

DriveGPT4-V2: Harnessing Large Language Model Capabilities for Enhanced Closed-Loop Autonomous Driving







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Motivation

- From a learning theory perspective, end-to-end autonomous driving can optimize the entire system on the final outputs, rather than through the isolated optimization of individual modules, which potentially improves overall performance.
- Given the versatility of multimodal LLMs, they have been applied to autonomous driving for tasks such as interpretability and vehicle control.
- Open-loop evaluation is not sufficient for real-world applications. Thus, MLLMs need to be designed and evaluated specifically for closed-loop autonomous driving scenarios.

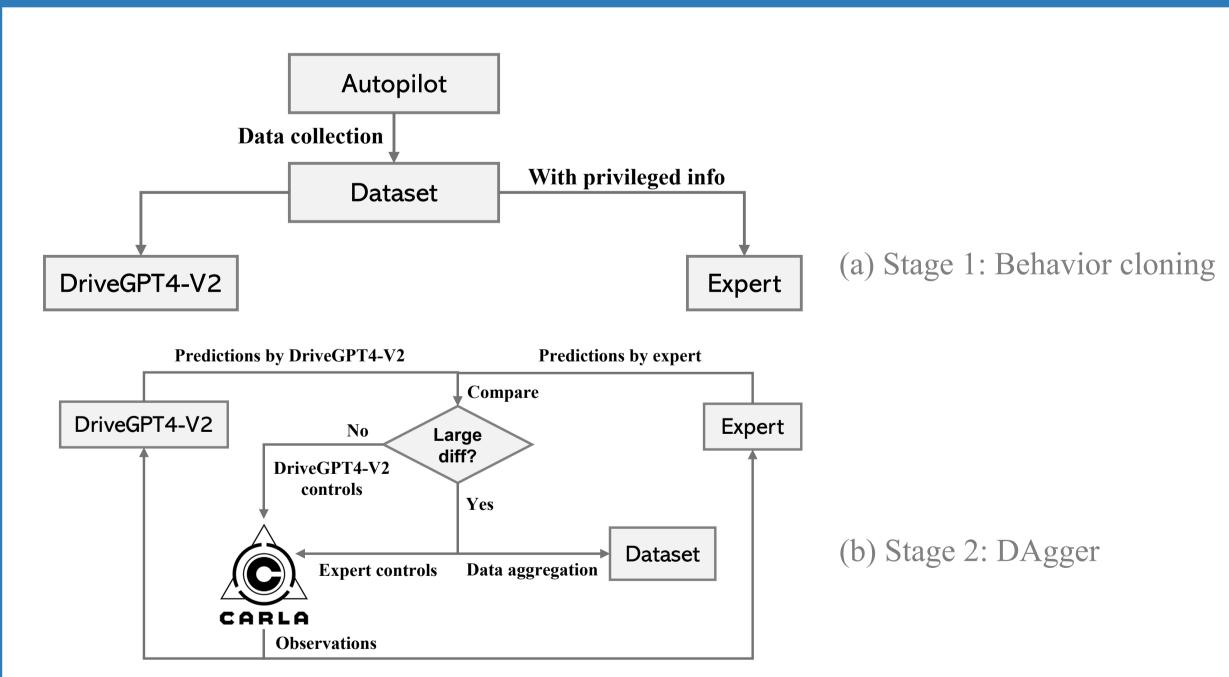
DriveGPT4-V2 <image>image>image> You are the brain of an autonomous vehicle. **Target point**: <Target_point> **Ego velocity**: <Ego_speed> **Mission Goal**: Develop a safe and feasible path. Multimodal observations High-level Decisions Target speed Target angle Waypoints Route Points Low-level Controls Throttle Steer Brake DriveGPT4 driving. Ta and vehica predicts high them to locate and the same and the

DriveGPT4-V2 for closed-loop autonomous driving. Taken as input multi-view camera images and vehicle state information, DriveGPT4-V2 predicts high-level vehicle decisions and converts them to low-level vehicle control signals in an end-to-end manner. DriveGPT4-V2 presents outstanding effectiveness and efficiency, serving as a reliable baseline method for future research on autonomous driving with LLMs.

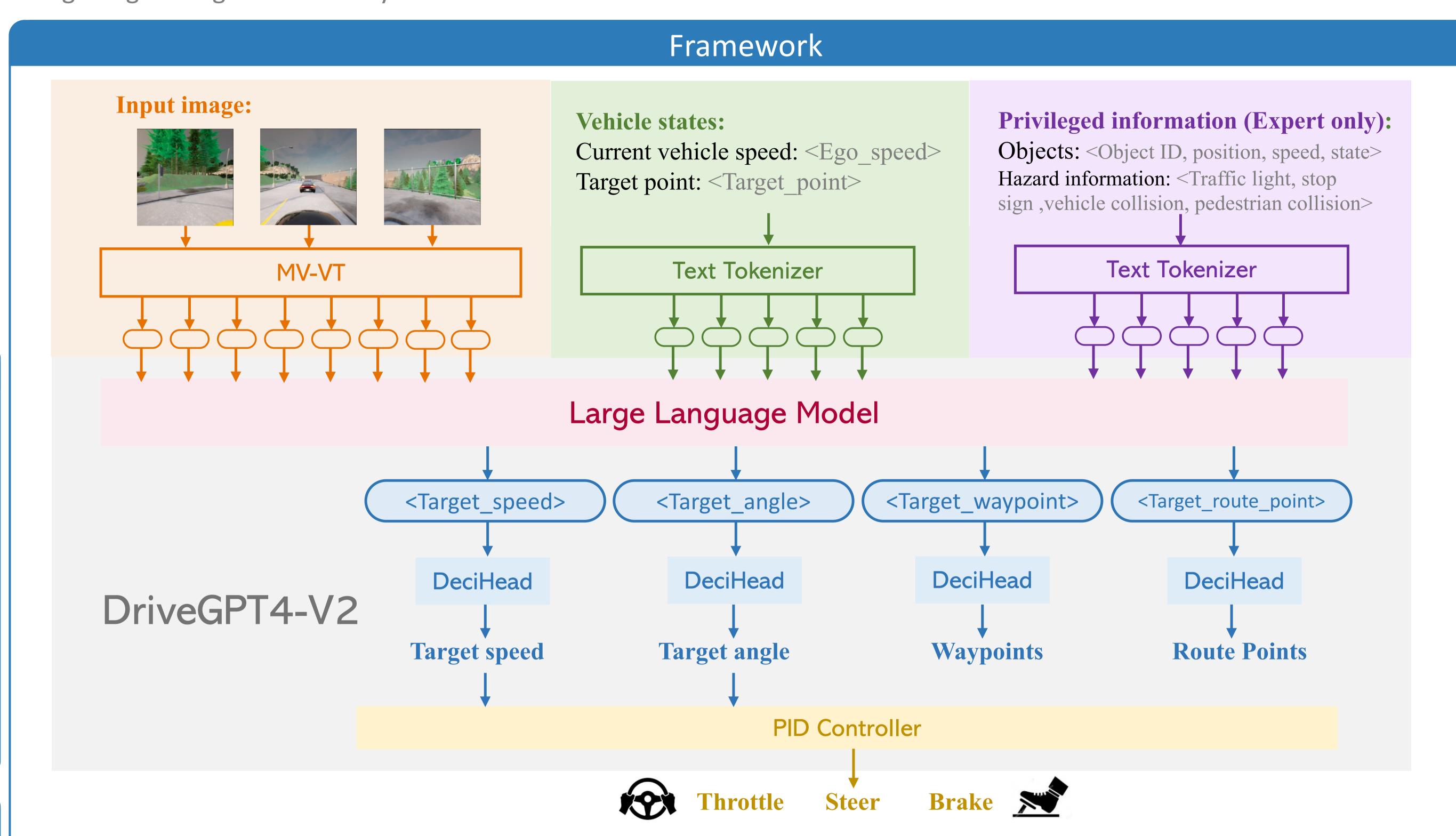
Front left Front right Visual Encoder Projector MV-VT

Multi-view visual tokenizer (MV-VT) structure. The input images consist of three front views. Each patch is processed through a visual encoder to extract features. Finally, a trained projection layer maps the downsampled feature into the text domain for further processing.

Two-stage Imitation Learning



(a) In the first stage, both DriveGPT4-V2 and the expert LLM are trained on data collected by a rule-based autopilot. (b) In the second stage, DriveGPT4-V2 runs on the training scenarios and routes. When the discrepancy between DriveGPT4-V2's predictions and those of the expert exceeds a predefined threshold, the expert's predictions are used to control the vehicle. Data from these cases is then added to the dataset for data aggregation.



• DriveGPT4-V2 takes multimodal input data to generate numerical control signals for end-to-end vehicle driving. The input includes multi-view images and vehicle state information. The LLM expert model, which shares a similar structure to DriveGPT4-V2, has access to privileged information about surroundings (shown in the purple module). The expert provides on-policy supervision to DriveGPT4-V2 to enhance closed-loop performance.

Experiments

Tab.1. Comparison results on CARLA Longest6 benchmark.

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Method	Visual	DS ↑	RC ↑	IS ↑	Ped ↓	Veh ↓	Stat ↓	Red ↓	Dev ↓	TO ↓	Block ↓
WOR [6]	C	21	48	0.56	0.18	1.05	0.37	1.28	0.88	0.08	0.20
LAV v1 [4]	C&L	33	70	0.51	0.16	0.83	0.15	0.96	0.06	0.12	0.45
Interfuser [42]	C	47	74	0.63	0.06	1.14	0.11	0.24	$\underline{0.00}$	0.52	<u>0.06</u>
TransFuser [12]	C&L	47	<u>93</u>	0.50	0.03	2.45	0.07	0.16	0.00	<u>0.06</u>	0.10
LAV v2 [4]	C&L	58	83	0.68	0.00	0.69	0.15	0.23	0.08	0.32	0.11
Perception PlanT [38]	C&L	58	88	0.65	0.07	0.97	0.11	0.09	$\underline{0.00}$	0.13	0.13
Transfuser++* [21]	C&L	<u>65</u>	90	0.72	0.00	0.99	<u>0.01</u>	0.07	0.00	0.10	0.12
Transfuser++* [†] [21]	C&L	58	89	0.65	0.01	1.15	<u>0.01</u>	0.10	<u>0.00</u>	0.14	0.13
LMDrive* [43]	C&L	36	69	0.52	0.07	1.03	0.18	1.01	0.09	0.11	0.22
DriveGPT4-V2		70	91	0.77	0.00	0.80	0.01	0.04	0.00	0.07	0.09

Tab.2. Efficiency analysis.					
LLM	DS	Train			
LLaVA-LLaMA3.1-8B	65	11.2h/epoch			
TinyLLaVA-LLaMA-1.5B	63	3.0h/epoch			

LLaVA-Qwen-0.5B

1.3h/epoch

Tab.3. Ablation studies on decision heads. "Additional tokens" indicates using more output tokens for prediction.

	DS	RC	IS	FPS
Additional tokens	64	91	0.70	1.4
DriveGPT4-V2	63	90	0.70	8.1

Tab.4. Ablation studies on PID controllers. "WP" indicates utilizing predicted waypoints for PID control; while "TS&RP" means PID control by predicted target speed and route points.

PID Controller	DS	RC	IS
WP TS & RP	53 59	85 88	0.62 0.67
DriveGPT4-V2	63	90	0.70

Tab.5. Ablation studies on system design. Ablation studies of DriveGPT4-V2. "WP" and "RP" represent waypoints and route points, respectively.

	DS	RC	IS
Baseline	47	78	0.60
+ LLM Visual Pretraining	56	87	0.64
+ Visual Tokenizer	60	88	0.68
+ WP&RP	63	90	0.70
+ Expert Supervision	70	91	0.77