

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 approach, 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 approach 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. Instinctively, a human driver would decelerate, watch out for the possible emergence of a chasing child. Human drivers leverage extensive experiential knowledge, not only perceiving the immediate presence of the ball, but also reasoning on the potential occurrence of the child. 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.

To integrate human prior knowledge into autonomous driving systems, previous approaches [6, 13, 14, 16, 27] deconstruct the human driving process into three systematic steps following Figure 1 (a). *Perception*: they interpret the human perceptual process as object detection [24] or occupancy estimation [26]. *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 [35] or by learning from data [41]. Despite its efficacy, this *perception-prediction-planning* framework overly simplifies the human driving process and cannot fully model the complexity of driving scenarios. For instance, perception modules in these methods are notably redundant, necessitating the detection of all objects in a vast perception range, potentially including distracting 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 obstacle of integrating human priors into autonomous driving lies in the incompatibility of human knowledge and neural-network-based driving systems. Human knowledge can be naturally stored 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

*indicates equal contribution.

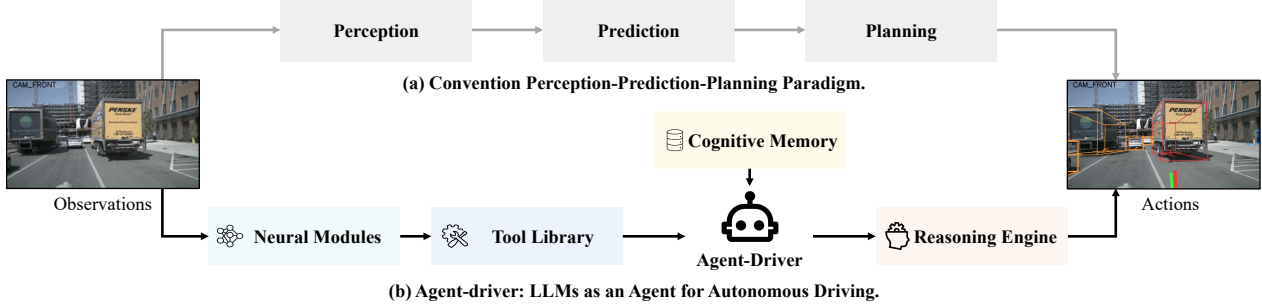


Figure 1. **Comparison between the conventional driving system (a) and the proposed Agent-Driver (b).** Our approach transforms the conventional perception-prediction-planning framework by introducing LLMs as an agent for driving.

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 integrating language-based human knowledge and reasoning ability into 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 a versatile tool library that interfaces with neural modules via dynamic function calls, streamlining perception with less redundancy. Additionally, we propose a configurable cognitive memory that explicitly stores common sense and driving experiences, infusing the system with human experiential knowledge. Moreover, we propose a reasoning engine that processes perception results and memory data to emulate human-like decision-making. 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. These modules, despite designed for autonomous driving, are immediately applicable to general robotic pipelines.
- 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.

2. 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 [21, 22, 24, 38] or object occupancy prediction [26, 32]. Prediction modules aim to estimate the future motions of objects, normally represented as predicted trajectories [5, 15, 30] or occupancy flows [1, 6]. Planning modules aim to derive a safe and comfortable trajectory, using rules [2, 7, 10, 18, 28, 31, 35, 36] or learning from human driving trajectories [8, 9, 23]. These three modules are generally performed sequentially, either trained separately or in an end-to-end manner [6, 13, 14, 20, 27]. 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, 25, 33, 34] 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 [23] 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 [40] proposed an end-to-end driving approach that leverages

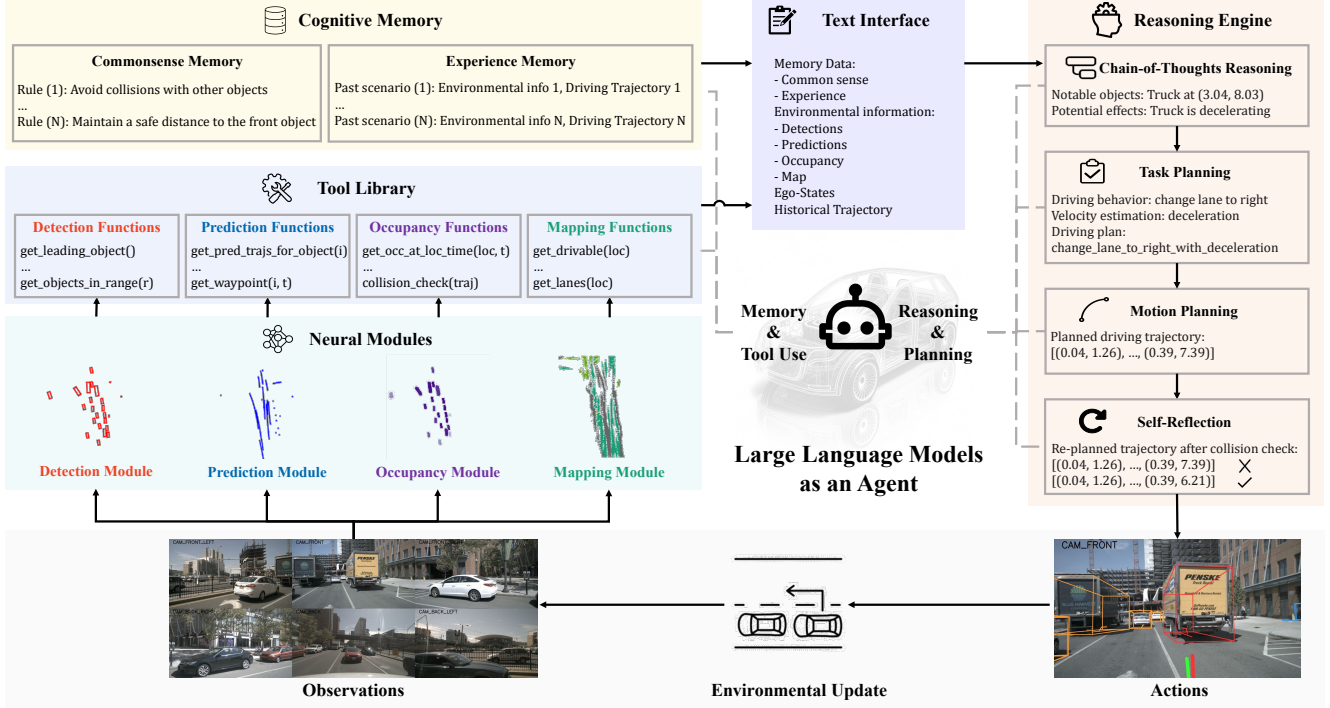


Figure 2. **Architecture of Agent-Driver.** Our system selectively gathers necessary environmental information from the output of neural modules via the **tool library**. The collected information is further utilized to query the **cognitive memory**. Consequently, the **reasoning engine** takes collected 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.

Vision-Language Models to directly map sensory inputs to actions. DiLu [39] 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 [40], planning [23], or control [29]. Some approaches [11, 39] are implemented and evaluated in naive simulated driving environments. Compared to the previous works, our 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.

3. 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 3.1. Then, we introduce the three key components of our method: tool library (Section 3.2), cognitive memory (Section 3.3), and reasoning engine (Section 3.4).

3.1. 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

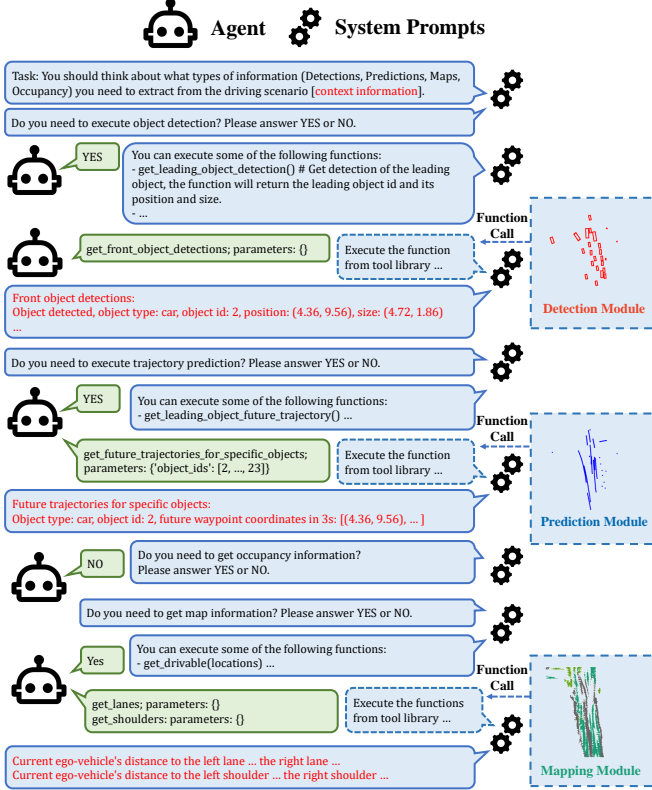


Figure 3. **Illustration of function calls in the tool library.** Agent-Driver can effectively collect necessary environmental information from neural modules through dynamic function calls.

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.

3.2. 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 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 and propose a tool library built upon the neural modules to dynamically collect text-based environmental information.

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 highly redundant, and most of the information doesn't affect the decision-making process. 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 learns to collect necessary environmental information through dynamic function calls. Specifically, the LLM is first provided with initial information such as the current state or visual inputs 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.

3.3. 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-

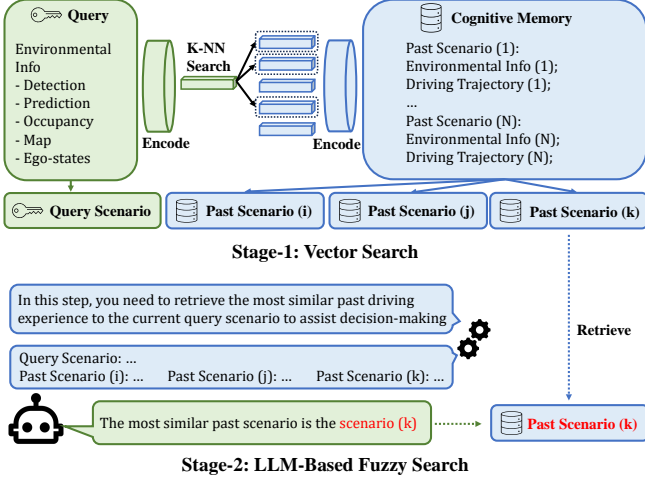


Figure 4. **Illustration of memory search.** The proposed two-stage search algorithm effectively retrieves the most similar driving experience and facilitates the subsequent decision-making process.

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 environmental information collected by function calls 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. **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 [19, 37], 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 search in the embedding space. Since the driving scenarios are quite diverse, the embedding-based search is inherently limited

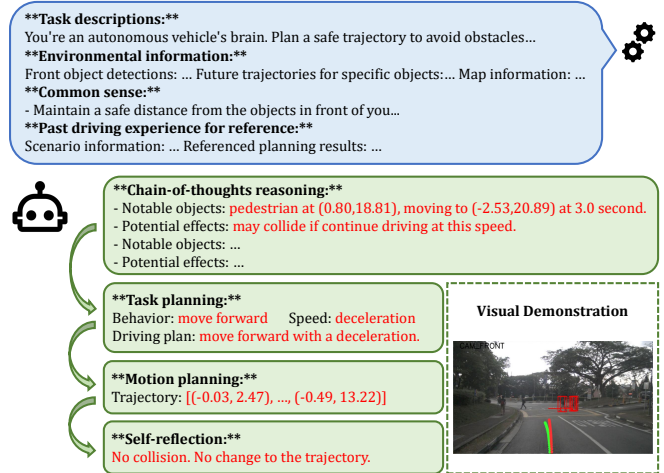


Figure 5. **Illustration of reasoning engine.** Agent-Driver makes driving decisions like human in a step-by-step procedure.

by the encoding methods employed, resulting in insufficient generalization capabilities. To overcome this challenge, the second stage incorporates an LLM-based fuzzy search. The LLM is then tasked with ranking 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 bridges the gap between neural perception results and human knowledge, thereby enhancing our system's compatibility.

3.4. 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. Our reasoning engine inputs environmental information and memory data, performs multi-stage reasoning, and eventually plans a safe and comfortable driving trajectory. It 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 approach, 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 [23], 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 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 the core 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, we first check its collision probability $\mathcal{F}_{col}(\tau)$ by calling the `collision_check` function in the tool library. If $\mathcal{F}_{col}(\tau)$ is higher than a threshold, 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 $\mathcal{F}_{col}(\tau)$ 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 rea-

soning, 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.

4. 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 4.1. Next, we compare our approach against state-of-the-art driving methods on the nuScenes dataset (Section 4.2). Then, we investigate the few-shot learning ability (Section 4.3), interpretability (Section 4.4), compatibility (Section 4.5), and stability (Section 4.6) of Agent-Driver. Finally, we conduct empirical studies to evaluate the effectiveness of different components and design choices of our approach in Section 4.7.

4.1. 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 [23] 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 [14]. More details can be found in the appendix.

Evaluation metrics. As argued in [14], 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,

	Method	L2 (m) ↓				Collision (%) ↓			
		1s	2s	3s	Avg.	1s	2s	3s	Avg.
<i>ST-P3 metrics</i>	ST-P3 [13]	1.33	2.11	2.90	2.11	0.23	0.62	1.27	0.71
	VAD [16]	0.17	0.34	0.60	0.37	0.07	0.10	0.24	0.14
	GPT-Driver [23]	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
<i>UniAD metrics</i>	NMP [41]	-	-	2.31	-	-	-	1.92	-
	SA-NMP [41]	-	-	2.05	-	-	-	1.59	-
	FF [12]	0.55	1.20	2.54	1.43	0.06	0.17	1.07	0.43
	EO [17]	0.67	1.36	2.78	1.60	0.04	0.09	0.88	0.33
	UniAD [14]	0.48	0.96	1.65	1.03	0.05	0.17	0.71	0.31
	GPT-Driver [23]	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.** Our approach significantly outperforms prior works in terms of L2 and collision rate.

in UniAD [14] the L2 error at 2s is the error at this certain timestep, while in ST-P3 [13] and following works [16, 23], the L2 error at 2s is in fact an average error from 0s to 2s. There are also differences in ground truth objects for collision calculation in different papers. We explain the details in metric implementations of different papers in the appendix for reference. For a fair comparison with these previous works, we group different methods based on their metric implementations (UniAD metric or ST-P3 metric), and we evaluate our method and report the motion planning performances on *both* two metrics respectively.

4.2. 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 **12%** and **32%** better than the second-best methods GPT-Driver [23] and UniAD [14], respectively. The promising performance on the collision rate verifies the effectiveness of the reasoning ability of Agent-Driver, which considerably increases the safety of the proposed autonomous driving system.

4.3. 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 [14] 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 comparable performance against the baseline. When exposed to 1% of training

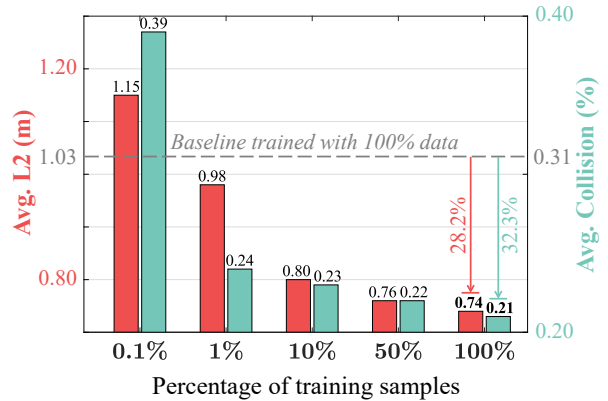
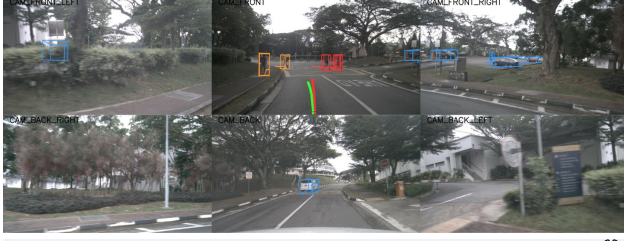


Figure 6. **Few-shot learning.** The motion planner in Agent-Driver fine-tuned with 1% data exceeds the state-of-the-art [14] trained on full data, verifying its few-shot learning ability.

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.

4.4. 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, Agent-Driver extracts necessary environmental information by calling functions in the tool library. Subsequently, the most similar past driving experiences and commonsense are retrieved from cognitive memory. Given environmental information and retrieved memories, the reasoning engine conducts step-by-step chain-of-thoughts reasoning, task planning, motion planning, and self-reflection. The whole process is recorded in text, ensuring the transparency and interpretability of our system.



****Environmental information:****
 Front object detections:
 Front object detected, object type: pedestrian, object id: 0, position: (-4.32, 13.85), size: (0.76, 0.91)
 ...
 Front object detected, object type: pedestrian, object id: 9, position: (2.23, 19.39), size: (0.57, 0.69)
 Future trajectories for specific objects:
 Object type: pedestrian, object id: 0, future waypoint coordinates in 3s: [(-4.44, 14.50), ...]
 ...
 Object type: pedestrian, object id: 9, future waypoint coordinates in 3s: [(1.74, 19.76), ...]
 Map information (road shoulders):
 Current ego-vehicle's distance to left shoulder is 0.5m and right shoulder is 4.5m

****Common sense:****
 - Maintain a safe distance from the objects in front of you...

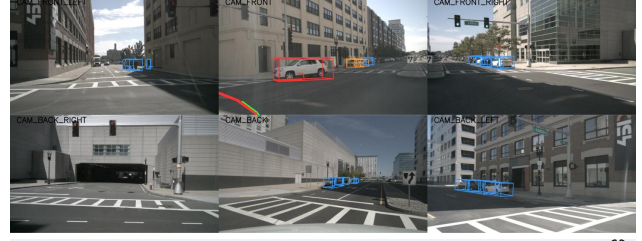
****Past driving experience for reference:****
 Most similar driving experience from memory with similarity score: 0.77:
 Scenario information: ...
 The planned trajectory in this scenario for your reference: [(0.04, 2.49), ..., (0.30, 12.26)]

****Chain-of-thoughts reasoning:****
 - Notable objects: pedestrian at (0.80, 18.81), moving to (-2.53, 20.89) at 3.0 second
 - Potential effects: may collide if continue driving at this speed.
 ...

****Task planning:****
 Behavior: forward; Speed: deceleration; Driving plan: move forward with a deceleration

****Motion planning:****
 Trajectory: [(-0.03, 2.47), (-0.10, 4.84), (-0.19, 7.10), (-0.29, 9.25), (-0.39, 11.29), (-0.49, 13.22)]

****Self-reflection:****
 No collision. No change to the motion planning result.



****Environmental information:****
 Front object detections:
 Front object detected, object type: car, object id: 4, position: (-2.11, 14.95), size: (1.96, 4.76)
 ...
 Front object detected, object type: car, object id: 6, position: (5.31, 32.79), size: (1.90, 4.48)
 Future trajectories for specific objects:
 Object type: pedestrian, object id: 4, future waypoint coordinates in 3s: [(-2.39, 14.80), ...]
 ...
 Object type: pedestrian, object id: 6, future waypoint coordinates in 3s: [(5.32, 32.78), ...]
 Map information (lanes):
 Current ego-vehicle's distance to left lane is 1.5m and right lane is unknown

****Common sense:****
 - Avoid collision with other objects...

****Past driving experience for reference:****
 Most similar driving experience from memory with similarity score: 0.45:
 Scenario information: ...
 The planned trajectory in this scenario for your reference: [(-0.14, 0.98), ..., (-5.10, 8.27)]

****Chain-of-thoughts reasoning:****
 - Notable objects: car at (-2.11, 14.95), moving to (-2.84, 14.53) at 1.5 second
 - Potential effects: inside the safety zone of the ego-vehicle at 1.5 second.
 ...

****Task planning:****
 Behavior: turn left; Speed: deceleration; Driving plan: turn left with a deceleration

****Motion planning:****
 Trajectory: [(-0.11, 0.94), (-0.31, 1.81), (-0.62, 2.75), (-1.16, 3.88), (-1.84, 4.93), (-2.95, 6.29)]

****Self-reflection:****
 No collision. No change to the motion planning result.

Figure 7. **Interpretability of Agent-Driver.** In the referenced images, the planned trajectories of Agent-Driver and the ground truth trajectories are in red and green, respectively. Initially, Agent-Driver extracts meaningful objects (yellow bounding boxes) from neural modules' outputs (blue bounding boxes) via the tool library. The reasoning engine further identifies notable objects (red bounding boxes). Messages from the tool library, cognitive memory, and reasoning engine are recorded in colored text boxes. The whole decision-making process is recorded in text, so our system can conduct driving in an interpretable and traceable way.

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.

4.5. Compatibility

Compatibility to different perception 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.

Compatibility to different LLMs. We tried leveraging

Method	L2 (m) ↓				Collision (%) ↓			
	1s	2s	3s	Avg.	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 3. **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 4. **Stability of Agent-Driver exposed to different amounts of training samples.** With few training samples, Agent-Driver still attains high output stability and produces 0 invalid output.

the Llama-2-7B [34], gpt-3.5-turbo-1106, and gpt-3.5-turbo-0613 models as the foundation LLMs in our system. Table 3 demonstrates that Agent-Driver powered by different LLMs can yield satisfactory performances, verifying the compatibility of our system with diverse LLM architectures.

ID	Tool Library	Common. Memory	Exp. Memory	CoT Reason.	Task Plan.	Self-Reflect.	L2 (m) ↓				Collision (%) ↓			
							1s	2s	3s	Avg.	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 5. **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.

4.6. Stability

LLMs typically suffer from arbitrary predictions—the LLMs 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 use different amounts of training data to fine-tune the LLMs in our system, and we tested the number of invalid outputs during inference on the validation set. As shown in Table 4, Agent-Driver exposed to only 1% of the training data sees *zero* invalid output during inference of 6,019 validation scenarios, indicating the output stability of our system.

4.7. Empirical Study

Effectiveness of system components. Table 5 shows the results of ablating different components in Agent-Driver. All variants utilize 10% training data for instructing or fine-tuning 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. At ID 3, removing experience memory greatly affects the collision rate, which validates the crucial of experiential knowledge. In addition, the collision rate increases when removing commonsense memory, chain-of-thought reasoning, and task planning, demonstrating the effectiveness of these components. Furthermore, self-reflection greatly reduces the collision rate.

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, benchmarking them on the downstream motion planning performance. As indicated in Table 6, in-

Modules		Avg. L2 (m)	Avg. Col. (%)
CoT Reason.+Task Plan.	Motion Plan.		
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.

context learning performs slightly better than fine-tuning in 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.

5. 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 further optimize the LLMs for real-time inference.

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References

- [1] Ben Agro, Quinlan Sykora, Sergio Casas, and Raquel Urtasun. Implicit Occupancy Flow Fields for Perception and Prediction in Self-Driving. In *Proceedings of the IEEE/CVF Conference*

- on *Computer Vision and Pattern Recognition*, pages 1379–1388, 2023. 2
- [2] Andrew Bacha, Cheryl Bauman, Ruel Faruque, Michael Fleming, Chris Terwelp, Charles Reinholtz, Dennis Hong, Al Wicks, Thomas Alberi, David Anderson, et al. Odin: Team VictorTango’s Entry in the DARPA Urban Challenge. *Journal of Field Robotics*, 25(8):467–492, 2008. 2
- [3] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language Models are Few-Shot Learners. In *Advances in neural information processing systems*, pages 1877–1901, 2020. 2
- [4] Holger Caesar, Varun Bankiti, Alex H Lang, Sourabh Vora, Venice Erin Liong, Qiang Xu, Anush Krishnan, Yu Pan, Giancarlo Baldan, and Oscar Beijbom. nuscenes: A multimodal dataset for autonomous driving. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 11621–11631, 2020. 6
- [5] Sergio Casas, Wenjie Luo, and Raquel Urtasun. Intentnet: Learning to predict intention from raw sensor data. In *Conference on Robot Learning*, pages 947–956, 2018. 1, 2
- [6] Sergio Casas, Abbas Sadat, and Raquel Urtasun. Mp3: A unified model to map, perceive, predict and plan. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14403–14412, 2021. 1, 2
- [7] Chenyi Chen, Ari Seff, Alain Kornhauser, and Jianxiong Xiao. Deepdriving: Learning affordance for direct perception in autonomous driving. In *Proceedings of the IEEE international conference on computer vision*, pages 2722–2730, 2015. 2
- [8] Kashyap Chitta, Aditya Prakash, Bernhard Jaeger, Zehao Yu, Katrin Renz, and Andreas Geiger. Transfuser: Imitation with transformer-based sensor fusion for autonomous driving. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2022. 2
- [9] Daniel Dauner, Marcel Hallgarten, Andreas Geiger, and Kashyap Chitta. Parting with misconceptions about learning-based vehicle motion planning. *arXiv preprint arXiv:2306.07962*, 2023. 2
- [10] Haoyang Fan, Fan Zhu, Changchun Liu, Liangliang Zhang, Li Zhuang, Dong Li, Weicheng Zhu, Jiangtao Hu, Hongye Li, and Qi Kong. Baidu apollo em motion planner. *arXiv preprint arXiv:1807.08048*, 2018. 2
- [11] Daocheng Fu, Xin Li, Licheng Wen, Min Dou, Pinlong Cai, Botian Shi, and Yu Qiao. Drive like a human: Rethinking autonomous driving with large language models. *arXiv preprint arXiv:2307.07162*, 2023. 3
- [12] Peiyun Hu, Aaron Huang, John Dolan, David Held, and Deva Ramanan. Safe local motion planning with self-supervised freespace forecasting. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12732–12741, 2021. 7
- [13] Shengchao Hu, Li Chen, Penghao Wu, Hongyang Li, Junchi Yan, and Dacheng Tao. St-p3: End-to-end vision-based autonomous driving via spatial-temporal feature learning. In *European Conference on Computer Vision*, pages 533–549. Springer, 2022. 1, 2, 7
- [14] Yihan Hu, Jiazhi Yang, Li Chen, Keyu Li, Chonghao Sima, Xizhou Zhu, Siqi Chai, Senyao Du, Tianwei Lin, Wenhai Wang, et al. Planning-oriented autonomous driving. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 17853–17862, 2023. 1, 2, 6, 7
- [15] Boris Ivanovic and Marco Pavone. The trajetron: Probabilistic multi-agent trajectory modeling with dynamic spatiotemporal graphs. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2375–2384, 2019. 2
- [16] Bo Jiang, Shaoyu Chen, Qing Xu, Bencheng Liao, Jiajie Chen, Helong Zhou, Qian Zhang, Wenyu Liu, Chang Huang, and Xinggang Wang. Vad: Vectorized scene representation for efficient autonomous driving. *arXiv preprint arXiv:2303.12077*, 2023. 1, 7
- [17] Tarasha Khurana, Peiyun Hu, Achal Dave, Jason Ziglar, David Held, and Deva Ramanan. Differentiable raycasting for self-supervised occupancy forecasting. In *European Conference on Computer Vision*, pages 353–369. Springer, 2022. 7
- [18] John Leonard, Jonathan How, Seth Teller, Mitch Berger, Stefan Campbell, Gaston Fiore, Luke Fletcher, Emilio Frazzoli, Albert Huang, Sertac Karaman, et al. A perception-driven autonomous urban vehicle. *Journal of Field Robotics*, 25(10):727–774, 2008. 2
- [19] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in Neural Information Processing Systems*, 33:9459–9474, 2020. 5
- [20] Ming Liang, Bin Yang, Wenyuan Zeng, Yun Chen, Rui Hu, Sergio Casas, and Raquel Urtasun. Pnpnet: End-to-end perception and prediction with tracking in the loop. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 11553–11562, 2020. 2
- [21] Jiageng Mao, Minzhe Niu, Haoyue Bai, Xiaodan Liang, Hang Xu, and Chunjing Xu. Pyramid r-cnn: Towards better performance and adaptability for 3d object detection. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2723–2732, 2021. 2
- [22] Jiageng Mao, Yujing Xue, Minzhe Niu, Haoyue Bai, Jiashi Feng, Xiaodan Liang, Hang Xu, and Chunjing Xu. Voxel transformer for 3d object detection. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 3164–3173, 2021. 2
- [23] Jiageng Mao, Yuxi Qian, Hang Zhao, and Yue Wang. Gpt-driver: Learning to drive with gpt. *arXiv preprint arXiv:2310.01415*, 2023. 2, 3, 6, 7
- [24] Jiageng Mao, Shaoshuai Shi, Xiaogang Wang, and Hongsheng Li. 3d object detection for autonomous driving: A comprehensive survey. *International Journal of Computer Vision*, pages 1–55, 2023. 1, 2
- [25] OpenAI. Gpt-4 technical report. 2023. 2
- [26] Songyou Peng, Michael Niemeyer, Lars Mescheder, Marc Pollefeys, and Andreas Geiger. Convolutional occupancy networks. In *Computer Vision–ECCV 2020: 16th European*

- Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part III 16*, pages 523–540, 2020. 1, 2
- [27] Abbas Sadat, Sergio Casas, Mengye Ren, Xinyu Wu, Pranaab Dhawan, and Raquel Urtasun. Perceive, predict, and plan: Safe motion planning through interpretable semantic representations. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XXIII 16*, pages 414–430. Springer, 2020. 1, 2
- [28] Axel Sauer, Nikolay Savinov, and Andreas Geiger. Conditional affordance learning for driving in urban environments. In *Conference on Robot Learning*, pages 237–252. PMLR, 2018. 2
- [29] Hao Sha, Yao Mu, Yuxuan Jiang, Li Chen, Chenfeng Xu, Ping Luo, Shengbo Eben Li, Masayoshi Tomizuka, Wei Zhan, and Mingyu Ding. Languagempc: Large language models as decision makers for autonomous driving. *arXiv preprint arXiv:2310.03026*, 2023. 3
- [30] Shaoshuai Shi, Li Jiang, Dengxin Dai, and Bernt Schiele. Motion transformer with global intention localization and local movement refinement. *Advances in Neural Information Processing Systems*, 35:6531–6543, 2022. 2
- [31] Sebastian Thrun, Mike Montemerlo, Hendrik Dahlkamp, David Stavens, Andrei Aron, James Diebel, Philip Fong, John Gale, Morgan Halpenny, Gabriel Hoffmann, et al. Stanley: The Robot that Won the DARPA Grand Challenge. *Journal of Field Robotics*, 23(9):661–692, 2006. 2
- [32] Wenwen Tong, Chonghao Sima, Tai Wang, Li Chen, Silei Wu, Hanming Deng, Yi Gu, Lewei Lu, Ping Luo, Dahua Lin, et al. Scene as occupancy. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 8406–8415, 2023. 2
- [33] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023. 2
- [34] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023. 2, 8
- [35] Martin Treiber, Ansgar Hennecke, and Dirk Helbing. Congested Traffic States in Empirical Observations and Microscopic Simulations. *Physical Review E*, 62(2):1805–1824, 2000. 1, 2
- [36] Chris Urmson, Joshua Anhalt, Drew Bagnell, Christopher Baker, Robert Bittner, MN Clark, John Dolan, Dave Duggins, Tugrul Galatali, Chris Geyer, et al. Autonomous driving in urban environments: Boss and the urban challenge. *Journal of field Robotics*, 25(8):425–466, 2008. 2
- [37] Jianguo Wang, Xiaomeng Yi, Rentong Guo, Hai Jin, Peng Xu, Shengjun Li, Xiangyu Wang, Xiangzhou Guo, Chengming Li, Xiaohai Xu, et al. Milvus: A purpose-built vector data management system. In *Proceedings of the 2021 International Conference on Management of Data*, pages 2614–2627, 2021. 5
- [38] Yue Wang, Vitor Campagnolo Guizilini, Tianyuan Zhang, Yilun Wang, Hang Zhao, and Justin Solomon. Detr3d: 3d object detection from multi-view images via 3d-to-2d queries. In *Conference on Robot Learning*, pages 180–191. PMLR, 2022. 2
- [39] Licheng Wen, Daocheng Fu, Xin Li, Xinyu Cai, Tao Ma, Pinlong Cai, Min Dou, Botian Shi, Liang He, and Yu Qiao. Dilu: A knowledge-driven approach to autonomous driving with large language models. *arXiv preprint arXiv:2309.16292*, 2023. 3
- [40] Zhenhua Xu, Yujia Zhang, Enze Xie, Zhen Zhao, Yong Guo, Kenneth KY Wong, Zhenguo Li, and Hengshuang Zhao. Drivegpt4: Interpretable end-to-end autonomous driving via large language model. *arXiv preprint arXiv:2310.01412*, 2023. 2, 3
- [41] Wenyuan Zeng, Wenjie Luo, Simon Suo, Abbas Sadat, Bin Yang, Sergio Casas, and Raquel Urtasun. End-to-end interpretable neural motion planner. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 8660–8669, 2019. 1, 7