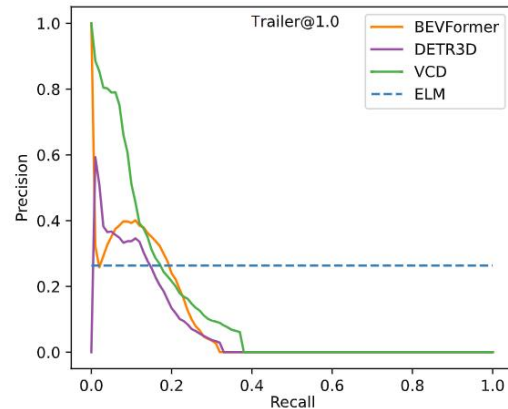
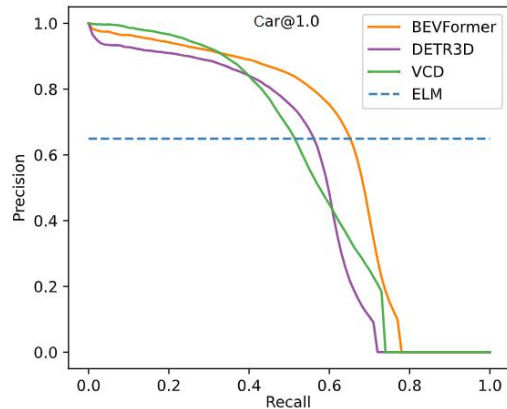


A: The scene shows a busy city street with a **construction site** on the side of the road. There is a traffic light visible in the background. The unusual element in this scene is **the presence of a construction site, which may cause traffic disruptions or delays**.



Embodied Understanding

Experiments



Q: What is the location and category of $\llbracket c1, 880.0, 457.5 \rrbracket$?
A: **Location:** [1, 17, 0], **category:** Truck.

Q: What is the object at $\llbracket c3, 1160.0, 417.3 \rrbracket$?
A: **Green Traffic Light.**

Q: What is the **moving status** of object $\llbracket c1, 880.0, 457.5 \rrbracket$?
A: **Going ahead.**

Q: In this scenario, what are **safe actions to take** for the ego vehicle?
A: **Keep going at the same speed, slightly offset to the right.**

Q: Given **keep_forward** instruction, what is the **future trajectory** of ego-car?
A: **[[0, 4], [0, 8], [1, 11], [2, 15], [2, 19], [3, 22]]**

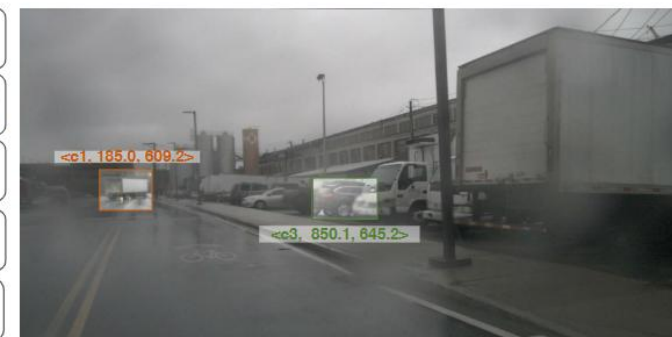
Q: What is the movement of object $\llbracket c1, 185.0, 609.2 \rrbracket$?
A: **Still.**

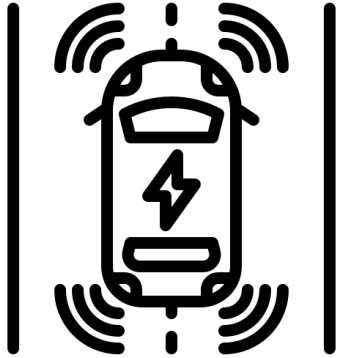
Q: What is the probability of colliding with $\llbracket c1, 185.0, 609.2 \rrbracket$ after the ego vehicle turns left at a constant speed?
A: **Low.**

Q: What **actions** can lead to a collision with $\llbracket c3, 850.1, 645.2 \rrbracket$?
A: **Accelerate and go straight.**

Q: Given this scenario, what **safe steps** should the ego vehicle take?
A: **Turn left, decelerate gradually without braking.**

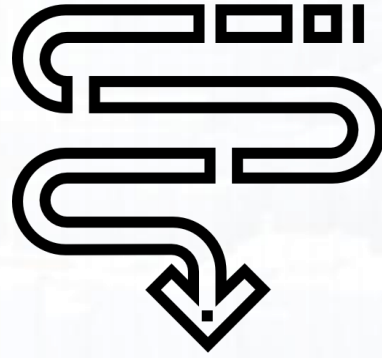
Q: In what **trajectory** will the ego-car move in the future?
A: **[0, 3], [-1, 6], [-2, 8], [-3, 11], [-4, 14], [-5, 16]**





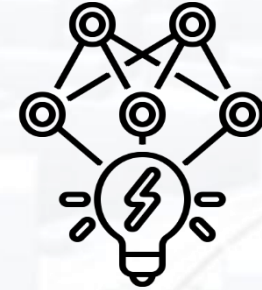
Driving-specific Inputs

ELM cannot handle common setting such as LiDAR or multi-view images as input, limiting its information source.



Closed-loop Planning

ELM is evaluated under an open-loop scheme, while closed-loop planning is necessary to see if it can handle corner cases.



Efficiency Constraints

Inheriting the drawbacks of LLMs, ELM suffers from long inference time, which may impact practical implementation.

One-page Takeaway



- End-to-end Autonomous Driving
 - Challenge: **Generalization & Explainability**
 - Recent trend: use vision language model to **embed “world knowledge”** to solve the challenges.
- ELM: Embodied Understanding of Driving Scenarios
 - Revive driving scene understanding by delving into **embodied** settings, along with capacities, tasks, and rubrics.
 - Expand vanilla VLMs to process long horizon **space** and **time** (open-world data & module design).

OpenDriveLab



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END