A Language Agent for Autonomous Driving

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https://usc-gvl.github.io/Agent-Driver

Abstract

Human-level driving is an ultimate goal of autonomous driving. Conventional approaches formulate autonomous driving as a perception-prediction-planning framework, yet their systems do not capitalize on the inherent reasoning ability and experiential knowledge of humans. In this paper, we propose a fundamental paradigm shift from current pipelines, exploiting Large Language Models (LLMs) as a cognitive agent to integrate human-like intelligence into autonomous driving systems. Our system, termed Agent-Driver, transforms the traditional autonomous driving pipeline by introducing a versatile tool library accessible via function calls, a cognitive memory of common sense and experiential knowledge for decision-making, and a reasoning engine capable of chain-of-thought reasoning, task planning, motion planning, and self-reflection. Powered by LLMs, our Agent-Driver is endowed with intuitive common sense and robust reasoning capabilities, thus enabling a more nuanced, human-like approach to autonomous driving. We evaluate our system on the large-scale nuScenes benchmark, and extensive experiments substantiate that our Agent-Driver significantly outperforms the state-of-the-art driving methods by a large margin. Our approach also demonstrates superior interpretability and few-shot learning ability to these methods. Code will be released.

1. Introduction

Imagine a car navigating a quiet suburban neighborhood. Suddenly, a ball bounces onto the road. A human driver, leveraging extensive experiential knowledge, would not only perceive the immediate presence of the ball, but also instinctively anticipate the possibility of a chasing child and consequently decide to decelerate. In contrast, an autonomous vehicle, devoid of such reasoning and experiential anticipation, might continue driving until sensors detect the child, only allowing for a narrower margin of safety. The importance of human prior knowledge in driving systems becomes clear: driving is not merely about reacting to the visible, but also to the conceivable scenarios where the system needs to reason and respond even in their absence.

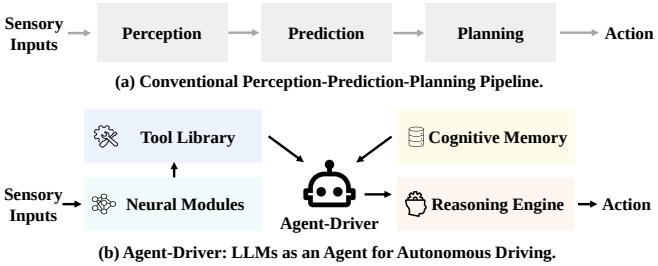

Figure 1. **Comparison between (a) the conventional driving system and (b) the proposed Agent-Driver.** Our approach transforms the conventional perception-prediction-planning framework by introducing LLMs as an agent for autonomous driving.

To integrate human prior knowledge into autonomous driving systems, previous approaches [6, 14, 15, 17, 30] deconstruct the human driving process into three systematic steps following Figure 1 (a). *Perception*: they interpret the human perceptual process as object detection [27] or occupancy estimation [29]. *Prediction*: they abstract human drivers' foresight of upcoming scenarios as the prediction of future object motions [5]. *Planning*: they emulate the human decision-making process by planning a collision-free trajectory, either using hand-crafted rules [38] or by learning from data [45]. Despite its efficacy, this *perception-prediction-planning* framework overly simplifies the human decision-making process and cannot fully model the complexity of driving. For instance, perception modules in these methods are notably redundant, necessitating the detection of all objects in a vast perception range, whereas human drivers can maintain safety by only attending to a few key objects. Moreover, prediction and planning are designed for collision avoidance with detected objects. Nevertheless, they lack deeper reasoning ability inherent to humans, *e.g.* deducing the connection between a visible ball and a potentially unseen child. Furthermore, it remains challenging to incorporate long-term driving experiences and common sense into existing autonomous driving systems.

In addressing these challenges, we found the major

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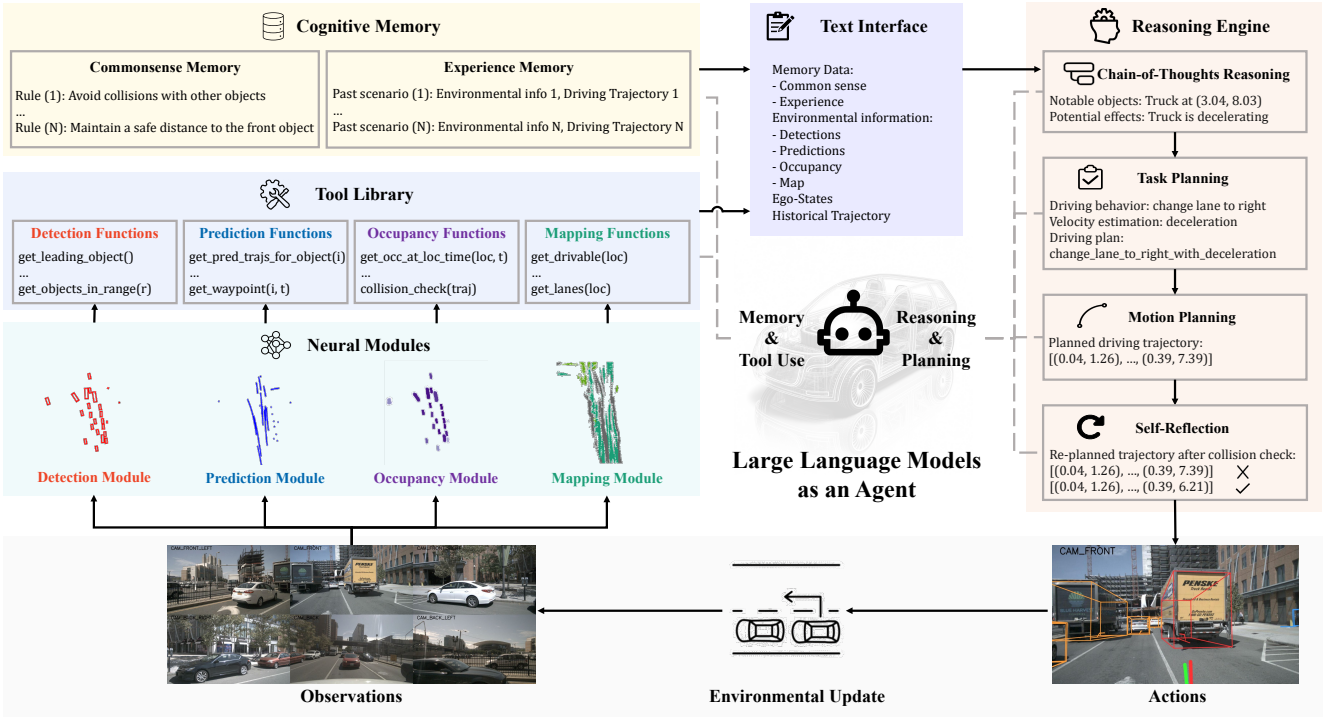

Figure 2. **Architecture of Agent-Driver.** Our system dynamically collects necessary environmental information from the output of neural modules via the **tool library**. The collected information is further utilized to query the **cognitive memory**. Consequently, the **reasoning engine** takes collected environmental information and retrieved memory data as input, and traceably derives a safe and comfortable trajectory for driving through chain-of-thought reasoning, task planning, motion planning, and self-reflection.

obstacle of integrating human priors into autonomous driving lies in the incompatibility of human knowledge and neural-network-based driving systems. Human knowledge is inherently encoded and utilized as language representations, and their reasoning process can also be interpreted by language. However, conventional driving systems rely on deep neural networks that are designed to process numerical data inputs, such as sensory signals, bounding boxes, and trajectories. The discrepancy between language and numerical representations poses a significant challenge to incorporating human experiential knowledge and reasoning capability into existing driving systems, thereby widening the chasm from genuine human driving performance.

Taking a step towards more human-like autonomous driving, we propose Agent-Driver, a cognitive agent empowered by Large Language Models (LLMs). The fundamental insight of our approach lies in the utilization of natural language as a unified interface, seamlessly bridging language-based human knowledge and reasoning ability with neural-network-based systems. Our approach fundamentally transforms the conventional perception-prediction-planning framework by leveraging LLMs as an interactive scheduler among system components. As depicted in Figure 1 (b), on top of the LLMs, we introduce: 1) a versatile tool library that interfaces with neural modules via dynamic function calls, streamlining perception with less redundancy, 2) a configurable cognitive memory that explicitly stores common sense and driving experiences, infusing the system with human experiential knowledge, and 3) a reasoning engine that processes perception results and memory data to emulate human-like decision-making. Specifically, the reasoning engine performs chain-of-thought reasoning to recognize key objects and events, task planning to derive a high-level driving plan, motion planning to generate a driving trajectory, and self-reflection to ensure the safety of the planned trajectory. These components, coordinated by LLMs, culminate in an anthropomorphic driving process. To conclude, we summarize our contributions as follows:

- We present Agent-Driver, an LLM-powered agent that revolutionizes the traditional perception-prediction-planning framework, establishing a powerful yet flexible paradigm for human-like autonomous driving.
- Agent-Driver integrates a tool library for dynamic perception and prediction, a cognitive memory for human knowledge, and a reasoning engine that emulates human decision-making, all orchestrated by LLMs to enable a more anthropomorphic autonomous driving process.
- Agent-Driver significantly outperforms the state-of-the-art autonomous driving systems by a large margin, with over 30% collision improvements in motion planning. Our approach also demonstrates strong few-shot learning ability and interpretability on the nuScenes benchmark.

- We provide a variety range of ablation study to dissect the proposed architecture and understand the efficacy of each module, to facilitate future research in this direction.

Due to the page limit, we leave further discussions of related works in the appendix for reference.

2. Agent-Driver

In this section, we present Agent-Driver, an LLM-based intelligent agent for autonomous driving. We first introduce the overall architecture of our Agent-Driver in Section 2.1. Then, we introduce the three key components of our method: tool library (Section 2.2), cognitive memory (Section 2.3), and reasoning engine (Section 2.4).

2.1. Overall Architecture

Conventional perception-prediction-planning pipelines leverage a series of neural networks as basic modules for different tasks. However, these neural-network-based systems lack direct compatibility with human prior knowledge, constraining their potential for leveraging such priors to enhance driving performance. To handle this challenge, we propose a novel framework that leverages text representations as a unified interface to connect neural networks and human knowledge. The overall architecture of Agent-Driver is shown in Figure 2. Our approach takes sensory data as input and introduces neural modules for processing these sensory data and extracting environmental information about detection, prediction, occupancy, and map. On top of the neural modules, we propose a **tool library** where a set of functions are designed to further abstract the neural outputs and return text-based messages. For each driving scenario, an LLM selectively activates the required neural modules by invoking specific functions from the tool library, ensuring the collection of necessary environmental information with less redundancy. Upon gathering the necessary environmental information, the LLM leverages this data as a query to search in a **cognitive memory** for pertinent traffic regulations and the most similar past driving experience. Finally, the retrieved traffic rules and driving experience, together with the formerly collected environmental information, are utilized as inputs to an LLM-based **reasoning engine**. The reasoning engine performs multi-round reasoning based on the inputs and eventually devises a safe and comfortable trajectory for driving. Our Agent-Driver architecture harnesses dynamic perception and prediction capability brought by the tool library, human knowledge from the cognitive memory, and the strong decision-making ability of the reasoning engine. This synergistic integration results in a more human-like driving system with enhanced decision-making capability.

2.2. Tool Library

The profound challenge of incorporating human knowledge into neural-network-based driving systems is reconciling the incompatibility between text-based human priors and the numerical representations from neural networks. While prior works [19] have attempted to translate text-based priors into semantic features or regularization terms for integration with neural modules, their performances are still constrained by the inherent cross-modal discrepancy. By contrast, we leverage text as a unified interface to connect neural modules and propose a tool library built upon the neural modules to dynamically collect text-based environmental information.

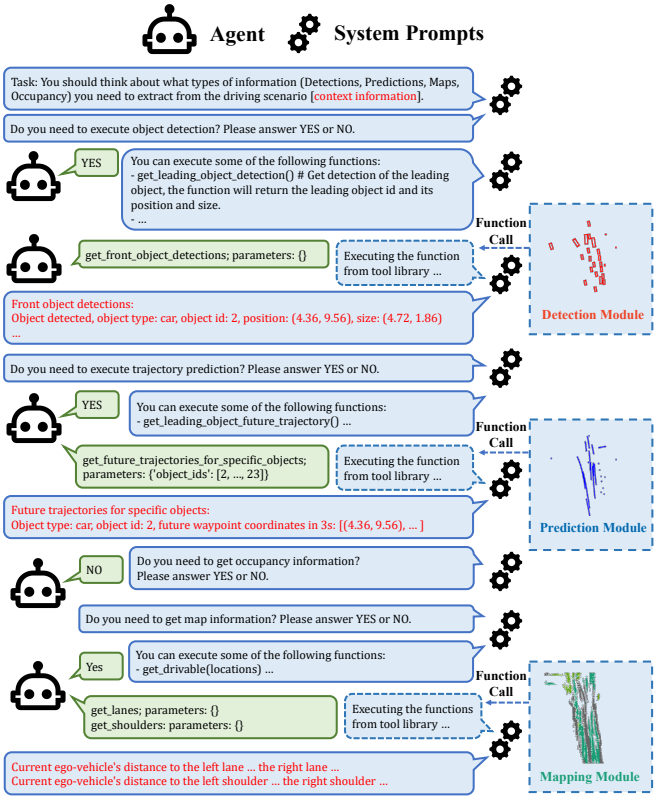

Figure 3. **Illustration of function calls in the tool library.** Agent-Driver can effectively collect necessary environmental information from neural modules through dynamic function calls.

The cornerstones of the tool library are four neural modules, *i.e.*, detection, prediction, occupancy, and map modules, which process sensory data from observations and generate detected bounding boxes, future trajectories, occupancy grids, and maps respectively. The neural modules cover various tasks in perception and prediction and extract environmental information from observations. However, this information is largely redundant, with a significant portion insignificant to decision-making. To dynamically extract necessary information from the neural module outputs, we propose a tool library—where a set of functions are designed—to summarize the neural outputs into text-based messages, and the information collection process can be established by dynamic function calls. An illustration of this process is shown in Figure 3.

Functions. We devised various functions for detection, prediction, occupancy, and mapping, in order to extract useful information from the neural module's outputs respectively. Our tool library contains more than 20 functions covering diverse usages. Here are some examples. For detection, `get_leading_object` returns a text description of the object in front of the ego-vehicle on the same lane. For prediction, `get_pred_trajs_for_object` returns a text-based predicted future trajectory for a specified object. For occupancy, `get_occ_at_loc_time` returns the probability that a specific location is occupied by other objects at a given timestep. For map, `get_lanes` returns the information of the left and right lanes to the ego-vehicle, and `get_shoulders` returns the information of the left and right road shoulders to the ego-vehicle. Detailed descriptions of all functions are in the appendix.

Tool Use. With the functions in the tool library, an LLM is instructed to collect necessary environmental information through dynamic function calls. Specifically, the LLM is first provided with initial information such as the current state for its subsequent decision-making. Then, the LLM will be asked whether it is necessary to activate a specific neural module, *i.e*. detection, prediction, occupancy, and map. If the LLM decides to activate a neural module, the functions related to this module will be provided to the LLM, and the LLM chooses to call one or some of these functions to collect the desired information. Through multiple rounds of conversations, the LLM eventually collects all necessary information about the current environment. Compared to directly utilizing the outputs of the neural modules, our approach reduces the redundancy in current systems by leveraging the reasoning power of the LLM to determine what environmental information is of real importance to the decision-making process. Furthermore, the neural modules are only activated when the LLM decides to call the relevant functions, which brings flexibility to the system.

2.3. Cognitive Memory

Human drivers navigate using their common sense, such as adherence to local traffic regulations, and draw upon driving experiences in similar situations. However, it is non-trivial to adapt this ability to the conventional perception-prediction-planning framework. By contrast, our approach tackles this problem through interactions with a cognitive memory. Specifically, the cognitive memory stores text-based common sense and driving experiences. For every driving scenario, we utilize the collected environmental information as a query to search in the cognitive memory for similar past experiences to assist decision-making. The cognitive memory contains two sub-memories: commonsense memory and experience memory.

Commonsense Memory. The commonsense memory encapsulates the essential knowledge a driver typically needs for driving safely on the road, such as traffic regulations and knowledge about risky behaviors. It is worth noting that the commonsense memory is purely text-based and fully configurable, that is, users can customize their own commonsense memory for different driving conditions by simply writing different types of knowledge into the memory.

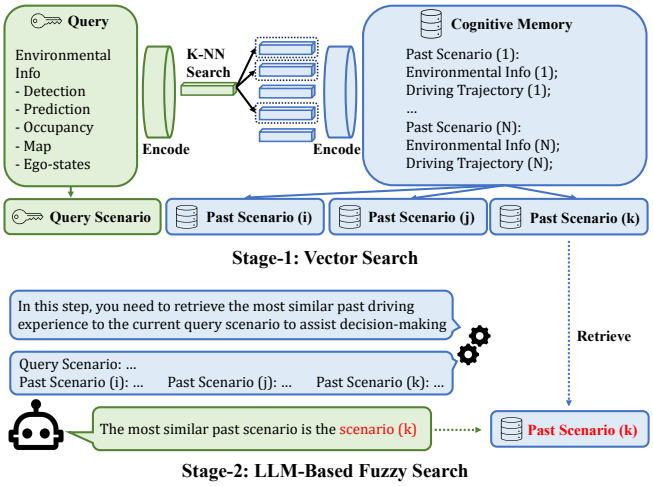

Figure 4. **Illustration of memory search.** The proposed two-stage search algorithm effectively retrieves the most similar driving experience and facilitates the subsequent decision-making process.

Experience Memory. The experience memory contains a series of past driving scenarios, where each scenario is composed of the environmental information and the subsequent driving decision at that time. By retrieving the most similar experiences and referencing their driving decisions, our system enhances its capacity for making more informed and resilient driving decisions.

Memory Search. As exhibited in Figure 4, we present an innovative two-stage search algorithm to effectively search for the most similar past driving scenario in the experience memory. The first stage of our algorithm is inspired by vector databases [21, 40], where we encode the input query and each record in the memory into embeddings and then retrieve the top-K similar records via K-nearest neighbors (K-NN) search in the embedding space. Since the driving scenarios are quite diverse, the embedding-based search is inherently limited by the encoding methods employed, resulting in insufficient generalization capabilities. To overcome this challenge, the second stage incorporates an LLM-based fuzzy search, where the LLM is tasked to rank these records according to their relevance to the query. This ranking is based on the implicit similarity assessment by the LLM, leveraging its capabilities in generalization and reasoning.

The cognitive memory equips our system with human knowledge and past driving experiences. The retrieved most similar experiences, together with commonsense and environmental information, collectively form the inputs to the reasoning engine. Text as a unified interface aligns the environmental information with human knowledge, thereby

enhancing our system's compatibility.

2.4. Reasoning Engine

Reasoning, a fundamental ability of humans, is critical to the decision-making process. Conventional methods directly plan a driving trajectory based on perception and prediction results, while they lack the reasoning ability inherent to human drivers, resulting in insufficient capability to handle complicated driving scenarios. Conversely, as shown in Figure 5, we propose a reasoning engine that effectively incorporates reasoning ability into the driving decision-making process. Given the environmental information and retrieved memory, our reasoning engine performs multi-round reasoning to plan a safe and comfortable driving trajectory. The proposed reasoning engine consists of four core components: chain-of-thought reasoning, task planning, motion planning, and self-reflection.

Chain-of-Thought Reasoning. Human drivers are able to identify the key objects and their potential effects on driving decisions, while this important capability is typically absent in conventional autonomous driving approaches. To embrace this reasoning ability in our system, we propose a novel chain-of-thought reasoning module, where we instruct an LLM to reason on the input environmental information and output a list of key objects and their potential effects in text. To guide this reasoning process, we instruct the LLM via in-context learning of a few human-annotated examples. We found this strategy successfully aligns the reasoning power of the LLM with the context of autonomous driving, leading to improved reasoning accuracy.

Task Planning. High-level driving plans provide essential guidance to low-level motion planning. Nevertheless, traditional methods directly perform motion planning without relying on this high-level guidance, leading to sub-optimal planning results. In our approach, we define high-level driving plans as a combination of discrete driving behaviors and velocity estimations. For instance, the combination of a driving behavior `change_lane_to_left` and a velocity estimation `deceleration` results in a high-level driving plan `change_lane_to_left_with_deceleration`. We instruct an LLM via in-context learning to devise a high-level driving plan based on environmental information, memory data, and chain-of-thought reasoning results. The devised high-level driving plan characterizes the ego-vehicle's coarse locomotion and serves as a strong prior to guide the subsequent motion planning process.

Motion Planning. Motion planning aims to devise a safe and comfortable trajectory for driving, and each trajectory is represented as a sequence of waypoints. Following [26], we re-formulate motion planning as a language modeling problem. Specifically, we leverage environmental information, memory data, reasoning results, and high-level driving plans collectively as inputs to an LLM, and we instruct the LLM

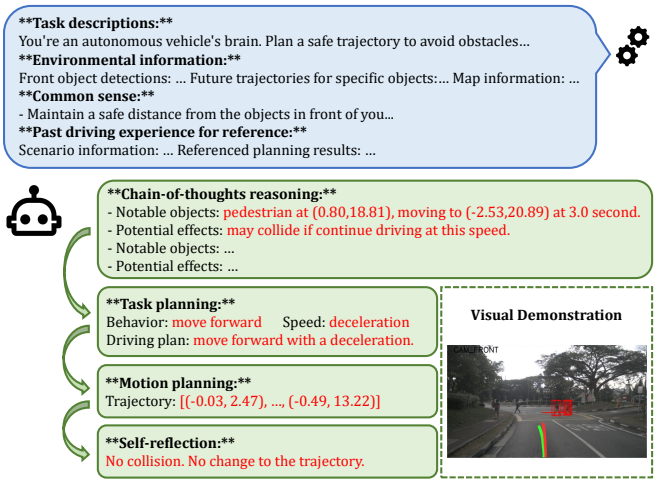

Figure 5. **Illustration of reasoning engine.** Agent-Driver makes driving decisions like human in a step-by-step procedure.

to generate text-based driving trajectories by reasoning on the inputs. By fine-tuning with human driving trajectories, the LLM can generate trajectories that closely emulate human driving patterns. Finally, we transform the text-based trajectories back into real trajectories for system execution.

Self-Reflection. Self-reflection is a crucial ability in humans' decision-making process, aiming to re-assess the former decisions and adjust them accordingly. To model this capability in our system, we propose a collision check and optimization approach. Specifically, for a planned trajectory $\hat{\tau}$ from the motion planning module, the `collision_check` function in the tool library is first invoked to check its collision. If collision detected, we refine the trajectory $\hat{\tau}$ into a new trajectory τ^* by optimizing the cost function $\mathcal{C}$:

$$\tau^* = \min_{\tau} \mathcal{C}(\tau, \hat{\tau}) = \min_{\tau} \lambda_1 ||\tau - \hat{\tau}||_2 + \lambda_2 \mathcal{F}_{col}(\tau). \quad (1)$$

Details about the formulation of collision probability $\mathcal{F}_{col}(\tau)$ can be found in the appendix. Self-reflection greatly improves the safety of our system.

Our reasoning engine models the human decision-making process in driving as a step-by-step procedure involving reasoning, hierarchical planning, and self-reflection. Compared to prior works, our approach effectively emulates the human decision-making process, leading to enhanced decision-making capability and superior planning performance.

3. Experiments

In this section, we demonstrate the effectiveness, few-shot learning ability, and other characteristics of Agent-Driver through extensive experiments on the large-scale nuScenes dataset [4]. First, we introduce the experimental settings and evaluation metrics in Section 3.1. Next, we compare our approach against state-of-the-art driving methods on the nuScenes dataset (Section 3.2). Subsequently, we investigate

	Method	L2 (m) ↓				Collision (%) ↓			
		1s	2s	3s	Avg.	1s	2s	3s	Avg.
ST-P3 metrics	ST-P3 [14]	1.33	2.11	2.90	2.11	0.23	0.62	1.27	0.71
	VAD [17]	0.17	0.34	**0.60**	0.37	0.07	0.10	0.24	0.14
	GPT-Driver [26]	0.20	0.40	0.70	0.44	0.04	0.12	0.36	0.17
	Agent-Driver (ours)	**0.16**	**0.34**	0.61	**0.37**	**0.02**	**0.07**	**0.18**	**0.09**
UniAD metrics	NMP [45]	-	-	2.31	-	-	-	1.92	-
	SA-NMP [45]	-	-	2.05	-	-	-	1.59	-
	FF [13]	0.55	1.20	2.54	1.43	0.06	0.17	1.07	0.43
	EO [18]	0.67	1.36	2.78	1.60	0.04	0.09	0.88	0.33
	UniAD [15]	0.48	0.96	1.65	1.03	0.05	0.17	0.71	0.31
	GPT-Driver [26]	0.27	0.74	1.52	0.84	0.07	0.15	1.10	0.44
	Agent-Driver (ours)	**0.22**	**0.65**	**1.34**	**0.74**	**0.02**	**0.13**	**0.48**	**0.21**

Table 1. **Motion planning performance compared to the state-of-the-art methods.** Agent-Driver significantly outperforms prior works in terms of L2 and collision rate. Our approach attains more than 30% performance gains in collisions compared to the state-of-the-art methods.

the few-show learning ability (Section 3.3), interpretability (Section 3.4), compatibility (Section 3.5), and stability (Section 3.6) of Agent-Driver. Finally, we conduct empirical studies to evaluate the effectiveness of different components and design choices of our approach in Section 3.7.

3.1. Experimental Setup

Dataset. The nuScenes [4] dataset is a large-scale and real-world autonomous driving dataset that contains $1,000$ driving scenarios and approximately $34,000$ key frames encompassing a diverse range of locations and weather conditions. We follow the general practice and split the whole dataset into training and validation sets. We utilize the training set to train the neural modules and instruct the LLMs, and we utilize the validation set to evaluate the performance of our approach, ensuring a fair comparison with prior works.

Implementation details. We utilize gpt-3.5-turbo-0613 as the foundation LLM for different components in our system. For motion planning, we follow [26] and fine-tune the LLM with human driving trajectories in the nuScenes training set for *one epoch*. For neural modules, we adopted the modules in [15]. More details can be found in the appendix.

Evaluation metrics. As argued in [15], autonomous driving systems should be optimized in pursuit of the ultimate goal, *i.e.*, planning of the self-driving car. Hence, we focus on the motion planning performances to evaluate the effectiveness of our system. There are two commonly adopted metrics for motion planning on the nuScenes dataset: L2 error (in meters) and collision rate (in percentage). The average L2 error is computed by measuring each waypoint's distance in the planned and ground-truth trajectories, reflecting the proximity of a planned trajectory to a human driving trajectory. The collision rate is calculated by placing an ego-vehicle box on each waypoint of the planned trajectory and then checking for collisions with the ground truth bounding boxes of other objects, reflecting the safety of a planned trajectory. We follow the common practice and evaluate the motion planning result in a 3-second time horizon.

We further note that in different papers there are subtle discrepancies in computing these two metrics. For instance, in UniAD [15] both metrics at k-th second are measured as the error or collision rate at this certain timestep, while in ST-P3 [14] and following works [17, 26], these metrics at k-th second is an average over k seconds. There are also differences in ground truth objects for collision calculation in different papers. We explain the details of metric implementations in appendix for reference. For a fair comparison, we group different methods based on their metric implementations (UniAD metric or ST-P3 metric) and evaluate Agent-Driver on *both* two metric implementations.

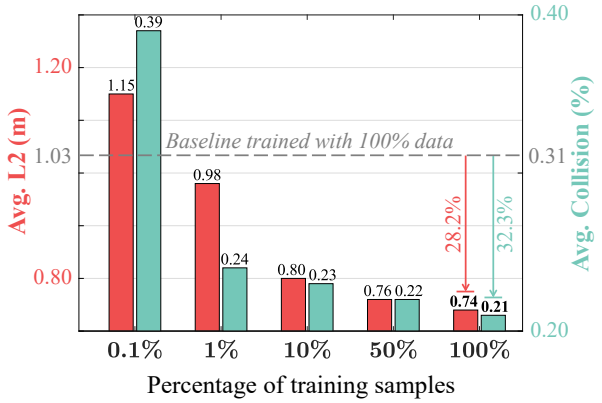

Figure 6. **Few-shot learning.** The motion planner in Agent-Driver fine-tuned with 1% data exceeds the state-of-the-art [15] trained on full data, verifying its few-shot learning ability.

3.2. Comparison with State-of-the-art Methods

As shown in Table 1, Agent-Driver surpasses state-of-the-art methods in both metrics and decreases the collision rate of the second-best performance by a large margin. Specifically, under ST-P3 metrics, Agent-Driver realizes the lowest average L2 error and greatly reduces the average collision rates by **35.7%** compared to the second-best performance. Under UniAD metrics, Agent-Driver achieves an L2 error of 0.74 and a collision rate of 0.21%, which are **11.9%** and **32.3%** better than the second-best methods GPT-Driver [26] and UniAD [15], respectively. The promising performance on the collision rate verifies the effectiveness of the reasoning

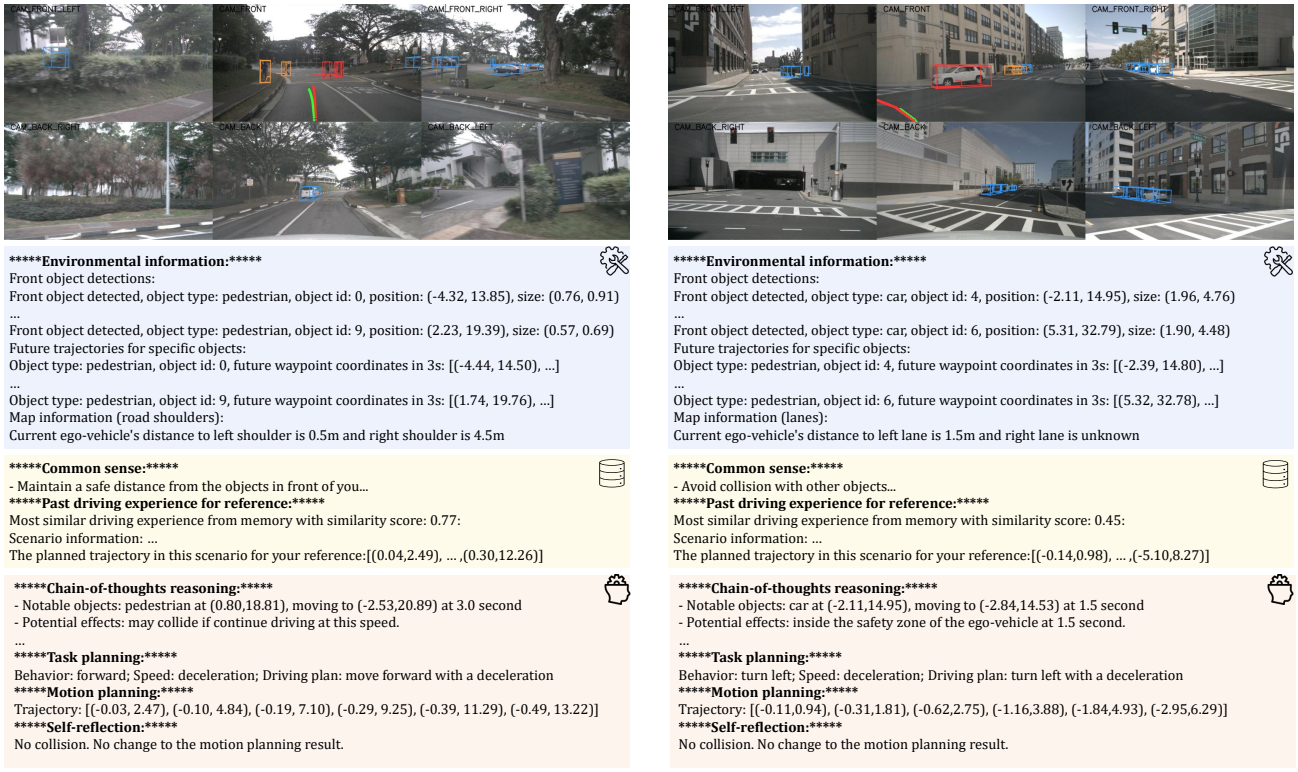

Figure 7. **Interpretability of Agent-Driver.** In the referenced images, the planned trajectories of our system and the human driving trajectories are in red and green respectively. Agent-Driver extracts meaningful objects (in yellow) from all detected objects (in blue) via the tool library. The reasoning engine further identifies notable objects (in red). Messages from the tool library, cognitive memory, and reasoning engine are recorded in colored text boxes. Every message is documented and our system is conducted in an interpretable and traceable way.

ability of Agent-Driver, which considerably increases the safety of the proposed autonomous driving system.

3.3. Few-shot Learning

To assess the generalization ability of motion planning in our approach, we conduct a few-shot learning experiment, where we keep other components the same and fine-tuned the core motion planning LLM with 0.1%, 1%, 10%, 50%, and 100% of the training data for *one epoch*. For comparison, we adopted the motion planner in UniAD [15] trained with 100% data as the baseline. The results are shown in Figure 6. Notably, with only 0.1% of the full training data, *i.e.*, 23 training samples, Agent-Driver realizes a promising performance. When exposed to 1% of training scenarios, the proposed method surpasses the baseline by a large margin, especially under the average collision rate. Furthermore, with increased training data, Agent-Driver stably achieves better motion planning performance.

3.4. Interpretability

Unlike conventional driving systems that rely on black-box neural networks to perform different tasks, the proposed Agent-Driver inherits favorable interpretability from LLMs. As shown in Figure 7, the output messages of LLMs from the tool library, cognitive memory, and reasoning engine are recorded during system execution. Hence the whole driving decision-making process is transparent and interpretable.

Neural Modules				Avg. L2 (m)	Avg. Col. (%)
Detection	Prediction	Occupancy	Mapping		
VAD	VAD	ST-P3	ST-P3	0.73	0.24
VAD	VAD	UniAD	UniAD	0.72	0.22
UniAD	UniAD	ST-P3	ST-P3	0.74	0.24
UniAD	UniAD	UniAD	UniAD	0.74	0.21

Table 2. **Compatibility to different perception modules.** Neural modules in Agent-Driver can be replaced in a *plug-and-play* manner while maintaining a promising planning performance.

3.5. Compatibility

Compatibility with different neural modules. As shown in Table 2, Agent-Driver constantly maintains a favorable performance with combinations of variable neural modules. We argue that discrepancy in perception and prediction performance can be compensated by strong reasoning systems and is no longer the bottleneck of our system. Notably, unlike conventional frameworks which need retraining upon any module change, attributed to the flexibility of Agent-Driver, all neural modules in our system can be displaced in a *plug-and-play* manner, indicating our system's compatibility.

Compatibility with different LLMs. We tried leveraging the Llama-2-7B [37], gpt-3.5-turbo-1106, and gpt-3.5-turbo-0613 models as the foundation LLMs in our system.

ID	Tool Library	Common. Memory	Exp. Memory	CoT Reason.	Task Plan.	Self-Reflect.	L2 (m) ↓ 1s	2s	3s	Avg.	Collision (%) ↓ 1s	2s	3s	Avg.
1	✗	✓	✓	✓	✓	✗	0.24	0.71	1.44	0.80	0.03	0.27	0.91	0.40
2	✓	✗	✓	✓	✓	✗	0.24	0.69	1.42	0.79	0.03	0.23	0.83	0.37
3	✓	✓	✗	✓	✓	✗	0.24	0.72	1.46	0.81	0.07	0.23	0.96	0.42
4	✓	✓	✓	✗	✓	✗	0.24	0.71	1.45	0.80	0.03	0.23	0.88	0.38
5	✓	✓	✓	✓	✗	✗	0.25	0.72	1.47	0.81	0.05	0.23	0.93	0.40
6	✓	✓	✓	✓	✓	✗	0.24	0.70	1.42	0.79	0.03	0.20	0.81	0.35
7	✓	✓	✓	✓	✓	✓	0.25	0.71	1.43	0.80	0.03	0.08	0.56	0.23

Table 3. **Ablation of components in Agent-Driver.** The removal of any component can influence the planning efficacy of our system, indicating the importance of all components in our system.

Method	L2 (m) ↓ 1s	2s	3s	Avg.	Collision (%) ↓ 1s	2s	3s	Avg.
Llama-2-7B	0.25	0.69	1.47	0.80	0.02	0.27	0.78	0.35
gpt-3.5-turbo-1106	0.24	0.71	1.47	0.80	0.03	0.08	0.63	0.25
gpt-3.5-turbo-0613	0.22	0.65	1.34	0.74	0.02	0.13	0.48	0.21

Table 4. **Compatibility to different LLMs.** Our approach realizes satisfactory motion planning performance utilizing different types of LLMs as agents, verifying the compatibility of our approach.

Percentage of training samples	0.10%	1%	10%	50%	100%
Number of invalid outputs	2	0	0	0	0

Table 5. **Stability of Agent-Driver exposed to different amounts of training samples.** With few training samples, Agent-Driver still attains high output stability and produces *zero* invalid output.

Table 4 demonstrates that Agent-Driver powered by different LLMs can yield satisfactory performances, verifying the compatibility of our system with diverse LLM architectures.

3.6. Stability

LLMs typically suffer from arbitrary predictions—they might produce invalid outputs (*e.g.*, hallucination or invalid formats)— which is detrimental to driving systems. To investigate this effect, we conducted a stability test of our Agent-Driver. Specifically, we used different amounts of training data to instruct the LLMs in our system, and we tested the number of invalid outputs during inference on the validation set. As shown in Table 5, Agent-Driver exposed to only 1% of the training data sees *zero* invalid output during inference of 6,019 validation scenarios, suggesting that our system attains high output stability with proper instructions.

3.7. Empirical Study

Effectiveness of system components. Table 3 shows the results of ablating different components in Agent-Driver. All variants utilize 10% training data for instructing the LLMs. From ID 1 to ID 5, we ablate the main components in Agent-Driver, respectively. We deactivate the self-reflection module and directly evaluate the trajectories output from LLMs to better assess the contribution of each other module. When the tool library is disabled, all perception results form the input to Agent-Driver without selection, which yields ∼2 times more input tokens and harms the system's efficiency. The removal of the tool library also increases the collision rate, indicating the effectiveness of this component. In addition, the collision rate gets worse by removing the commonsense and experience memory, reasoning, and task planning modules, demonstrating the necessity of these components. Besides, we further note that self-reflection also greatly reduces the collision rate.

Modules CoT Reason.+Task Plan.	Motion Plan.	Avg. L2 (m)	Avg. Col. (%)
Fine-tuning	In-context learning	1.81	0.79
In-context learning	In-context learning	1.90	0.79
Fine-tuning	Fine-tuning	0.72	0.22
In-context learning	Fine-tuning	0.74	0.21

Table 6. **In-context learning vs. fine-tuning.** In-context learning performs slightly better in reasoning and task planning. Fine-tuning is indispensable to instruct LLMs for motion planning.

In-context learning vs. fine-tuning. Two prevalent strategies to instruct an LLM for novel tasks are in-context learning and fine-tuning. To determine which is the most effective strategy, we apply these two strategies to the LLMs of the chain-of-thought reasoning, task planning, and motion planning modules respectively, benchmarking them on the downstream motion planning performance. As indicated in Table 6, in-context learning performs slightly better than fine-tuning in collision rates for reasoning and task planning, suggesting that in-context learning is a favorable choice in these modules. In motion planning, the fine-tuning strategy significantly outperforms in-context learning, demonstrating the necessity of fine-tuning LLMs in motion planning.

4. Conclusion

This work introduces Agent-Driver, a novel human-like paradigm that fundamentally transforms autonomous driving pipelines. Our key insight is to leverage LLMs as an agent to schedule different modules in autonomous driving. On top of the LLMs, we propose a tool library, a cognitive memory, and a reasoning engine to bring human-like intelligence into driving systems. Extensive experiments on the real-world driving dataset substantiate the effectiveness, few-shot learning ability, and interpretability of Agent-Driver. These findings shed light on the potential of LLMs as an agent in

human-level intelligent driving systems. For future works, we plan to optimize the LLMs for real-time inference.

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Appendix

1. Related Works

Perception-Prediction-Planning in Driving Systems. Modern autonomous driving systems rely on a perception-prediction-planning paradigm to make driving decisions based on sensory inputs. Perception modules aim to recognize and localize objects in a driving scene, typically in a format of object detection [24, 25, 27, 41] or object occupancy prediction [29, 35]. Prediction modules aim to estimate the future motions of objects, normally represented as predicted trajectories [5, 16, 33] or occupancy flows [1, 6]. Planning modules aim to derive a safe and comfortable trajectory, using rules [2, 7, 11, 20, 31, 34, 38, 39] or learning from human driving trajectories [8, 10, 26]. These three modules are generally performed sequentially, either trained separately or in an end-to-end manner [6, 14, 15, 22, 30]. This perception-prediction-planning framework overly simplifies the human driving process and cannot effectively incorporate human priors such as common sense and past driving experiences. By contrast, our Agent-Driver transforms the conventional perception-prediction-planning framework by introducing LLMs as an agent to bring human-like intelligence into the autonomous driving system.

LLMs in Autonomous Driving. Trained on Internet-scale data, LLMs [3, 28, 36, 37] have demonstrated remarkable capabilities in commonsense reasoning and natural language understanding. How to leverage the power of LLMs to tackle the problem of autonomous driving remains an open challenge. GPT-Driver [26] handled the planning problem in autonomous driving by reformulating motion planning as a language modeling problem and introducing fine-tuned LLMs as a motion planner. DriveGPT4 [44] proposed an end-to-end driving approach that leverages Vision-Language Models to directly map sensory inputs to actions. DiLu [42] introduced a knowledge-driven approach with Large Language Models. These methods mainly focus on an individual component in conventional driving systems, e.g. question-answering [44], planning [26], or control [32]. Some approaches [12, 42] are implemented and evaluated in simple simulated driving environments. By contrast, Agent-Driver presents a systematic approach that leverages LLMs as an agent to schedule the whole driving system, leading to a strong performance on the real-world driving benchmark.

2. Tool Library

In this section, we will first introduce the detailed descriptions of all functions in the tool library (Section 2.1). Next, we will provide a detailed example of how the agent interacts with the tool library (Section 2.2).

2.1. Functions

We include all function definitions in the tool library in Tables 2 and 3. The proposed functions cover detection,

prediction, occupancy, and mapping, and enable flexible and versatile environmental information collection.

2.2. Tool Use

A detailed example of how the LLM leverages tools to collect environmental information is shown in Figures 1 and 2. System prompts are shown in blue, the response of LLMs is shown in green, and the collected data is shown in orange. System prompts provide sufficient context and guidance for instructing the LLM to dynamically invoke the functions in the tool library to collect necessary environmental information.

3. Cognitive Memory

In this section, we detail the data format and retrieving process of the commonsense and experience memory.

3.1. Memory Data

As shown in Figure 5, the commonsense memory consists of essential knowledge for safe driving, which is cached in a text-based format and is fully configurable.

We build the experience memory by caching the environmental information of driving scenarios and corresponding driving trajectories in the training set. Please note that this experience memory can be editable online, meaning that expert demonstrations conducted by human drivers can be easily inserted into the memory and benefit the subsequent decision-making of Agent-Driver.

3.2. Memory Search

We propose a two-stage searching strategy for retrieving the most similar past driving scenario to the query scenario.

In the first stage, we generate a vectorized key $k_i \in \mathbb{R}^{1\times(n_e+n_g+n_h)}$ for each past scenario i by vectorizing its ego-states $e_i \in \mathbb{R}^{1\times n_e}$, mission goals $g_i \in \mathbb{R}^{1\times n_g}$, and historical trajectories $h_i \in \mathbb{R}^{1\times n_h}$. The N past scenarios in the experience memory collectively construct a key tensor $K \in \mathbb{R}^{N\times(n_e+n_g+n_h)}$:

$$K = \{[e_i, g_i, h_i] | i = \{1, 2, ..., N\}\}. \tag{1}$$

Similarly, we can vectorize the query scenario into $Q = [e, g, h] \in \mathbb{R}^{1\times(n_e+n_g+n_h)}$.

Subsequently, we compute the similarity scores $S \in \mathbb{R}^N$ between the querying scenario Q and the past scenarios K:

$$S = Q\Lambda K^\top, \tag{2}$$

where $\Lambda = \mathrm{diag}(\lambda_e, \lambda_g, \lambda_h) \in \mathbb{R}^{(n_e+n_g+n_h)\times(n_e+n_g+n_h)}$ indicates the weights of different components.

Finally, top-K samples with the K highest similarity scores are selected as candidates for the second-stage search.

In the second stage, we propose an LLM-based fuzzy search. A detailed example of this stage is illustrated in Figures 3 and 4. The top-K past driving scenarios selected in the first stage are provided to the LLM. Then, the LLM is tasked to understand the text descriptions of these scenarios and determine the most similar past driving scenario to the query scenario. The driving trajectory corresponding to the selected scenario is also retrieved for reference.

With the proposed vector search and LLM-based fuzzy search, Agent-Driver can effectively retrieve the most similar past driving experience. The past experience and driving decision could help the current decision-making process.

4. Reasoning Engine

In this section, we provide detailed information on the workflow of the reasoning engine. The reasoning engine takes environmental information and memory data as inputs, performs chain-of-thought reasoning, task planning, motion planning, and self-reflection, and eventually generates a driving trajectory for execution. Figures 6, 7, and 8 show an example of how the reasoning engine works. We denote the input environmental information as $\mathcal{O}$ and the retrieved memory data as $\mathcal{M}$. Please note that $\mathcal{O}$ and $\mathcal{M}$ are in the text format.

4.1. Chain-of-Thought Reasoning

Chain-of-thought reasoning aims to emulate the human reasoning process and generate text-based reasoning results $\mathcal{R}$, which can be formulated as:

$$\mathcal{R} = F_{\mathrm{LLM}}(\mathcal{O}, \mathcal{M}), \tag{3}$$

where F_{LLM} is a LLM. To avoid arbitrary reasoning outputs of LLMs which might lead to hallucination and results not relevant to planning, we constrain $\mathcal{R}$ to contain two essential parts: notable objects and potential effects. Specifically, we first instruct the LLM to identify those notable objects that have critical impacts on decision-making from the input environmental information. Then, we instruct the LLM to assess how these notable objects will influence the subsequent decision-making process. The instruction can be established by two strategies: in-context learning and fine-tuning.

For in-context learning, each time we leverage two human-annotated examples $\mathcal{E}$ of notable objects and potential effects in addition to $\mathcal{O}$ and $\mathcal{M}$ collectively as inputs to the LLM:

$$\mathcal{R} = F_{\mathrm{LLM}}(\mathcal{O}, \mathcal{M}, \mathcal{E}). \tag{4}$$

For fine-tuning, we auto-generate the reasoning targets $\hat{\mathcal{R}}$ leveraging the technique proposed in [26]. Then we fine-tune the LLM to make its reasoning outputs $\mathcal{R}$ approaching the targets $\hat{\mathcal{R}}$.

Both in-context learning and fine-tuning effectively reduce invalid outputs. As shown in Table 6 of the main paper, compared to the fine-tuning strategy, in-context learning

Driving behavior	Speed estimation
`move_forward`	`constant_speed`
`change_lane_to_left`	`deceleration`
`change_lane_to_right`	`quick_deceleration`
`turn_left`	`deceleration_to_zero`
`turn_right`	`acceleration`
`stop`	`quick_acceleration`

Table 1. Driving behaviors and speed estimations.

enables the LLMs to generate more diverse reasoning outputs, and results in better motion planning performance.

4.2. Task Planning

Task planning aims to generate high-level driving plans $\mathcal{P}$ for autonomous vehicles, taking the reasoning results $\mathcal{R}$ as well as the environmental information $\mathcal{O}$ and memory data $\mathcal{M}$ as inputs. The process can be formulated as

$$\mathcal{P} = F_{\text{LLM}}(\mathcal{O}, \mathcal{M}, \mathcal{R}). \tag{5}$$

We define the driving plan as a combination of discrete driving behaviors and speed estimations. In this paper, we proposed 6 discrete driving behaviors: `move_forward`, `change_lane_to_left`, `change_lane_to_right`, `turn_left`, `turn_right`, and `stop`. We also propose 6 speed estimations: `constant_speed`, `deceleration`, `quick_deceleration`, `deceleration_to_zero`, `acceleration`, `quick_acceleration`. The combinations of driving behaviors and speed estimations result in 31 different driving plans (`stop` has no speed estimation). These driving plans can cover most driving scenarios and they are fully configurable, which means that we can add more behavior and speed types to cover those long-tailed scenarios. See Table 1 for details.

Similar to the reasoning module, in-context learning and fine-tuning can also be applied to instruct the LLM to generate driving plans. As shown in Table 6 of the main paper, in-context learning is more appropriate for instructing the LLM for task planning.

4.3. Motion Planning

Motion planning aims to plan a safe and comfortable driving trajectory τ, with the driving plan $\mathcal{P}$, reasoning results $\mathcal{R}$, environmental information $\mathcal{O}$, and memory data $\mathcal{M}$ as inputs. The process can be formulated as

$$\tau = F_{\text{LLM}}(\mathcal{O}, \mathcal{M}, \mathcal{R}, \mathcal{P}). \tag{6}$$

The planned trajectory τ can be represented as 6 waypoint coordinates in 3 seconds: $\tau = [(x_1, y_1), \cdots, (x_6, y_6)]$. A recent finding [26] suggests a fine-tuned LLMs can generate text-based coordinates quite accurately. That is, the LLM can generate a text string "(1.23, 0.32)" representing a coordinate, and this can be easily transformed back into its numerical format $(1.23, 0.32)$ for subsequent execution. In particular, given a trajectory τ, we first transform it into a sequence of language tokens w using a tokenizer T:

$$\tau = T(\{(x_1, y_1), \cdots, (x_6, y_6)\}) = \{w_1, \cdots, w_n\}. \tag{7}$$

With these language tokens, we then reformulate motion planning as a language modeling problem:

$$\mathcal{L}_{\text{LM}} = -\sum_{i=1}^{N} \log P(\hat{w}_i | w_1, \cdots, w_{i-1}), \tag{8}$$

where w and $\hat{w}$ are the language tokens of the planned trajectory τ from the LLM and the human driving trajectory $\hat{\tau}$ respectively. By learning to maximize the occurrence probability P of the tokens $\hat{w}$ derived from the human driving trajectory $\hat{\tau}$, the LLM can generate human-like driving trajectories. We suggest readers refer to [26] for more details.

With proper fine-tuning, the LLM is able to generate a text-based trajectory that can be further transformed into its numerical format. This step maps natural-language-based perception, memory, and reasoning into executable driving trajectories, enabling our agent to perform low-level actions.

4.4. Self-Reflection

Self-reflection is designed to reassess and rectify the driving trajectory τ planned by the LLM. Specifically, the `collision_check` function is first invoked to check the collision of τ utilizing the estimated occupancy map. Specifically, we place the ego-vehicle at each waypoint in a trajectory, and then we will mark the trajectory as collision if there is an obstacle within a safe margin η to the ego-vehicle in the occupancy map. If a trajectory is not marked with collision, we directly use this trajectory as output without further rectification. Otherwise, for those trajectories that have collisions, we leverage an optimization approach to rectify the trajectory τ into a collision-free one τ^*. Following [15], we sample the obstacle points O_t near each waypoint at timestep t in the occupancy map. Then, an optimization problem is formulated and solved through the Newton iteration method:

$$\begin{aligned}\tau^* = \arg\min_{\tau} (&\|\tau - \tau^*\|_2 + \\ &\sum_t \sum_{(x,y)\in O_t} \frac{\lambda}{\sigma\sqrt{2\pi}} \exp\left(-\frac{\|\tau_t^* - (x,y)\|_2^2}{2\sigma^2}\right)) \quad ,\end{aligned} \tag{9}$$

where λ and σ are hyperparameters. The first term regulates the optimized trajectory τ^* to be similar to the original τ, and the second term pushes the waypoint τ_t^* in the trajectory away from the obstacle points O_t for each timestep t.

Attributing to self-reflection, those unreliable decisions made by the LLM can further be corrected, and collisions in the planned trajectories can be effectively mitigated.

5. Experiments

5.1. Implementation Details

We employ gpt-3.5-turbo-0613 as the foundation LLM in our Agent-Driver. We leverage the same LLM for every task except motion planning, and we fine-tuned another LLM specially for motion planning.

For tool use and memory search, the LLM is guided by system prompts without fine-tuning or exemplar-based in-context learning. In chain-of-thought reasoning and task planning, the LLM is instructed by two randomly selected exemplars derived from the training set. This approach encourages the models to develop various insightful chain-of-thought processes and detailed plans for tasks independently. Please note that we utilize the original pre-trained LLM with different system prompts and user input for the above tasks. In motion planning, we fine-tune an LLM with human driving trajectories in the training set for only *one epoch*.

5.2. Evaluation Metrics

In this section, we provide more details about the evaluation metrics used in this work. The output trajectory τ is formatted as 6 waypoints in a 3-second horizon, *i.e.*, $\tau = [(x_1, y_1), (x_2, y_2), (x_3, y_3), (x_4, y_4), (x_5, y_5), (x_6, y_6)]$. For τ in each driving scenario, the L2 error is computed as:

$$l_2 = \sqrt{(\tau - \hat{\tau})^2} = \left[\sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}\right]_{i=1}^{6}, \tag{10}$$

where $l_2 \in \mathbb{R}^{6\times 1}$ and $\hat{\tau}$ denotes human driving trajectory. Then, the average L2 error $\bar{l}_2 \in \mathbb{R}^{6\times 1}$ can be computed by averaging l_2 for each sample in the test set.

In the UniAD metric [15], the L2 error at the k-th second ($k = 1, 2, 3$) is reported as the error at this timestep:

$$L_{2,k}^{\text{uniad}} = \bar{l}_2[2k]. \tag{11}$$

The average L2 error is then computed by averaging $L_{2,k}^{\text{uniad}}$ of the 3 timesteps.

In the ST-P3 metric [14] and following works [17, 26], the L2 error at the k-th second is reported as the average error from 0 to k second:

$$L_{2,k}^{\text{stp3}} = \frac{\sum_{t=1}^{2k} \bar{l}_2[t]}{2k}. \tag{12}$$

The average L2 error is computed by averaging the $L_{2,k}^{\text{stp3}}$ of the 3 timesteps again (average over average in other words).

In terms of the collision, it is computed by counting the number of times a planned trajectory collides with other objects in the ground truth occupancy map for all scenarios in the test set. We denote $\mathcal{C} \in \mathbb{N}^{6\times 1}$ as the total collision times at each timestep.

Similarly, UniAD reports the collision $\mathcal{C}_k^{\text{uniad}}$ at the k-th second ($k = 1, 2, 3$) as $\mathcal{C}[2k]$, while ST-P3 reports $\mathcal{C}_k^{\text{stp3}}$ as the average from 0 to k second:

$$\mathcal{C}_k^{\text{stp3}} = \frac{\sum_{t=1}^{2k} \mathcal{C}[t]}{2k}. \tag{13}$$

In addition to the differences in calculation methods, there is also a difference in how the ground truth occupancy maps are generated in the two metrics. Specifically, UniAD only considers the vehicle category when generating ground truth occupancy, while ST-P3 considers both the vehicle and pedestrian categories. This difference leads to varying collision rates for identical planned trajectories when measured by these two metrics, yet it does not impact the L2 error.

In this paper, we faithfully evaluated our approach and the baseline methods using the officially implemented evaluation metrics in the two papers [14, 15], ensuring a completely fair comparison with other methods.

5.3. Limitations

Due to the limitations of the OpenAI APIs, we are unable to obtain the accurate inference time of our Agent-Driver. Thus it remains uncertain whether our approach can meet the real-time demands of commercial driving applications. However, we argue that recent advances in accelerating LLM inference [9, 23, 43] shed light on a promising direction to enable LLMs for real-time applications. We believe the inference problem of LLMs will be resolved in the future.

6. Qualitative Analysis

6.1. Qualitative Results

Figure 9 provides more examples to show the interpretablility of Agent-Driver. Figures 10, 11 and 12 visualize critical objects identified by Agent-Driver and the planned driving trajectories, from which we can see our system progressively identifies critical objects via tool use and reasoning, and eventually plans a safe trajectory for driving. Driving videos are shown in Figures 13, 14, and 15. The qualitative results verify the effectiveness and interpretability of our Agent-Driver.

6.2. Failure Cases

We provide failure cases in Agent-Driver in Figure 16. We observed that heading errors of large objects, *e.g.*, buses, have a critical impact on motion planning, which indicates the importance of accurate heading prediction in detection networks.

Task	Function Name	Function Descriptions	Parameters
Detection	get_leading_object_detection	Get the detection of the leading object, the function will return the leading object id and its position and size. If there is no leading object, return None.	Null
	get_surrounding_object_detections	Get the detections of the surrounding objects in a 20m*20m range, the function will return a list of surrounding object ids and their positions and sizes. If there is no surrounding object, return None.	Null
	get_front_object_detections	Get the detections of the objects in front of you in a 20m*40m range, the function will return a list of front object ids and their positions and sizes. If there is no front object, return None.	Null
	get_object_detections_in_range	Get the detections of the objects in a customized range (x_start, x_end)*(y_start, y_end)m^2, the function will return a list of object ids and their positions and sizes. If there is no object, return None.	[“x_start”, “x_end”, “y_start”, “y_end”]
	get_all_object_detections	Get the detections of all objects in the whole scene, the function will return a list of object ids and their positions and sizes. Always avoid using this function if there are other choices.	Null
Prediction	get_leading_object_future_trajectory	Get the predicted future trajectory of the leading object, the function will return a trajectory containing a series of waypoints. If there is no leading vehicle, return None.	Null
	get_future_trajectories_for_specific_objects	Get the future trajectories of specific objects (specified by a List of object ids), the function will return trajectories for each object. If there is no object, return None.	[“object_ids”]
	get_future_trajectories_in_range	Get the future trajectories where any waypoint in this trajectory falls into a given range (x_start, x_end)*(y_start, y_end)m^2, the function will return each trajectory that satisfies the condition. If there is no trajectory satisfied, return None	[“x_start”, “x_end”, “y_start”, “y_end”]
	get_future_waypoint_of_specific_objects_at_timestep	Get the future waypoints of specific objects at a specific timestep, the function will return a list of waypoints. If there is no object or the object does not have a waypoint at the given timestep, return None.	[“object_ids”, “timestep”]
	get_all_future_trajectories	Get the predicted future trajectories of all objects in the whole scene, the function will return a list of object ids and their future trajectories. Always avoid using this function if there are other choices.	Null

Table 2. Function definitions in the tool library.

Task	Function Name	Function Descriptions	Parameters
Map	get_drivable_at_locations	Get the drivability at the locations $[(x_1, y_1), ..., (x_n, y_n)]$. If the location is out of the map scope, return None.	["locations"]
	check_drivable_of_planned_trajectory	Check the drivability at the planned trajectory.	["trajectory"]
	get_lane_category_at_locations	Get the lane category at the locations $[(x_1, y_1), ..., (x_n, y_n)]$. If the location is out of the map scope, return None.	["locations", "ret_prob"]
	get_distance_to_shoulder_at_locations	Get the distance to both sides of road shoulders at the locations $[(x_1, y_1), ..., (x_n, y_n)]$. If the location is out of the map scope, return None.	["locations"]
	get_current_shoulder	Get the distance to both sides of road shoulders for the current ego-vehicle location.	Null
	get_distance_to_lane_divider_at_locations	Get the distance to both sides of road lane dividers at the locations $[(x_1, y_1), ..., (x_n, y_n)]$. If the location is out of the map scope, return None.	["locations"]
	get_current_lane_divider	Get the distance to both sides of road lane dividers for the current ego-vehicle location.	Null
	get_nearest_pedestrian_crossing	Get the location of the nearest pedestrian crossing to the ego-vehicle. If there is no such pedestrian crossing, return None.	Null
Occupancy	get_occupancy_at_locations_for_timestep	Get the probability whether a list of locations $[(x_1, y_1), ..., (x_n, y_n)]$ is occupied at the timestep t. If the location is out of the occupancy prediction scope, return None.	["locations", "timestep"]
	check_collision_for_planned_trajectory	Check the probability of whether a planned trajectory $[(x_1, y_1), ..., (x_n, y_n)]$ collides with other objects.	["trajectory"]

Table 3. Function definitions in the tool library. Cont'd.

A Language Agent for Autonomous Driving
Role: You are the brain of an autonomous vehicle (a.k.a. ego-vehicle). In this step, you need to extract necessary information from the driving scenario. The information you extracted must be useful to the next-step motion planning.

Necessary information might include the following:
- Detections: The detected objects that you need to pay attention to.
- Predictions: The estimated future motions of the detected objects.
- Maps: Map information includes traffic lanes and road boundaries.
- Occunpancy: Occupancy implies whether a location has been occupied by other objects.

Task
- You should think about what types of information (Detections, Predictions, Maps, Occupancy) you need to extract from the driving scenario.
- Detections and Predictions are quite important for motion planning. You should call at least one of them if necessary.
- Maps information are also important. You should pay more attention to road shoulder and lane divider information to your current ego-vehicle location.
- I will guide you through the thinking process step by step.

*****Context Information:*****
Current State:
- Velocity (vx,vy): (-0.01,0.92)
- Heading Angular Velocity (v_yaw): (0.00)
- Acceleration (ax,ay): (-0.00,-0.50)
- Can Bus: (-0.74,0.14)
- Heading Speed: (0.95)
- Steering: (-0.02)
Historical Trajectory (last 2 seconds): [(-0.07,-6.43), (-0.05,-4.34), (-0.02,-2.32), (-0.01,-0.91)]
Mission Goal: FORWARD

Do you need to perform detections in this driving scenario?
Please answer YES or NO.

YES

You can execute one of the following functions to get object detection results (don't execute functions that have been used before):
- get_leading_object_detection() #Get the detection of the leading object, the function will return the leading object id and its position and size. If there is no leading object, return None
- get_object_detections_in_range(x_start, x_end, y_start, y_end) #Get the detections of the objects in a given range (x_start, x_end)*(y_start, y_end)m^2, the function will return a list of object ids and their positions and sizes. If there is no object, return None
- get_surrounding_object_detections() #Get the detections of the surrounding objects in a 20m*20m range, the function will return a list of surroundind object ids and their positions and sizes. If there is no surrounding object, return None
- get_front_object_detections() #Get the detections of the objects in front of you in a 10m*20m range, the function will return a list of front object ids and their positions and sizes. If there is no front object, return None
- get_all_object_detections() #Get the detections of all objects in the whole scene, the function will return a list of object ids and their positions and sizes. Always avoid using this function if there are other choices.

{“name”: “get_front_object_detections”, “arguments”: “{}”}

Front object detections:
Front object detected, object type: car, object id: 2, position: (4.36, 9.56), size: (1.86, 4.72)
Front object detected, object type: car, object id: 3, position: (-3.70, 13.08), size: (2.01, 4.92)

Do you need to perform future trajectory predictions for the detected objects?
Please answer YES or NO.

YES

Figure 1. An example of the tool use process.

You can execute one of the following functions to get object future trajectory predictions (don't execute functions that have been used before):
- get_leading_object_future_trajectory() #Get the predicted future trajectory of the leading object, the function will return a trajectory containing a series of waypoints. If there is no leading vehicle, return None
- get_future_trajectories_for_specific_objects(object_ids) #Get the future trajectories of specific objects (specified by a List of object ids), the function will return trajectories for each object. If there is no object, return None
- get_future_trajectories_in_range(x_start, x_end, y_start, y_end) #Get the future trajectories where any waypoint in this trajectory falls into a given range (x_start, x_end)*(y_start, y_end)m^2, the function will return each trajectory that satisfies the condition. If there is no trajectory satisfied, return None
- get_future_waypoint_of_specific_objects_at_timestep(object_ids, timestep) #Get the future waypoints of specific objects at a specific timestep, the function will return a list of waypoints. If there is no object or the object does not have a waypoint at the given timestep, return None
- get_all_future_trajectories() #Get the predicted future trajectories of all objects in the whole scene, the function will return a list of object ids and their future trajectories. Always avoid using this function if there are other choices.

{“name”: “get_future_trajectories_for_specific_objects”, “arguments”: “'object_ids': [2, 3]”}

Future trajectories for specific objects:
Object type: car, object id: 2, future waypoint coordinates in 3s: [(4.36, 9.56), (4.36, 9.56), (4.36, 9.57), (4.36, 9.57), (4.36, 9.56), (4.36, 9.56)]
Object type: car, object id: 3, future waypoint coordinates in 3s: [(-2.66, 13.82), (-1.69, 14.79), (-0.99, 16.13), (-0.25, 17.73), (0.19, 19.42), (0.57, 21.35)]

Do you need to get occupancy information for this driving scenario?
Please answer YES or NO.

NO

Do you need to get map information for this driving scenario?
Please answer YES or NO.

YES

You can execute one of the following functions to get map information (don't execute functions that have been used before):
- get_drivable_at_locations(locations) #Get the drivability at the locations [(x_1, y_1), ..., (x_n, y_n)]. If the location is out of the map scope, return None
- get_lane_category_at_locations(locations, return_score) #Get the lane category at the locations [(x_1, y_1), ..., (x_n, y_n)]. If the location is out of the map scope, return None
- get_distance_to_shoulder_at_locations(locations) #Get the distance to both sides of road shoulders at the locations [(x_1, y_1), ..., (x_n, y_n)]. If the location is out of the map scope, return None
- get_current_shoulder() #Get the distance to both sides of road shoulders for the current ego-vehicle location.
- get_distance_to_lane_divider_at_locations(locations) #Get the distance to both sides of road lane_dividers at the locations [(x_1, y_1), ..., (x_n, y_n)]. If the location is out of the map scope, return None
- get_current_lane_divider() #Get the distance to both sides of road lane_dividers for the current ego-vehicle location
- get_nearest_pedestrian_crossing() #Get the location of the nearest pedestrian crossing to the ego-vehicle. If there is no such pedestrian crossing, return None

{“name”: “get_current_shoulder”, “arguments”: “{}”}

Distance to both sides of road shoulders of current ego-vehicle location:
Current ego-vehicle's distance to left shoulder is 7.5m and right shoulder is 4.0m

Figure 2. An example of the tool use process. Cont’d.

A Language Agent for Autonomous Driving
Role: You are the brain of an autonomous vehicle (a.k.a. ego-vehicle). In this step, you need to retrieve the most similar past driving experience to help decision-making.

Task
- You will receive the current driving scenario.
- You will also receive several past driving experiences.
- You should decide ONLY ONE experience that is most similar to the current scenario based on the information provided.
- Please answer ONLY the index (e.g., 0, 1, 2) of the most similar experience.

A Language Agent for Autonomous Driving
Role: You are the brain of an autonomous vehicle (a.k.a. ego-vehicle). In this step, you need to retrieve the most similar past driving experience to help decision-making.

Task
- You will receive the current driving scenario.
- You will also receive several past driving experiences.
- You should decide ONLY ONE experience that is most similar to the current scenario based on the information provided.
- Please answer ONLY the index (e.g., 0, 1, 2) of the most similar experience.

Current Scenario:
*****Environmental Information:*****
Current State:
- Velocity (vx,vy): (-0.01,0.92)
- Heading Angular Velocity (v_yaw): (0.00)
- Acceleration (ax,ay): (-0.00,-0.50)
- Can Bus: (-0.74,0.14)
- Heading Speed: (0.95)
- Steering: (-0.02)

Historical Trajectory (last 2 seconds): [(-0.07,-6.43), (-0.05,-4.34), (-0.02,-2.32), (-0.01,-0.91)]
Mission Goal: FORWARD

Front object detections:
Front object detected, object type: car, object id: 2, position: (4.36, 9.56), size: (1.86, 4.72)
Front object detected, object type: car, object id: 3, position: (-3.70, 13.08), size: (2.01, 4.92)

Future trajectories for specific objects:
Object type: car, object id: 2, future waypoint coordinates in 3s: [(4.36, 9.56), (4.36, 9.56), (4.36, 9.57), (4.36, 9.57), (4.36, 9.56), (4.36, 9.56)]
Object type: car, object id: 3, future waypoint coordinates in 3s: [(-2.66, 13.82), (-1.69, 14.79), (-0.99, 16.13), (-0.25, 17.73), (0.19, 19.42), (0.57, 21.35)]

Distance to both sides of road shoulders of current ego-vehicle location:
Current ego-vehicle's distance to left shoulder is 7.5m and right shoulder is 4.0m

Found 3 relevant experiences:

Past Driving Experience 1:
*****Past Environmental Information:*****
Current State:
- Velocity (vx,vy): (0.00,1.07)
- Heading Angular Velocity (v_yaw): (-0.00)
- Acceleration (ax,ay): (-0.02,-0.43)
- Can Bus: (-0.67,0.03)
- Heading Speed: (1.00)
- Steering: (0.13)

Historical Trajectory (last 2 seconds): [(-0.16,-6.66), (-0.08,-4.46), (-0.03,-2.55), (-0.00,-1.06)]
Mission Goal: FORWARD

Future trajectories for specific objects:
Object type: car, object id: 2, future waypoint coordinates in 3s: [(-1.13, -13.82), (-1.09, -12.18), (-1.05, -10.66), (-0.98, -9.22), (-0.98, -7.96), (-0.93, -6.74)]
Object type: car, object id: 3, future waypoint coordinates in 3s: [(-25.19, -17.79), (-25.19, -17.79), (-25.18, -17.78), (-25.18, -17.78), (-25.18, -17.78), (-25.17, -17.78)]

Figure 3. An example of the memory search process.

Past Driving Experience 2:
*****Past Environmental Information:*****
Current State:
- Velocity (vx,vy): (-0.01,0.97)
- Heading Angular Velocity (v_yaw): (0.00)
- Acceleration (ax,ay): (-0.01,-0.46)
- Can Bus: (-0.68,0.11)
- Heading Speed: (1.16)
- Steering: (0.04)
Historical Trajectory (last 2 seconds): [(-0.06,-6.03), (-0.04,-4.10), (-0.02,-2.40), (-0.01,-0.97)]
Mission Goal: FORWARD

Front object detections:
Front object detected, object type: car, object id: 0, position: (-0.58, 9.54), size: (1.75, 3.99)
Front object detected, object type: car, object id: 2, position: (3.57, 7.27), size: (1.88, 4.49)
Front object detected, object type: truck, object id: 3, position: (-0.08, 19.97), size: (2.93, 9.04)
Future trajectories for specific objects:
Object type: car, object id: 2, future waypoint coordinates in 3s: [(3.59, 12.47), (3.61, 17.78), (3.68, 23.26), (3.70, 28.79), (3.66, 34.46), (3.65, 40.07)]
Object type: truck, object id: 3, future waypoint coordinates in 3s: [(-0.08, 19.96), (-0.08, 19.93), (-0.09, 19.93), (-0.09, 19.92), (-0.08, 19.92), (-0.09, 19.91)]

Past Driving Experience 3:
*****Past Environmental Information:*****
Current State:
- Velocity (vx,vy): (-0.01,1.06)
- Heading Angular Velocity (v_yaw): (-0.00)
- Acceleration (ax,ay): (0.00,-0.32)
- Can Bus: (-0.77,0.04)
- Heading Speed: (1.06)
- Steering: (-0.01)
Historical Trajectory (last 2 seconds): [(-0.08,-6.01), (-0.05,-4.12), (-0.04,-2.43), (-0.02,-1.06)]
Mission Goal: FORWARD

Front object detections:
Front object detected, object type: car, object id: 1, position: (-3.08, 2.56), size: (1.88, 4.52)
Future trajectories for specific objects:
Object type: car, object id: 2, future waypoint coordinates in 3s: [(-18.54, -24.30), (-18.54, -24.30), (-18.54, -24.30), (-18.54, -24.30), (-18.54, -24.31), (-18.54, -24.31)]
Object type: car, object id: 3, future waypoint coordinates in 3s: [(-3.26, -31.78), (-3.43, -28.27), (-3.36, -25.04), (-3.45, -22.14), (-3.46, -19.62), (-3.51, -17.45)]

Please return the index 1-3 of the most similar experience:

2

*****Past Driving Experience for Reference:*****
Most similar driving experience from memory with confidence score: 0.75:
The planned trajectory in this experience for your reference:
[(0.01,0.98), (0.01,1.87), (0.02,2.40), (0.02,2.64), (0.02,2.76), (0.02,2.86)]

Figure 4. An example of the memory search process. Cont'd.

*****Common Sense:*****
- Avoid collision with other objects.
- Always drive on drivable regions.
- Avoid driving on occupied regions.
- Pay attention to your ego-states and historical trajectory when planning.
- Maintain a safe distance from the objects in front of you.

Figure 5. Retrieved commonsense memory.

A Language Agent for Autonomous Driving
Role: You are the brain of an autonomous vehicle (a.k.a. ego-vehicle). In this step, you need to first determine notable objects and identify their potential effects on your driving route, and then derive a high-level driving plan.

Context:
- Coordinates: X-axis is perpendicular, and Y-axis is parallel to the direction you're facing. You're at point (0,0). Units: meters.

Input
- You will receive your current ego-states.
- You will also receive current perception results.

Task
- You need to determine the notable objects based on perception results and ego-states. Notable objects are the objects that will have potential effects on your driving route. So you should always pay attention to the objects in front (with positive y) of you, and the objects that are close (within 1.5 meters) to you.
- You need to describe the potential effects of those notable objects on your driving route.
- You need to derive a high-level driving plan based on the former information and reasoning results.
The driving plan should be a combination of a meta action from ["STOP", "MOVE FORWARD", "TURN LEFT", "CHANGE LANE TO LEFT", "TURN RIGHT", "CHANE LANE TO RIGHT"], and a speed description from ["A CONSTANT SPEED", "A DECELERATION", "A QUICK DECELERATION", "A DECELERATION TO ZERO", "AN ACCELERATION", "A QUICK ACCELERATION"] if the meta action is not "STOP".
- **Strictly follow the output format.**

Output:
*****Chain-of-Thoughts Reasoning:*****
- Notable Objects:
  Potential Effects:
- Notable Objects:
  Potential Effects:
*****Task Planning:*****
Behavior: , Speed:
Driving plan:

Here are examples for your reference:

Example 1
Input:
*****Environmental Information:*****
Current State:
- Velocity (vx,vy): (-0.02,2.66)
- Heading Angular Velocity (v_yaw): (-0.01)
- Acceleration (ax,ay): (0.00,0.00)
- Can Bus: (-1.72,-0.95)
- Heading Speed: (2.83)
- Steering: (1.12)
Historical Trajectory (last 2 seconds): [(-1.16,-10.63), (-0.87,-7.97), (-0.58,-5.32), (-0.29,-2.66)]
Mission Goal: RIGHT

Front object detections:
Front object detected, object type: bicycle, object id: 0, position: (-1.02, 7.49), size: (0.49, 1.67)
Front object detected, object type: car, object id: 1, position: (8.71, 18.66), size: (1.92, 4.55)

Future trajectories for specific objects:
Object type: bicycle, object id: 0, future waypoint coordinates in 3s: [(-1.02, 7.51), (-1.02, 7.52), (-1.02, 7.54), (-1.03, 7.55), (-1.02, 7.59), (-1.02, 7.61)]
Object type: car, object id: 1, future waypoint coordinates in 3s: [(8.71, 18.66), (8.70, 18.65), (8.69, 18.65), (8.69, 18.64), (8.69, 18.63), (8.69, 18.65)]

Distance to both sides of road shoulders of current ego-vehicle location:
Current ego-vehicle's distance to left shoulder is 1.0m and right shoulder is 0.5m

Expected Output:
*****Chain-of-Thoughts Reasoning:*****
- Notable Objects: bicycle at (-1.02,7.49), moving to (-1.02,7.51) at 0.5 second
  Potential Effects: within the safe zone of the ego-vehicle at 0.5 second
*****Task Planning:*****
Behavior: TURN RIGHT, Speed: A CONSTANT SPEED
Driving plan: TURN RIGHT WITH A CONSTANT SPEED

Figure 6. An example of chain-of-thought reasoning and task planning.

Example 2
Input:
*****Environmental Information:*****
Current State:
- Velocity (vx,vy): (-0.10,5.42)
- Heading Angular Velocity (v_yaw): (-0.00)
- Acceleration (ax,ay): (0.02,1.14)
- Can Bus: (0.92,0.25)
- Heading Speed: (4.53)
- Steering: (0.03)
Historical Trajectory (last 2 seconds): [(-0.17,-17.86), (-0.11,-13.82), (-0.07,-9.70), (-0.04,-5.42)]
Mission Goal: FORWARD

Front object detections:
Front object detected, object type: pedestrian, object id: 4, position: (6.49, 16.88), size: (0.66, 0.72)

Future trajectories for specific objects:
Object type: pedestrian, object id: 4, future waypoint coordinates in 3s: [(6.46, 17.53), (6.44, 18.20), (6.42, 18.89), (6.38, 19.57), (6.37, 20.26), (6.34, 20.91)]

Distance to both sides of road shoulders of selected locations:
Location (6.49, 16.88) distance to left shoulder is 2.5m and distance to right shoulder is uncertain

Expected Output:
*****Chain-of-Thoughts Reasoning:*****
- Notable Objects: car at (2.44,44.97)
  Potential Effects: within the safe zone of the ego-vehicle at 2.5 second
*****Task Planning:*****
Behavior: MOVE FORWARD, Speed: A DECELERATION
Driving plan: MOVE FORWARD WITH A DECELERATION

*****Environmental Information:*****
Current State:
- Velocity (vx,vy): (-0.01,0.92)
- Heading Angular Velocity (v_yaw): (0.00)
- Acceleration (ax,ay): (-0.00,-0.50)
- Can Bus: (-0.74,0.14)
- Heading Speed: (0.95)
- Steering: (-0.02)
Historical Trajectory (last 2 seconds): [(-0.07,-6.43), (-0.05,-4.34), (-0.02,-2.32), (-0.01,-0.91)]
Mission Goal: FORWARD

Front object detections:
Front object detected, object type: car, object id: 2, position: (4.36, 9.56), size: (1.86, 4.72)
Front object detected, object type: car, object id: 3, position: (-3.70, 13.08), size: (2.01, 4.92)

Future trajectories for specific objects:
Object type: car, object id: 2, future waypoint coordinates in 3s: [(4.36, 9.56), (4.36, 9.56), (4.36, 9.57), (4.36, 9.57), (4.36, 9.56), (4.36, 9.56)]
Object type: car, object id: 3, future waypoint coordinates in 3s: [(-2.66, 13.82), (-1.69, 14.79), (-0.99, 16.13), (-0.25, 17.73), (0.19, 19.42), (0.57, 21.35)]

Distance to both sides of road shoulders of selected locations:
Location (4.36, 9.56) distance to left shoulder is 16.5m and right shoulder is 0.5m
Location (-3.70, 13.08) distance to left shoulder is 13.0m and right shoulder is 8.5m

*****Chain of Thoughts Reasoning:*****
- Notable Objects: car at (4.36,9.56)
  Potential Effects: within the safe zone of the ego-vehicle at 0.5 second
- Notable Objects: car at (-3.70,13.08)
  Potential Effects: within the safe zone of the ego-vehicle at 0.5 second
*****Task Planning:*****
Driving plan: MOVE FORWARD WITH A DECELERATION

Figure 7. An example of chain-of-thought reasoning and task planning. Cont'd.

Autonomous Driving Planner
Role: You're an autonomous vehicle's brain. Plan a 3-second safe trajectory to avoid obstacles.

Context:
- Coordinates: X-axis is perpendicular, and Y-axis is parallel to the direction you're facing. You're at point (0,0). Units: meters.
- Goal: Plan a 3-second route using 6 waypoints (0.5s intervals).

Inputs:
1. Ego States (important): Current stats (velocity, acceleration), past trajectory, goal direction.
2. Perception Results.
3. Past Experiences (important): Previous similar experiences with confidence scores and referenced planned trajectory.
4. Traffic Rules.
5. Reasoning (important): Notable objects affecting your plan and a top-level driving plan.

Task:
- Based on inputs, plan a safe, feasible 3-second trajectory of 6 waypoints.

Output:
Planned Trajectory:
[(x1,y1), (x2,y2), ... , (x6,y6)]

*****Environmental Information:*****
Current State:
- Velocity (vx,vy): (-0.01,0.92)
- Heading Angular Velocity (v_yaw): (0.00)
- Acceleration (ax,ay): (-0.00,-0.50)
- Can Bus: (-0.74,0.14)
- Heading Speed: (0.95)
- Steering: (-0.02)
Historical Trajectory (last 2 seconds): [(-0.07,-6.43), (-0.05,-4.34), (-0.02,-2.32), (-0.01,-0.91)]
Mission Goal: FORWARD

Front object detections:
Front object detected, object type: car, object id: 2, position: (4.36, 9.56), size: (1.86, 4.72)
Front object detected, object type: car, object id: 3, position: (-3.70, 13.08), size: (2.01, 4.92)

Future trajectories for specific objects:
Object type: car, object id: 2, future waypoint coordinates in 3s: [(4.36, 9.56), (4.36, 9.56), (4.36, 9.57), (4.36, 9.57), (4.36, 9.56), (4.36, 9.56)]
Object type: car, object id: 3, future waypoint coordinates in 3s: [(-2.66, 13.82), (-1.69, 14.79), (-0.99, 16.13), (-0.25, 17.73), (0.19, 19.42), (0.57, 21.35)]

Distance to both sides of road shoulders of selected locations:
Location (4.36, 9.56) distance to left shoulder is 16.5m and right shoulder is 0.5m
Location (-3.70, 13.08) distance to left shoulder is 13.0m and right shoulder is 8.5m

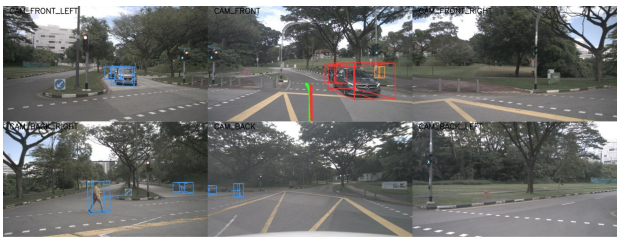
*****Past Driving Experience for Reference:*****
Most similar driving experience from memory with confidence score: 0.75:
The planned trajectory in this experience for your reference:
[(0.01,0.98), (0.01,1.87), (0.02,2.40), (0.02,2.64), (0.02,2.76), (0.02,2.86)]

*****Common Sense:*****
- Avoid collision with other objects.
- Always drive on drivable regions.
- Avoid driving on occupied regions.
- Pay attention to your ego-states and historical trajectory when planning.
- Maintain a safe distance from the objects in front of you.

*****Chain of Thoughts Reasoning:*****
Thoughts:
- Notable Objects: car at (4.36,9.56), moving to (4.36,9.57) at 0.5 second
  Potential Effects: within the safe zone of the ego-vehicle at 0.5 second
- Notable Objects: car at (-3.70,13.08), moving to (0.57,21.35) at 2.5 second
  Potential Effects: within the safe zone of the ego-vehicle at 2.5 second
*****Task Planning:*****
Driving plan: MOVE FORWARD WITH A DECELERATION

Planned Trajectory:
[(0.01,0.77), (0.01,1.43), (0.02,1.92), (0.02,2.27), (0.02,2.47), (0.02,2.57)]

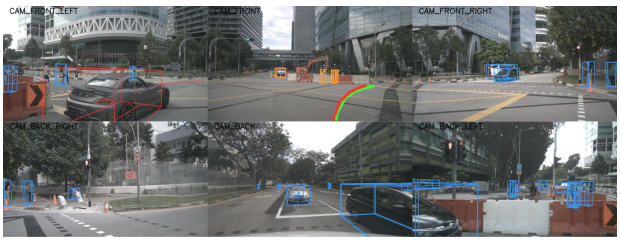
Figure 8. An example of motion planning.



*****Environmental information:*****
Front object detections:
Front object detected, object type: car, object id: 1, position: (2.40, 10.22), size: (1.91, 4.66)
...
Front object detected, object type: car, object id: 8, position: (2.39, 10.21), size: (1.92, 4.67)
Future trajectories for specific objects:
Object type: car, object id: 1, future waypoint coordinates in 3s: [(2.44, 9.83),...]
...
Object type: car, object id: 8, future waypoint coordinates in 3s: [(2.43, 9.84),...]
Map information (road shoulders):
Current ego-vehicle's distance to left shoulder is 8.5m and right shoulder is 13.0m

*****Common sense:*****
- Avoid collision with other objects...
*****Past driving experience for reference:*****
Most similar driving experience from memory with similarity score: 0.75:
Scenario information: ...
The planned trajectory in this scenario for your reference: [(0.00,2.15), ..., (-0.11,12.99)]

*****Chain-of-thoughts reasoning:*****
- Notable Objects: car at (2.40,10.22), moving to (2.47,9.46) at 1.0 second
- Potential Effects: within the safe zone of the ego-vehicle at 1.0 second
...
*****Task planning:*****
Behavior: forward; Speed: acceleration; Driving plan: move forward with an acceleration
*****Motion planning:*****
Trajectory: [(-0.02,2.15), (-0.07,4.56), (-0.10,7.11), (-0.17,9.92), (-0.32,12.92), (-0.63,16.20)]
*****Self-reflection:*****
No collision. No change to the motion planning result.



*****Environmental information:*****
Surrounding object detections:
Surrounding object detected, object type: car, object id: 5, position: (-4.53, 3.85), size: (1.80, 4.37)
...
Future trajectories for specific objects:
Object type: car, object id: 5, future waypoint coordinates in 3s: [(-5.36, 6.26),...]
...
Map information (road shoulders):
Current ego-vehicle's distance to left shoulder is 5.0m and right shoulder is 1.0m

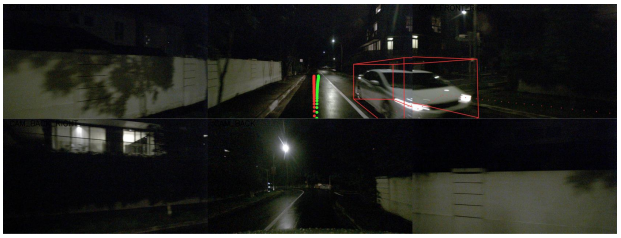
*****Common sense:*****
- Avoid collision with other objects...
*****Past driving experience for reference:*****
Most similar driving experience from memory with similarity score: 0.50:
Scenario information: ...
The planned trajectory in this scenario for your reference:[(0.12,2.12), ... , (4.79,13.52)]

*****Chain-of-thoughts reasoning:*****
- Notable objects: car at (-4.53,3.85)
- Potential effects: within the safe zone of the ego-vehicle at 0.5 second.
...
*****Task planning:*****
Behavior: turn right; Speed: constant; Driving plan: turn right with a constant speed.
*****Motion planning:*****
Trajectory: [(0.22,2.70), (0.65,5.15), (1.36,7.68), (2.44,10.22), (3.78,12.48), (5.04,14.15)]
*****Self-reflection:*****
No collision. No change to the motion planning result.

*****Environmental information:*****
Leading object detections:
Leading object detected, object type: car, object id: 0, position: (0.17, 11.05), size: (1.82, 4.34)
...
Future trajectories for specific objects:
Object type: car, object id: 0, future waypoint coordinates in 3s: [(0.18, 12.21),...]
...
Map information (road shoulders):
Current ego-vehicle's distance to left shoulder is 1.0m and right shoulder is 4.0m

*****Common sense:*****
- Avoid collision with other objects...
*****Past driving experience for reference:*****
Most similar driving experience from memory with similarity score: 0.89:
Scenario information: ...
The planned trajectory in this scenario for your reference: [(0.03,2.64), ..., (0.01,10.13)]

*****Chain-of-thoughts reasoning:*****
- Notable Objects: car at (0.17,11.05)
- Potential Effects: within the safe zone of the ego-vehicle at 1.5 second
...
*****Task planning:*****
Behavior: forward; Speed: deceleration; Driving plan: move forward with a deceleration
*****Motion planning:*****
Trajectory: [(0.01,2.26), (0.02,4.22), (0.02,5.82), (0.01,7.14), (0.02,8.19), (0.02,8.92)]
*****Self-reflection:*****
No collision. No change to the motion planning result.



*****Environmental information:*****
Front object detections:
Front object detected, object type: car, object id: 0, position: (2.79, 6.20), size: (1.83, 4.37)
Future trajectories for specific objects:
Object type: car, object id: 0, future waypoint coordinates in 3s: [(2.73, 2.45),...]
Map information (road shoulders):
Current ego-vehicle's distance to left shoulder is 1.5m and right shoulder is 3.5m

*****Common sense:*****
- Avoid collision with other objects...
*****Past driving experience for reference:*****
Most similar driving experience from memory with similarity score: 0.79:
Scenario information: ...
The planned trajectory in this scenario for your reference:[(0.04,3.99), ... , (-0.04,25.64)]

*****Chain-of-thoughts reasoning:*****
- Notable objects: car at (2.79,6.20)
- Potential effects: within the safe zone of the ego-vehicle at 0.5 second.
...
*****Task planning:*****
Behavior: forward; Speed: constant; Driving plan: move forward with a constant speed.
*****Motion planning:*****
Trajectory: [(0.07,3.95), (0.22,9.04), (0.39,13.77), (0.61,18.50), (0.82,23.20), (0.93,27.92)]
*****Self-reflection:*****
No collision. No change to the motion planning result.

Figure 9. Interpretability of Agent-Driver.

Figure 10. Visualization of how Agent-Driver progressively identifies critical objects and performs motion planning.

Figure 11. Visualization of how Agent-Driver progressively identifies critical objects and performs motion planning.

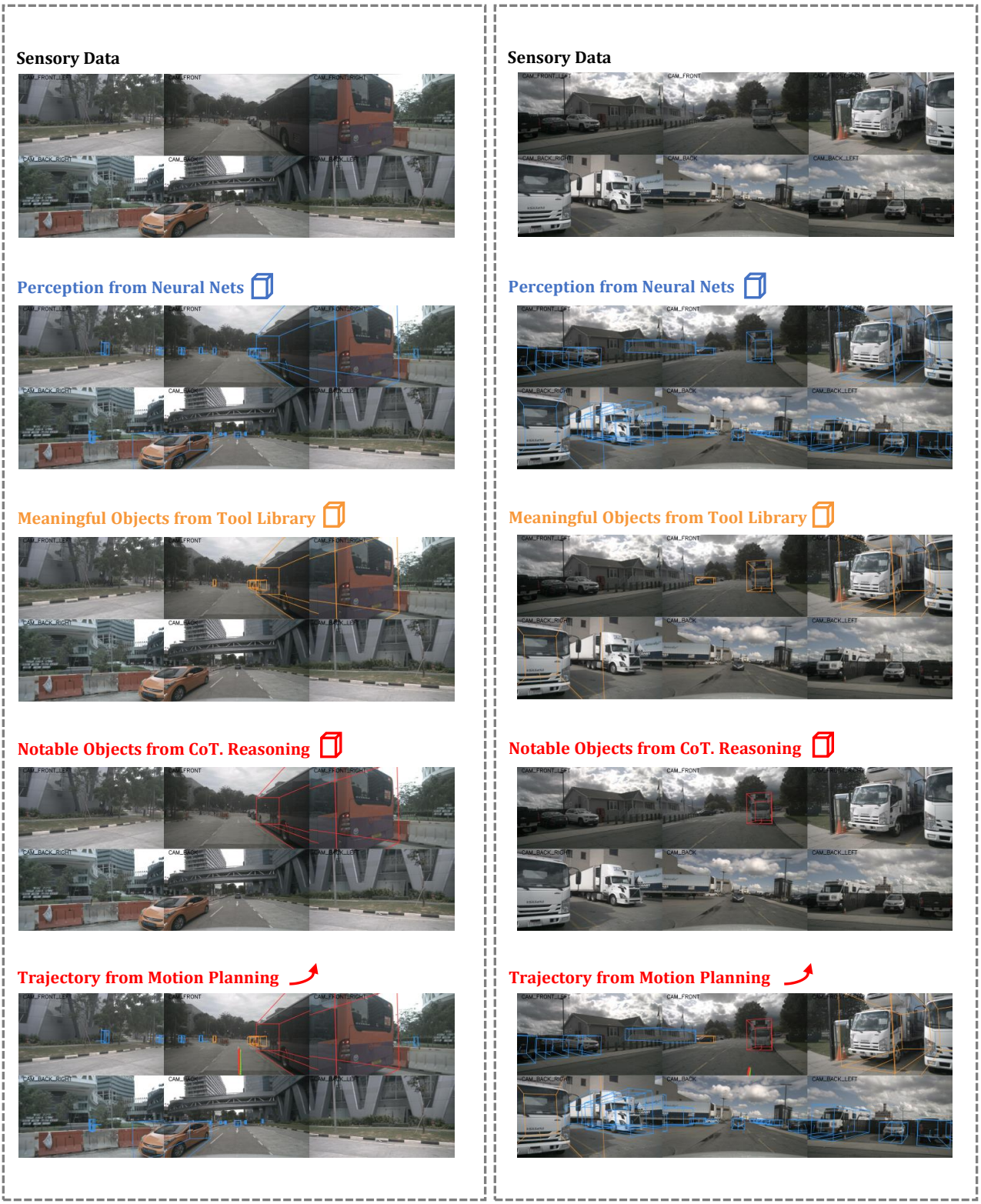


Figure 12. Visualization of how Agent-Driver progressively identifies critical objects and performs motion planning.

Figure 13. Driving video of Agent-Driver.

Figure 14. Driving video of Agent-Driver.

Figure 15. Driving video of Agent-Driver.

Failure Case 1:
Inaccurate heading estimations for large objects, such as buses, result in a more conservative turning trajectory.

Failure Case 2:
Inaccurate heading estimations for large objects, such as buses, result in different driving behaviors from deceleration to acceleration.

Figure 16. Failure cases in Agent-Driver.