MASTER THESIS

Toward a Multi Agent Approach for LLM-Based Dynamic Vehicle Control and Communication in Accidental Condition

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Abstract

In autonomous vehicles (AVs), making the right decision in unknown traffic situations remains a critical challenge. Traditional AVs, which are based on pre-programmed rules or pre-trained models, often struggle in scenarios where human-like reasoning is required. This research examines how Large Language Models (LLMs) can act as a main decision agent for AVs, responding to text-based real-world traffic situations simulation.

We propose a multi-agent framework consisting of two key components, a Decision Agent powered by LLMs, and a Communication Agent that enables Vehicle-to-Vehicle (V2V) information exchange. The Communication Agent shares structured, real-time data such as obstacle presence, speed, and intended actions, which is then incorporated into the Decision Agent's reasoning process.

To evaluate the proposed system, we conducted a series of text-based simulations that simulate real-world traffic conditions. These scenarios are used to test whether LLMs, when provided with scenario-specific prompts and contextual V2V data, can generate consistent and human-like decisions. Our results indicate that while LLMs show strong reasoning abilities, their precision and reliability of decision improve significantly when augmented with contextual information through V2V communication. This research presents a preliminary approach to bridge the gap between current AV capabilities and the demands of real-world accidental conditions.

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List of Abbreviations

AI	**A**rtificial **I**ntelligence
AV	**A**utonomous **V**ehicle
ADS	**A**utonomous **D**riving **S**ystem
LLM	**L**arge **L**anguage **M**odel
MAS	**M**ulti-**A**gent **S**ystem
NLP	**N**atural **L**anguage **P**rocessing
RL	**R**einforcement **L**earning
V2V	**V**ehicle-**t**o-**V**ehicle

Chapter 1

Introduction

The advancement of autonomous vehicle technology brings us closer to the long-held vision of fully automated transportation, where vehicles operate without human intervention. However, achieving this goal of complete automation remains a significant challenge, particularly in ensuring safe and reliable decision-making in complex and uncertain environments.

1.1 Research Background

Our research investigates the potential of integrating Large Language Models (LLMs) [1] into a multi-agent framework [2] to improve decision-making in autonomous vehicles (AVs), particularly in the unknown-unsafe driving domain. Our main concern is to explore the use of an LLM as the primary decision-making agent within an autonomous driving system (ADS) [3], evaluating its ability to reason [4] and handle uncertain traffic situations. We aim to contribute to the development of safer and more reliable Level 5 (complete automation) autonomous vehicles, as defined by the Society of Automotive Engineers (SAE International) [5], [6]. Although traditional AVs can handle predictable 'known-safe' and 'known-unsafe' situations, they struggle with highly unpredictable events, such as a pedestrian unexpectedly crossing the road while the light is red for oncoming traffic representing an unknown unsafe condition. These scenarios, which are difficult to cover in training datasets, represent the primary barrier to achieving complete automation. Human drivers use common sense [7] and past experiences to navigate these unexpected events. However, current AV systems, even those that use advanced reinforcement learning (RL) [8], struggle in these scenarios. This limitation is especially evident where the correct action is not immediately clear [9]. Addressing these unknown-unsafe scenarios is critical for improving an AV's ability to handle real-world driving environments and ensuring the development of truly reliable autonomous systems.

1.2 Research Objectives

Determining how autonomous vehicles (AVs) should make decisions in complex or fully unknown traffic situations remains a major challenge in the development of fully autonomous systems. This problem has been widely explored in the fields of artificial intelligence, robotics, and autonomous system design [10], [11]. Traditional autonomous vehicle systems used these approaches to take driving decisions,

- Rule-based system, which operates on predefined logic and hard-coded behaviors such as "if-then" conditions. These systems cannot take decisions in unfamiliar or edge-case situations that fall outside of their rule sets.

- Supervised learning or machine learning-based models, which are heavily dependent on training data. They often fail in new contexts because they cannot reason beyond the patterns they have learned.

The ability to make safe and contextually appropriate decisions in real-time becomes especially critical when AVs encounter unknown-unsafe scenarios traffic conditions not represented in training data or handled poorly by traditional algorithms.

And this could be a solution to simulate all the situation of this Unknown Unsafe domain and make a dataset to train a model that will work as a decision agent for the AVs. However, a fundamental challenge is to prepare for truly unknown situations. Any scenario researchers create is technically **known** even if unfamiliar to AVs, making it difficult to test how vehicles handle genuinely unknown-unsafe situations. In addition, recreating complex real-world scenarios in simulation environments is a challenge. And accurately simulating unpredictable human actions or complicated environmental conditions remains nearly impossible. In real life, it is nearly impossible to include all the uncertain situations in training datasets for traditional autonomous driving systems. Human drivers rely on common sense to navigate these situations effectively. To address this limitation, we are going to investigate whether LLMs can provide human-like reasoning [12] that traditional systems lack, such as how human drivers handle unexpected situations. The main objective of this research is to evaluate how effectively LLMs can act as decision agents in unfamiliar traffic conditions, and potentially bridging the gap between programmed responses and adaptive decision making in autonomous vehicle systems.

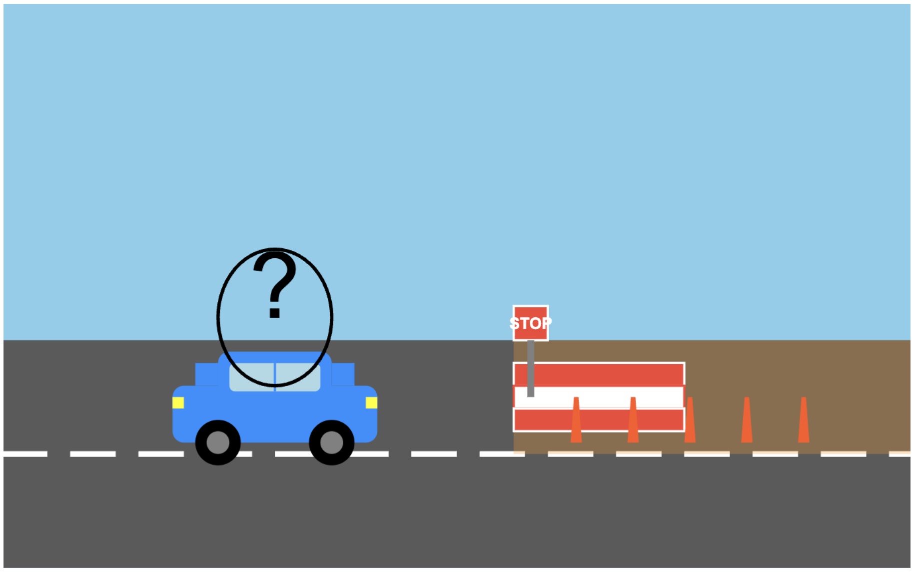


FIGURE 1.1: What a current AV might do in this situation

1.3 Research Motivation

1.3.1 Motivating Example 1 : What a current AV might do in Unknown situation

Imagine a traffic situation where a road is partially blocked by construction cones, with a 'STOP' sign placed near the cones shown in Figure 1.1. A traditional autonomous vehicle might see the 'STOP' sign and interpret it as a complete road closure, coming to a complete stop because that is what its preprogrammed data tell it to do.

However, a human driver would use common sense to recognize that the road is only partially closed, slow down, and safely navigate through the open section. This scenario highlights the need for a reasoning system that can interpret context beyond literal rules. Although the situation described in Figure 1.1 can now be handled with some additional rules, it highlights a key limitation of current AVs. They struggle to reason in unfamiliar or uncertain situations that are not covered by pre-programmed logic or training data.

1.3.2 Motivating Example 2 : Lack of communication between vehicles

Now imagine a more complicated situation where an autonomous truck comes to a sudden stop when it sees the 'STOP' sign. There is another car, driven by a human or another AV, right behind it. This sudden stop could easily cause a crash, as shown in Figure 1.2. An autonomous truck (AV1) suddenly brakes

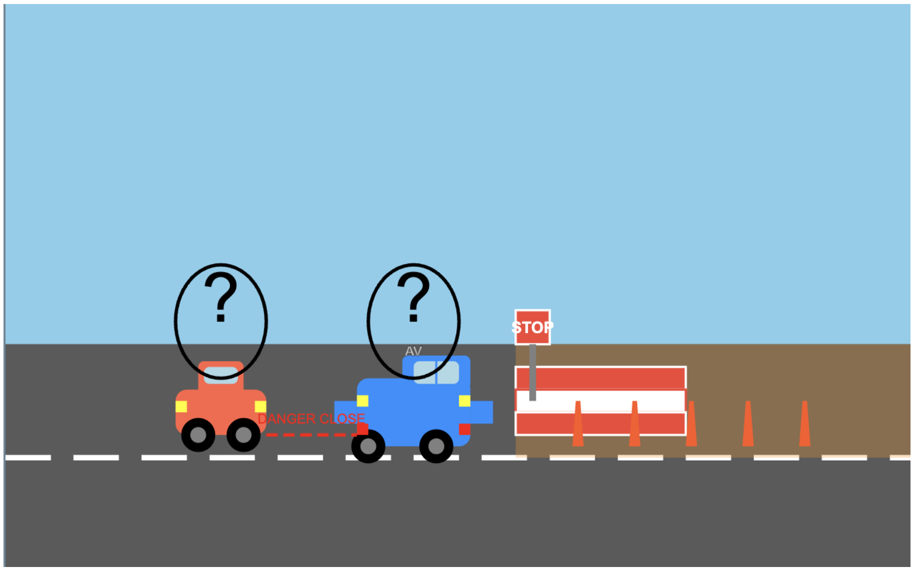


FIGURE 1.2: Lack of communication between vehicles may lead to an accident

upon detecting a partially visible 'STOP' sign, an action based on its own perception. Behind it, another vehicle (AV2), which could be human-driven or autonomous, is following closely. Due to AV1's size, AV2 has no perception of the sign and no prior indication that AV1 is about to stop. Without any communication between vehicles, AV2 is unaware of the hazard ahead, greatly increasing the risk of a rear-end collision. This scenario illustrates a limitation of perception in autonomous systems. The issue is not only whether each vehicle can make the right decision for itself but also whether it can contribute to a collectively safe environment. In the near future autonomous vehicles will begin to share the road with human drivers, and this limitation will become even more common. Because human drivers cannot anticipate AV decisions and AVs cannot rely on human predictability, this mix mode can lead to rear-end collision more often. In our research, we will investigate how Large Language Models (LLMs) utilize this shared V2V information to make driving decisions. Specifically, our goal is to assess whether the inclusion of contextual data, such as obstacle positions, speed, and vehicle intentions, enables the LLM to produce safer and more accurate decisions in complex traffic scenarios.

1.4 Research Questions

One of the primary objectives of this investigation is to answer two main research questions.

- **Research Question 1**: Can an agent make decisions with the help of an

LLM without undergoing a specific learning process for each new situation?

- **Research Question 2**: Is a single centralized decision-making agent sufficient to process all incoming Vehicle-to-Vehicle (V2V) data, or is a multi-agent system required for improved efficiency and scalability?
- **Sub-Research Question**: Does repeated querying of LLMs on the same scenario lead to variations in decision-making outcomes?

1.5 Research Contribution

This research introduces a novel multi-agent architecture that integrates Large Language Models (LLMs) with Vehicle-to-Vehicle (V2V) communication [13] to enhance autonomous vehicle decision-making in unknown-unsafe driving scenarios. This work demonstrates how their combined use enables emerging reasoning capabilities and allows autonomous vehicles to make more accurate and context-aware decisions in safety-critical scenarios. This research presents a standardized text-based simulation framework that replicates real traffic situations, used to test the capabilities of LLMs in logical reasoning, rule compliance, and dynamic decision-making for autonomous vehicles.

Additionally, a multi-agent communication system is implemented, enabling the vehicle to share structured information such as obstacle locations, speed, and future intentions in a certain radius. This data serves as a contextual input for the LLM-based Decision Agent. Our work demonstrates how contextual information sharing can improve the decision-making process in potentially uncertain scenarios to safe outcomes. Through empirical experimentation, this research provides definitive evidence that structured V2V communication data significantly improves the accuracy of LLM-based decision making. Our research develops novel approaches for quantifying the consistency and reliability of decisions in LLM-based systems, addressing one of the most critical concerns for the deployment of AI in safety-critical applications. By addressing these research areas, our work contributes to the advancement of both theoretical understanding and practical implementation of AI-enhanced autonomous driving systems, with particular emphasis on navigation through safety-critical scenarios.

1.6 Thesis Outline

This thesis is organized into six different chapters as follows:

Chapter 1 ***Introduction***: This chapter describes a brief introduction to the thesis, including the research background, objectives, questions, contributions, and key motivations.

Chapter 2 ***Background and Related Work***: This chapter introduces the research topics of autonomous vehicle decision-making, unknown-unsafe scenarios, Large Language Models (LLMs), and Multi-Agent Systems, defining the basic concepts and discussing related work in the field.

Chapter 3 ***Approach and Example-based Analysis***: This chapter describes the challenges and solving approach of this research and introduces the detailed multi-agent framework and example scenarios used for evaluation.

Chapter 4 ***Simulation and Results***: This chapter presents the simulation setup and implementation process used to evaluate the performance of Large Language Models (LLMs) in autonomous vehicle decision-making. It describes the design of text-based scenarios, the multi-agent architecture including the Decision and Communication Agents, and how vehicle-to-vehicle (V2V) data was integrated. The chapter also analyzes the results across various models, highlights improvements by V2V communication, and discusses limitations such as consistency, unpredictability, and model selection challenges.

Chapter 5 ***Conclusion***: This chapter describes the summary of the work, discusses the key findings, and outlines directions for future research as a conclusion.

Appendix: This section provides the simulation code used to create and test the experimental scenarios described in this thesis.

Chapter 2

Background and Related Work

This chapter introduces the fundamental concepts and technologies that form the basis for this research. We examine the current state of autonomous vehicle decision-making systems, identify the critical challenges they face, and explore emerging technologies that can potentially address these limitations.

2.1 Autonomous Vehicle Decision-Making

The existing definitions of autonomous driving specified by the SAE [6] for Levels 1 to 5 can be interpreted as, At level 1 vehicles, driving assistance systems that can sometimes help the driver complete some lateral or longitudinal driving tasks. At Level 2 vehicles can automatically provide multidimensional assistance. At level 3, vehicles can perform automatic acceleration and deceleration steering in a specific environment without the driver's intervention. At level 4, if a vehicle is currently in an autonomous driving state under limited conditions, the driver is not required to continuously control the steering wheel. At Level 5, vehicles can run automatically under any conditions and scenarios. At this level, the automatic system of a vehicle completely replaces the human driver and achieves complete automation. A complete AV is capable of sensing its environment and operating without human involvement. The decision-making process in autonomous vehicles follows a fundamental three-stage pipeline: perception, planning, and control.

- **Perception (See)**: The vehicle uses a variety of sensors and cameras, such as LiDAR (Light Detection and Ranging), and radar systems to construct a comprehensive three-dimensional representation of its environment. This stage involves detecting and classifying objects such as other vehicles, pedestrians, traffic signs, and lane markings.

- **Planning and Decision-Making (Think)**: This represents the core focus of our research. Based on the perceived environmental information, the vehicle's computational system must determine the appropriate course of action. This involves planning and taking decisions such as lane changes, speed adjustments, and navigation through complex traffic scenarios. Traditional rule-based approaches perform well in structured and predictable traffic environments. They can only execute actions that have been explicitly predefined and encoded. When unexpected or novel situations arise that fall outside the scope of their programmed rules, these systems often do not respond appropriately [14]. Our research focuses on improving the intelligence of this decision-making component through advanced reasoning capabilities.

- **Control (Act)**: Once a decision is made, the system translates the planned actions into control signals that activate the vehicle's physical components, including steering, acceleration, and braking systems. The decision-making module is particularly critical, as it is responsible for planning and performing safely.

2.2 The Challenge of Unknown-Unsafe Scenarios

The driving domain can be divided into three primary categories: known-safe, known-unsafe, and unknown-unsafe. Although traditional AV systems can take proper decisions in the first two categories, which can be addressed with pre-programmed rules, their primary limitation lies in handling the complex and unpredictable nature of unknown-unsafe scenarios shown in Figure 2.1.

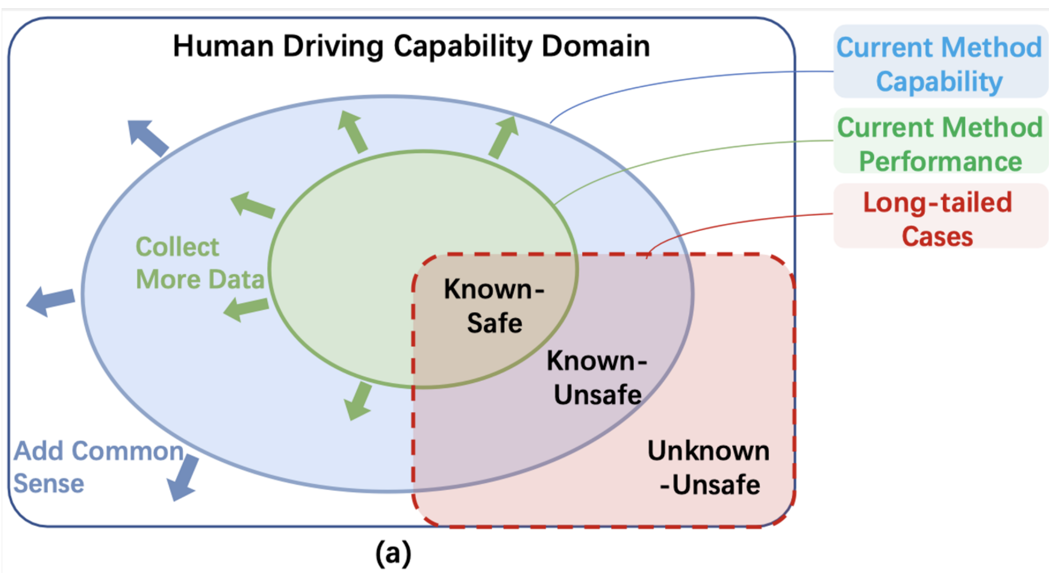


FIGURE 2.1: Human driving Domain and existing autonomous driving systems [15]

- Known Safe Scenarios: These are routine traffic conditions where the environment is predictable and the appropriate response is well-established.

For example, driving straight on an empty highway or stopping at a red light. AVs can reliably navigate these situations using pre-defined logic.

- Known Unsafe Scenarios: These are situations where a clear and present danger is identifiable based on established rules. Examples include an object stationary on the road, a speeding in a school zone, or another vehicle running a red light. AVs can be trained to recognize and react to these predictable hazards.
- Unknown-Unsafe Scenarios: These are unexpected and unplanned situations that are not explicitly covered by pre-programmed rules and can occur without warning or precedent. Examples include a ball rolling onto the road, a pedestrian unexpectedly crossing a red light, or ambiguous hand signals from another driver. These situations require quick context-aware judgment and are difficult to cover exhaustively in training datasets.

Traditional AVs are generally capable of handling known-safe and known-unsafe scenarios effectively using pre-programmed rules, supervised learning, or reinforcement learning models. For example, they can detect and respond to traffic lights, lane markings, and other common characteristics of the driving environment. However, they struggle when faced with new or unusual situations that are not directly covered by their programming. Human drivers, on the other hand, use common sense and past experiences to handle unexpected events, such as recognizing that traffic cones on a moving truck are not a stationary obstacle. Current AV systems, even those that use advanced reinforcement learning (RL), will struggle to make such a nuanced distinction. This limitation poses a serious safety risk in real-world driving and can lead to several critical failure modes, such as AVs can incorrectly identify a safe situation as dangerous, leading to unnecessary and potentially disruptive actions to sudden braking. For example, an AV might stop for a tree shadow across the road, treating it as a solid obstacle. The AVs can fails to recognize an actual danger because it does not fit a pre-programmed pattern. This is the most critical failure mode, as it can lead directly to collisions. Addressing this gap is essential for the development of fully autonomous systems that can be trusted to operate safely and reliably in the complexity of real-world environments.

2.3 Large Language Models (LLMs) for Reasoning

An important development in artificial intelligence is represented by Large Language Models (LLMs). LLMs are a type of Machine Learning (ML) model trained in vast amounts of text and code from the Internet, allowing them to comprehend and produce language similar to that of a human. LLMs represent a significant leap in natural language processing and artificial intelligence. Unlike traditional rule-based systems, these machine learning models, driven by deep learning techniques, excel at comprehending and generating extensive human-like text. Reasoning is a fundamental aspect of human intelligence, essential for problem solving, decision-making, and critical thinking. In recent years, Large Language Models (LLMs) have demonstrated emerging abilities [16], such as in-context learning [17], role play [18], and analogical reasoning [19]. These abilities allow LLMs to go beyond natural language processing problems to facilitate a wider range of tasks, such as code generation [20], robotic control [21], and autonomous agents [22]. Among these abilities, human-like reasoning has garnered significant attention from both academia and industry, since it demonstrates great potential for LLMs to generalize to complex real-world problems through abstract and logical reasoning. A notable breakthrough in this area is the 'chain of thought' prompting technique [23], which can obtain step-by-step human-like reasoning processes at the test time without additional training.

This research investigates the potential of LLMs to serve as the main decision makers within AV systems, assessing whether they can reason and react more like humans in complex scenarios.

2.4 Multi-Agent Systems and V2V Communication

A Multi-Agent System (MAS) is a computerized system composed of multiple interacting intelligent agents. In the context of autonomous driving, MAS is particularly relevant as it allows the overall system to function more efficiently by dividing the responsibilities among individual agents. Each agent operates individually with a limited view of the environment, but through coordination and communication, they work together to achieve a common goal [24]. This research [25] presents an autonomous vehicle system based on multi-agents to reduce the complexity of the autonomous system by splitting tasks between different agents, which in turn reduces execution time and allows quicker intervention in complex scenarios. The proposed MAS can be applied to all vehicle brands, unlike existing systems that are dedicated to specific brands.

In the context of autonomous driving, this paradigm is highly relevant. **Vehicle-to-Vehicle (V2V) communication** is a key enabling technology for a multi-agent approach to driving. V2V allows vehicles to wirelessly exchange information about their position, speed, direction, and intended actions. This creates a collective awareness that extends far beyond the perception range of any single vehicle's onboard sensors (e.g., LiDAR, cameras). By structuring a V2V system within a multi-agent framework, we can address some of the fundamental limitations of single-agent AVs: This research proposes to integrate LLM-based decision-making within a multi-agent framework, where V2V communication provides the crucial context needed for robust reasoning in accidental conditions.

2.5 Related Work

2.5.1 Traditional Approaches to Decision-Making in AVs

Automatic control as an area of development is not new. The need for control systems, such as vehicles and industrial systems, has been of interest for a long time. Research in autonomous vehicle decision making has evolved through several paradigms. Traditional autonomous vehicles are based on data-driven approaches, which are categorized into modular and end-to-end frameworks [26]. Modular-based systems break the entire autonomous driving process into separate components, such as the perception module, the prediction module, and the planning module. Including tasks such as object detection [27] and object occupancy prediction. Early systems relied heavily on rule-based and finite-state machines, which are effective for predictable structured environments, but lack the flexibility to handle novel situations. [28], [29]

2.5.2 Multi-Agent Systems In AVs

In autonomous driving, incorporation of multi-agent is very useful. Instead of one system doing everything, different agents can handle different tasks, such as making decisions, detecting obstacles, or sharing vehicle information. Research in this area has often focused on optimizing traffic flow, coordinating intersections, and cooperative path planning [30]. However, these works typically used simpler, more formally defined agent behaviors. This research [31] presents experiments on learning decision-making policies in multi-agent environments for autonomous systems like connected autonomous vehicles. The agents were able to learn to navigate their environment and avoid collisions even in a partially observable environment with obstacles and other moving agents. However, learning decision-making policies is challenging due to the non-stationary nature of the environment. This research [32] explores a multi-agent system (MAS) architecture designed to facilitate cooperative control of CAVs. This hierarchical architecture enables vehicles to collaborate effectively in complex traffic environments, sharing information and making collective decisions that enhance safety and efficiency. The study emphasizes the importance of cooperation among autonomous vehicles, particularly in scenarios where rapid decision-making and coordination are critical to preventing accidents and ensuring smooth traffic flow.

2.5.3 LLMs in Autonomous Driving

Recent advancements have introduced Large Language Models (LLMs) as potential decision-makers in AV systems. The work of Fu et al. [33] established the concept of 'Drive like a human', demonstrating that LLMs can generate plausible driving behaviors in response to textual descriptions of traffic scenes.

Their work primarily focused on a single agent perspective and highlighted the promise of LLMs for high-level reasoning. In this research [34], they introduced a method for training systems to better understand driving situations. They connected numerical driving data with GPT-3.5, a powerful LLM, which helped the system answer questions and make better driving decisions. The 'DriveMLM' research [35] created a new self-driving system that connects LLMs with vehicle planning tasks. This allowed the car to make decisions on a simulator and control the vehicle more effectively by using a standard planning module. The 'Drive As You Speak' [36] research took things a step further by allowing drivers to talk to the car using natural language. This made it possible for LLMs to understand and follow voice commands, improving the user experience and making driving more intuitive. This study [37] looks to explore the ability of integrating LLMs into autonomous driving (AD) structures to emulate human-like behavior. LLMs can use their memory to apply past experiences to future decision-making, improving adaptability and decision-making in AD systems. It can improve reliability and safety by enabling human-like reasoning and adaptability. Human drivers instinctively reason with common sense knowledge to predict hazards in unfamiliar scenarios and to understand the intentions of other road users. However, this essential capability is completely missing from traditional decision-making systems in autonomous driving. In this research [38], they explored how the combination of large language models (LLMs) with visual models, called Vision Foundation Models (VFMs), can make autonomous driving systems smarter and more capable. Their work explains how technology evolved from basic sensors in early systems to more advanced deep learning methods that improve the way self-driving cars see, plan, and make decisions. In this research, AccidentGPT [39] introduced a model that can analyze traffic accidents. It uses different types of data (such as text and images) to recreate accident scenes and generate detailed reports. This helps generate detailed reports on what may have caused the accident. It shows that LLMs can also be useful after an accident, not just while driving. This research [40] reviews the integration of large language models (LLMs) into autonomous driving systems, highlighting their potential to improve decision-making, perception, and interaction through advanced reasoning and contextual understanding. The survey categorizes their research into planning, perception, question answering, and addressing the challenges of transparency, scalability of real-world application. This paper presents DriveLLM [41], a decision-making framework that integrates large language models (LLMs) with existing autonomous driving stacks. This integration allows for the use of common sense in decision-making. DriveLLM also features a unique cyber-physical feedback system, allowing it to learn and improve from its mistakes.

The intersection of LLMs and multi-agent communication presents a promising new direction for autonomous driving research. Existing work has shown that LLMs can replicate human-like reasoning and MAS frameworks improve coordination. In real-world case studies, the proposed framework outperforms traditional decision-making methods in complex scenarios, including difficult edge cases. However, using massive amounts of human-generated data to train these models introduces potential bias issues, as the models can unintentionally reinforce the social biases found in the data [42]. This study [43] shows a potential approach of using large language models(LLMs) to evaluate even fairness. However, our research uniquely combines these strengths, and the use of LLMs as decision agents within a cooperative V2V-enabled architecture represents a novel integration.

Chapter 3

A Multi-Agent Approach for LLM-Based Decision-Making

This chapter begins by introducing the overall approach and then provides a detailed explanation of our methodology, including how the experiments were set up, what assumptions were made, and the key factors considered when selecting models for evaluation. This is followed by illustrative example scenarios that demonstrate the system's behavior in representative traffic situations.

3.1 Conceptual Framework: A Multi Agent Approach

To contribute to the advancement of full automation in AVs, this research proposes a conceptual framework based on a multi-agent architecture. The framework is designed to emulate human-like reasoning while enabling cooperative behavior among vehicles through structured communication. The framework focused on two primary agents: the Decision Agent and the Communication Agent, which work collaboratively to enhance decision -making capabilities in dynamic and uncertain traffic scenarios. The interaction between the Decision Agent and the Communication Agent is the core of this framework. The Decision Agent uses both its internal scenario understanding and externally shared V2V data to make informed decisions. This hybrid reasoning system provides the AV with both self-perception and extended perception capabilities with shared information.

- We investigated whether Large Language Models (LLMs) as a decision agent can replicate human-like decision-making processes in autonomous vehicle contexts.

- We also investigated how the information sharing facilitated by the communication agent impacts and potentially improves the accuracy decision in the autonomous driving system.

During this investigation with various LLMs as main decision agent, we proceed under two assumptions.

- 1) Certain AI systems can transform real-world situations into text-based explanations, which are later used as input for the LLMs
- 2) the outputs generated by the LLMs can be translated into actual decisions made by the decision agent by interpreting the responses from the LLMs.

We have investigated the effectiveness of various LLMs for use as decision-making agents in autonomous driving systems. Our initial objective was to answer the research question (Research Question 1): Can an agent make decisions with the help of an LLM without undergoing a specific learning process for each new situation? We have also assumed that vehicle-to-vehicle (V2V) communication has already been achieved through a standardized networking protocol, such as LAN-based direct communication or a low-latency wireless system. Under this assumption, each vehicle can communicate with other vehicles within a defined radius (e.g., 10 meters). When a vehicle enters the information sharing radius of another vehicle, it can exchange data regarding their current status, such as obstacle detection, traffic conditions, direction, and future intended actions. To evaluate the impact of V2V communication on autonomous decision-making, we have investigated how LLMs process and utilize this information. Specifically, we have examined whether the incorporation of V2V exchanged data improves decision accuracy and enables AVs to make more precise and context-aware decisions. However, V2V communication introduces a critical question (Research Question 2): Is a single centralized decision-making agent sufficient to process all incoming V2V data and make autonomous driving decisions, or is a multi-agent system required for improved efficiency and scalability? In this research, we have investigated the answers to these two research questions. Through this multi-agent approach, the research aims to bridge the gap between current autonomous vehicle capabilities and the complex decision-making requirements of fully automated transportation systems.

To test large language models as decision agent, we have prepared a set of simple, text-based simulation scenarios of different traffic situations using Python. These scenarios are designed to cover situations that require logical reasoning or the application of common sense knowledge, such as recognizing a traffic red light and stopping accordingly. These scenarios will be used as input for various LLMs to assess how effectively they handle both types of challenges. The experiments will be conducted using the LLM selected in Figure 3.3.

3.2 The Decision Agent

The Decision Agent is responsible for making context-aware driving decisions. It leverages the reasoning capabilities of pre-trained Large Language Models (LLMs), such as GPT-4, Claude, and open-source alternatives. These models are capable of processing natural language prompts that describe traffic scenarios and generate corresponding driving actions (e.g. STOP or FORWARD).

Hugging Face[1] is a platform where various open LLM models are available. LM Studio[2] is a platform to test and integrate LLM available on Hugging Face into a locally available system on ordinary computing devices, even without powerful GPUs. Now, **the question is what factors were considered in the selection of LLMs for this study?**

One key factor in our model selection was quantization, which optimizes model performance while reducing computational requirements. This research [44] indicates that 8-bit quantization enables the majority of LLMs to maintain a performance level comparable to their nonquantized equivalents, regardless of model size (e.g. 7B to 70B parameters). Moreover, LLMs that are quantized to 4 bits can also up hold similar performance to their non-quantized versions across most benchmarks. This approach achieves memory reduction of 50 to 75% while preserving precision in complex tasks such as reasoning, decision making, and domain-specific applications. The models chosen for this investigation were selected using a structured approach based on three key factors, **popularity and performance in text-to-text generation**, **LM Studio recommendations for optimized accuracy**, and **comparative evaluations of the top commercial services**. More specifically,

- 1) Some models were chosen based on the highest number of downloads from Hugging Face, ensuring widespread adoption and benchmark effectiveness.
- 2) Models suggested by LM Studio were included due to their strong performance and compatibility with local inference environments.
- 3) The best commercial services were selected based on their comparative performance with open-source counterparts, prioritizing accuracy, interpret ability, and real-time inference.

The selected models are shown in Figure 3.1. However, all the Hugging Face models are not fully compatible with the LM Studio runtime. As a result, some models were tested directly on the Hugging Face interface to avoid compatibility issues. Furthermore, while models such as OpenAI o1, DeepSeek R1, and Llama 3.1 405B have demonstrated strong benchmark performance, they were not included in this study due to limited quantization support, lack of local deployment feasibility, and limited open source availability.

[1]https://huggingface.co/
[2]https://lmstudio.ai/

Recommendation	Model Name	Benchmark Performance
LM Studio Recommended Models	Mistral 7B	74.6% (MMLU), 83.5% (GSM8K)
	OpenHermes 2.5	72.1% (MMLU), 79.2% (BIG-bench)
	DeepSeek 7B	76.3% (MMLU), 85.4% (GSM8K)
Hugging Face Open-Source Models	LLaMA 2 13B	75.8% (MMLU), 80.7% (BIG-bench)
	Mixtral 8x7B	78.2% (MMLU), 88.1% (GSM8K)
Top Commercial Services	Claude 3 Sonnet	82.3% (MMLU), 90.2% (BIG-bench)
	GPT-4 Turbo	85.6% (MMLU), 92.4% (GSM8K)
	Falcon 7B/40B	73.4% (MMLU), 78.9% (BIG-bench)

FIGURE 3.1: Selected Models for the Experimentation

3.3 The Communication Agent

The **Communication Agent** facilitates structured Vehicle-to-Vehicle (V2V) information exchange, allowing AVs within a defined communication radius to share and receive critical environmental data. This includes information such as obstacle presence, road conditions, current speed, and the intended action of the vehicle. To ensure compatibility with Large Language Models (LLMs), the data is formatted in a simple, human-readable structure that can be seamlessly incorporated into text-based prompts. Table 3.1 defines the standardized message schema used by the Communication Agent.

The Communication Agent ensures that all AVs within the information-sharing radius can access and benefit from collective situational awareness. For example, if a vehicle cannot directly see a stop sign due to traffic or any reason to sight block, it can still receive a warning from another vehicle that has a clear line of sight. This enables more accurate and safer decisions, particularly in complex or uncertain scenarios.

The structured data format allows for seamless integration into the LLM-based Decision Agent, allowing it to reason with both local observations and external context. Figure 3.2 illustrates the information exchange process facilitated by the Communication Agent. This multi-agent communication approach

Field	Type	Description
`Vehicle_ID`	String	A unique identifier for the broadcasting vehicle.
`Current_Speed`	Float	The vehicle's current speed in meters per second (m/s).
`Obstacle_Presence`	Boolean	Indicates whether the vehicle detects a critical obstacle in its immediate path.
`Obstacle_Type`	Enum / Null	Type of detected obstacle (e.g., '`stop sign`', '`pedestrian`', '`road block`'). This is `null` if `Obstacle_Presence` is `False`.
`Obstacle_Proximity`	Float	Distance to the detected obstacle in meters.
`Intended_Action`	Enum	Planned action from the broadcasting vehicle Decision Agent (e.g., '`stop`', '`forward`'

TABLE 3.1: Structured Information Schema for V2V Communication Messages.

significantly improves the accuracy of the AVs decision by expanding its environmental perception beyond the local perception limit.

3.4 Text-Based Simulation and Scenario Design

The core concept is to investigate the reasoning capabilities of LLMs for AVs. In this research, we initially used a series of traffic situations and developed text-based simulation scenarios using Python to evaluate the effectiveness of LLMs as the decision agent in AV. These scenarios were designed to test the capabilities of LLMs in these three domains, logical reasoning, rule compliance, and dynamic decision making. as shown in Figure 3.3. We did extend our experiment however, capability checking domain of LLMs was the same.

- **Scenario 1: Rule compliance** This scenario tested whether the LLM could correctly interpret a green traffic light and determine that the AV should proceed. It would assess the basic understanding of large language models of common traffic rules. This simulation is shown in figure 3.3(A)
- **Scenario 2: Common sense** In this case, a stop sign appears on a partially blocked road. The goal was to evaluate how the LLM interprets such ambiguous situations and whether it can determine an appropriate action based on partial cues. This simulation is shown in figure 3.3(B)

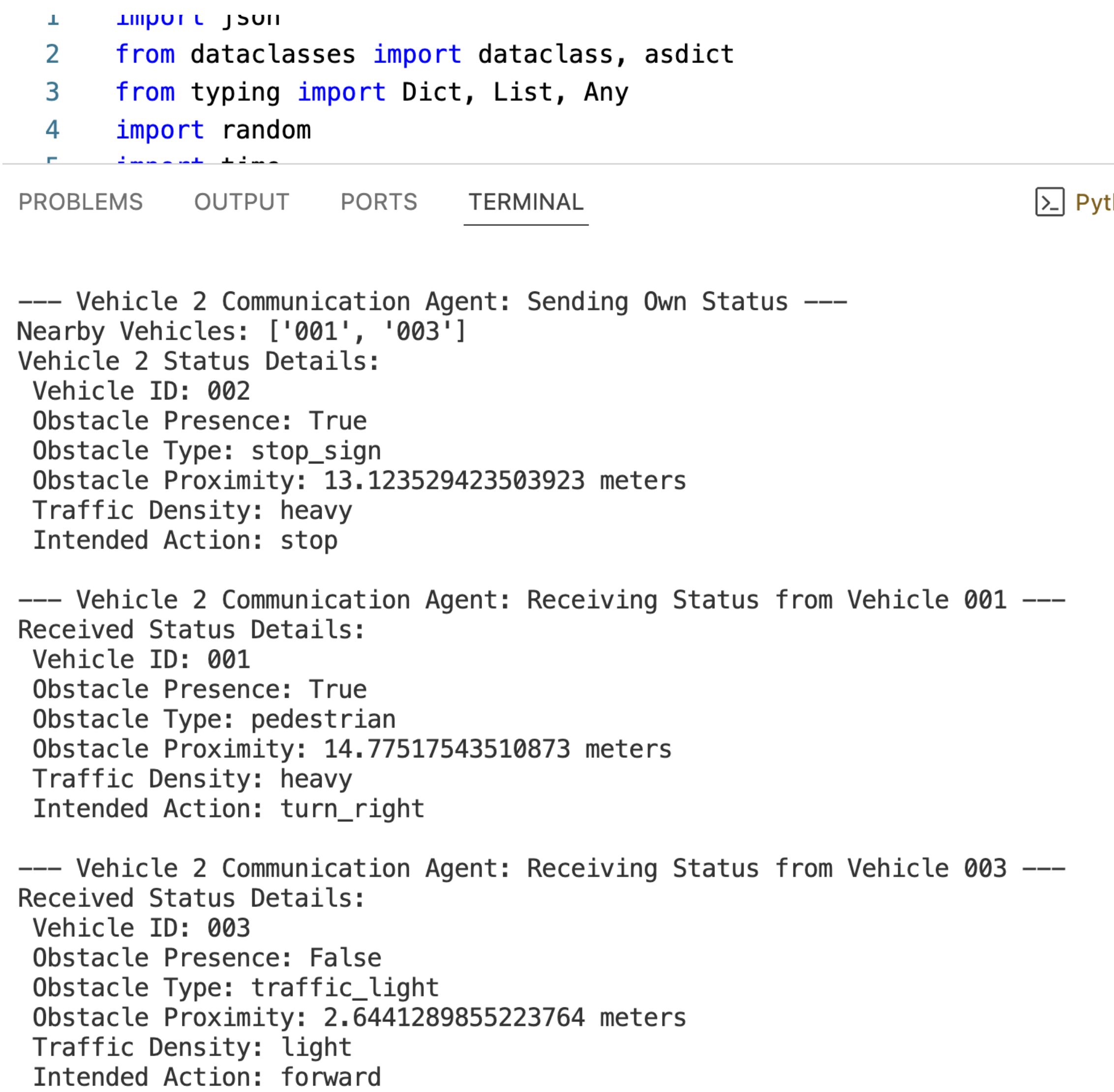
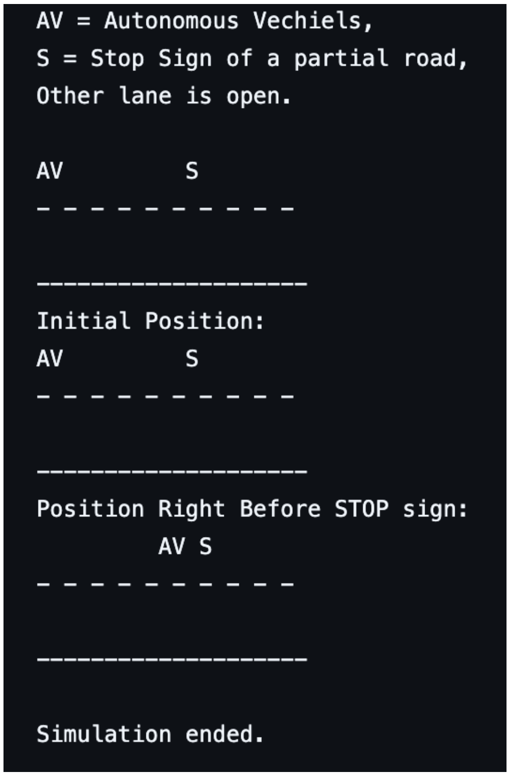


FIGURE 3.2: An illustration of Communication Agent

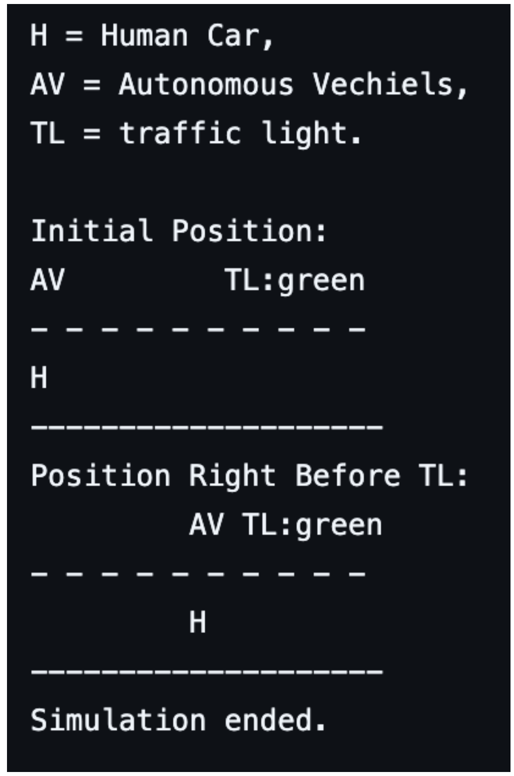
- **Scenario 3: Dynamic Decision Making** A more complex test involving a pedestrian suddenly crossing in front of the AV. This scenario assessed whether the LLM could dynamically adapt its decision to an unexpected and potentially hazardous situation. This simulation is shown in Figure 3.3(C)

3.5 Prompt Engineering

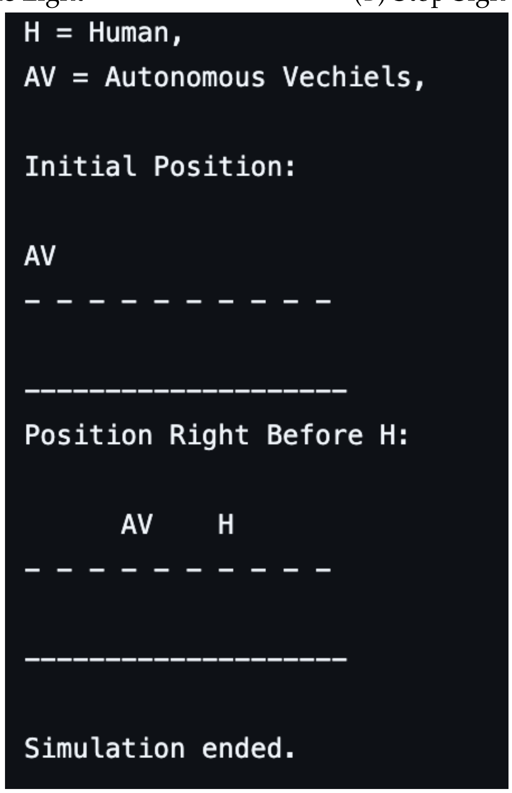
The Natural Language Processing capabilities of Large Language Models and the growing interest in their potential applications have made prompt engineering increasingly important, as the primary method of interaction with LLMs



(A) Traffic Light



(B) Stop Sign on Partial Road



(C) Human Suddenly Crossing Road

FIGURE 3.3: Illustration of real-life traffic scenarios tested in the LLM-based decision system.

is through prompts [45]. The design of the prompt determines LLM behavior, making prompt engineering critical, since the prompt acts as a guide and directly impacts the results. To carry out our experiment, we tested different LLM models with text-based traffic simulation scenarios using a simple prompt. Each scenario was presented to various LLM models using this simple prompt asking the models to simply respond with a single word without further explanation,

"What would the AV do? Please, just answer STOP or FORWARD."

We are assuming that the output from the LLMs would be used as a real decision in the autonomous driving system.

Chapter 4

Simulation and Results

4.1 Simulation-based Analysis

This section details the responses generated by a diverse set of LLMs when presented with these foundational text-based scenarios. The scenarios were designed to test fundamental aspects of AV intelligence such as basic rule following, common sense, and dynamic decision making. The models' outputs were analyzed for these characteristics:

- Decision Correctness: We evaluated whether LLMs can make safe and reasonable decisions in unfamiliar situations when provided with appropriate contextual data, without requiring specific training for each individual scenario.
- Following to Instructions: Whether the model's output conformed to the prompt's explicit formatting constraints (e.g., "Please just answer STOP or FORWARD").
- Consistency: We also investigated the consistency of the LLMs response in multiple runs. Inconsistent response is unacceptable in autonomous vehicle driving systems, where safety depends on stable and reliable decision-making behavior.

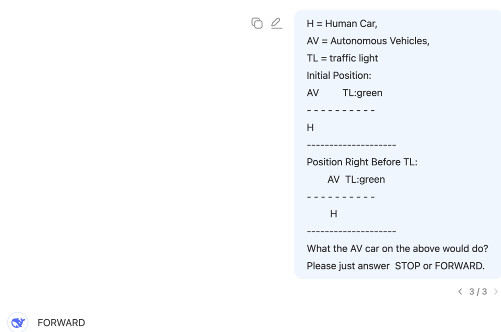
4.2 Experiment 1: Basic Rule-Following

For initial testing, we selected a basic traffic scenario involving an AV approaching a green traffic light, as illustrated in Figure 3.3 (B), and presented it to various language models to evaluate their decision-making behavior. The scenario was communicated through the prompt: 'What would the AV on the above do? Please just answer STOP or FORWARD.' The selected models included Claude[1] 3.7 Sonnet, GPT[2]-4 Turbo, Falcon[3] 3 7B and open-source alternatives such as

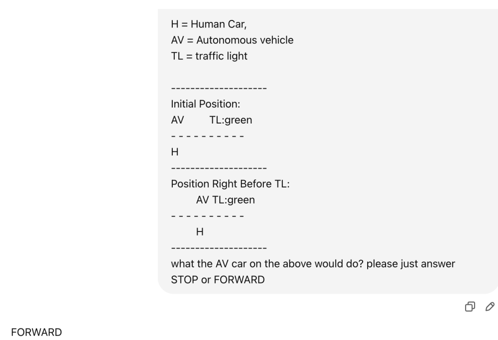
[1]https://claude.ai/chats
[2]https://chat.openai.com/
[3]https://chat.falconllm.tii.ae/

OpenHermes-2.5-Mistral-7B and google/flan-t5-large. The responses of these models, sourced from Hugging Face, LM Studio, and commercial providers.

GPT-4 Turbo and DeepSeek-V3 provided direct and expected responses **FORWARD**, which aligns with the logic of the situation shown in Figure 4.1. However, Claude deviated from the expected format by including an explanatory response, despite the prompt requesting a one-word answer. OpenHermes-2.5 and Falcon3 7B also responded with a clear **FORWARD**, demonstrating alignment with the input instructions shown in Figure 4.2. Surprisingly, the google/flan-t5-large output differed from all others by responding **STOP**, contradicting the intended logic of the scenario.

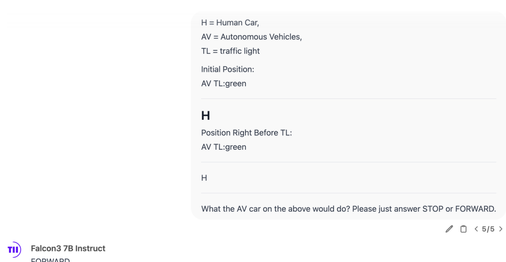


(A) Output from DeepSeek-V3

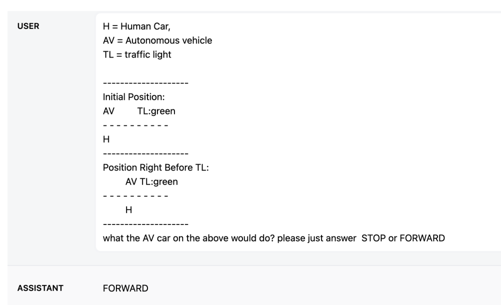


(B) Output from GPT-4 turbo

FIGURE 4.1: Responses from different LLMs on Scenario 1: DeepSeek-V3, GPT-4 turbo



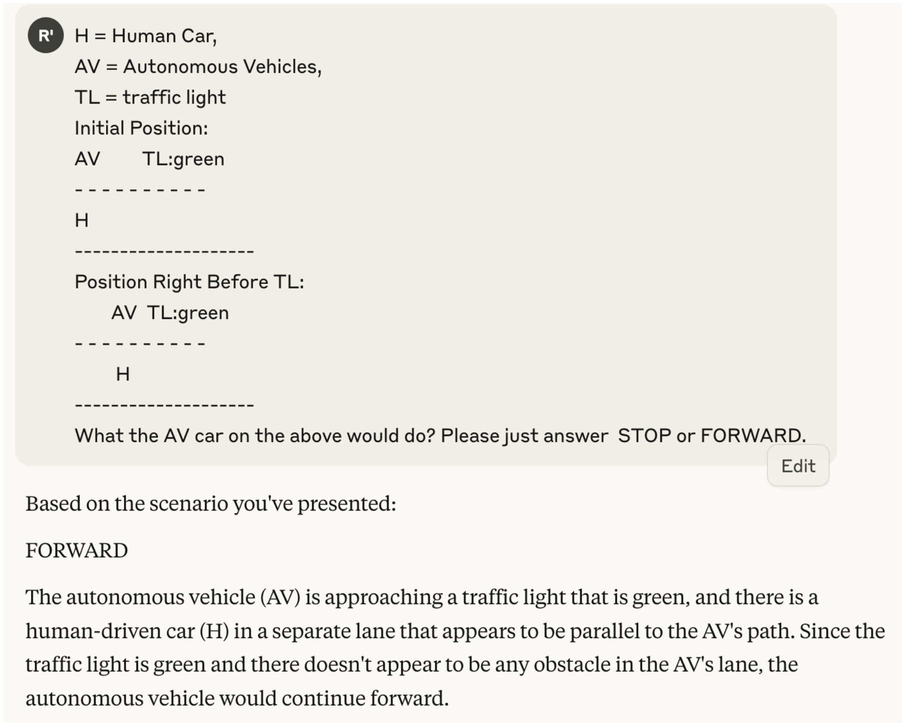
(A) Output from Falcon3 7B



(B) Output from OpenHermes-2.5-Mistral-7B

FIGURE 4.2: Responses from different LLMs on Scenario 1: Falcon3 7B, and OpenHermes-2.5-Mistral-7B

The Claude 3 Sonnet model also determined that the correct action was **FORWARD**. However, it failed to follow the prompt's constraint to 'just answer STOP or FORWARD.' Instead, it provided a full sentence explanation of its reasoning shown in Figure 4.3.



H = Human Car,
AV = Autonomous Vehicles,
TL = traffic light
Initial Position:
AV TL:green
- - - - - - - - - -
H

Position Right Before TL:
AV TL:green
- - - - - - - - - -
H

What the AV car on the above would do? Please just answer STOP or FORWARD.

Edit

Based on the scenario you've presented:

FORWARD

The autonomous vehicle (AV) is approaching a traffic light that is green, and there is a human-driven car (H) in a separate lane that appears to be parallel to the AV's path. Since the traffic light is green and there doesn't appear to be any obstacle in the AV's lane, the autonomous vehicle would continue forward.

FIGURE 4.3: Responses from different LLMs on Scenario 1: Claude 3

The google/flan-t5-large model responded with **STOP** and provided an alternative explanation for its decision shown in Figure 4.4. However, stopping at a green light is incorrect and dangerous.

Most of the response was as expected and also demonstrated that not all LLMs can be used as a decision agent, both the promise and the current limitations of this approach. The results emphasize the importance of careful model selection, as most of the other tested models produced the expected and appropriate response that shows the LLM has the potential to make driving decisions. However, choosing the right model is a critical factor in ensuring consistent and safe behavior in autonomous vehicle systems.

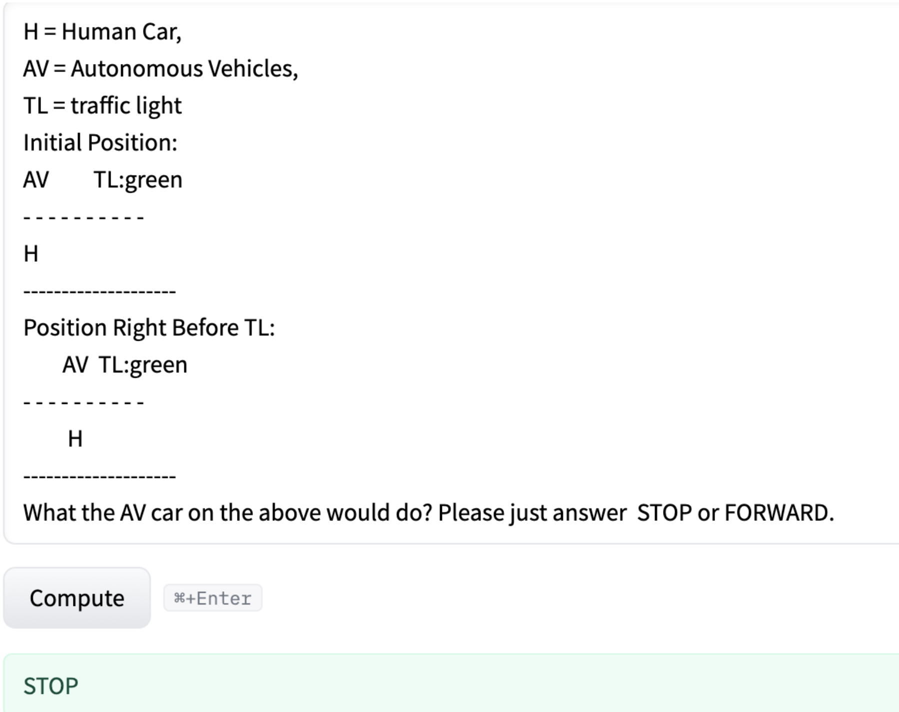


FIGURE 4.4: Responses from different LLMs on Scenario 1: google/flan-t5

4.3 Consistency test of Decision Agent : Experiment 1

In safety-critical domains like autonomous driving, consistent decision-making is as vital as correctness. For autonomous vehicles, it is not enough for the decision agent to give the correct answer once, it must give the same correct answer every time when faced with the same situation. Even a wrong decision, such as stopping when the traffic light is green, can lead to accidents. To address our sub-research question, 'Does repeated querying of LLMs in the same scenario lead to variations in decision-making outcomes?' To investigate this, we conducted an experiment to test the stability responses of LLMs.

We selected the model, OpenHermes-2.5-Mistral-7B and presented the scenario of recognizing a green traffic light. The prompt was executed 20 times and the responses were mapped such as **FORWARD** = 1 (the correct action) and **STOP** = 0 (an incorrect and unsafe action). We then calculated the mean and variance of the responses to quantify consistency. As shown in Figure 4.5, out of the 20 responses, the model responded **FORWARD** 19 times and **STOP** once. This resulted in a mean of 0.95 and a variance of 0.0475. Although this result indicates that the model is generally reliable in this scenario, even a single incorrect response in real-world traffic can lead to hazardous consequences.

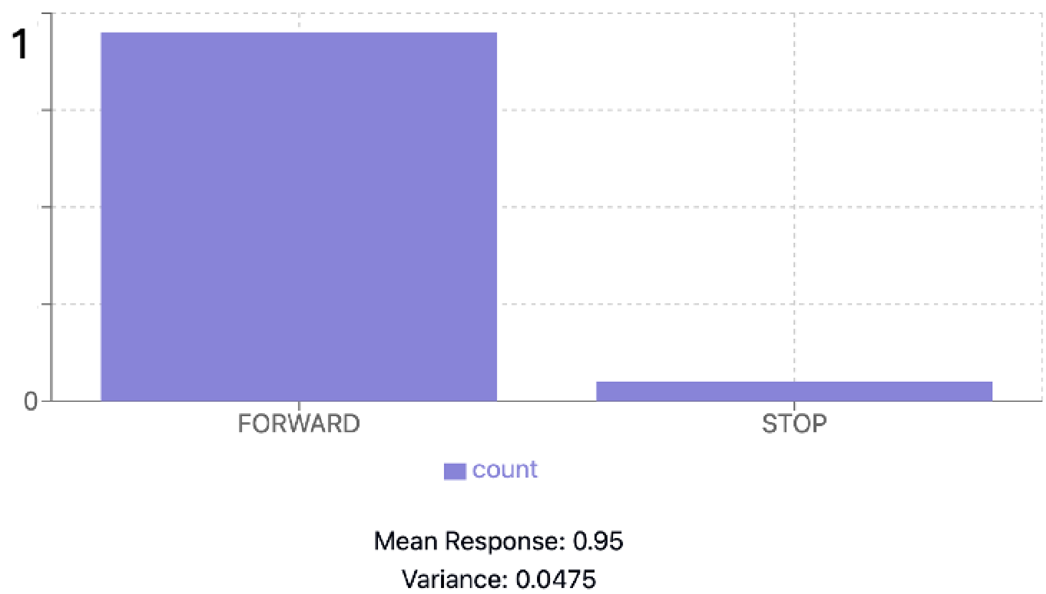


FIGURE 4.5: LLM Model Consistency on the Tested Scenario

To further enhance decision reliability and reduce such variance, this research adopted a multi-agent framework. In this setup, a dedicated 'Communication Agent' is responsible for transmitting and receiving structured Vehicle-to-Vehicle (V2V) data. This agent ensured consistent information sharing in a standardized text format, such as obstacle presence, vehicle speed, and intended actions. The Decision Agent would utilize this extended contextual information to make safer and more informed driving decisions.

4.4 Experiment 2: Stop sign view blocked from the following vehicle

To demonstrate how a multi-agent framework can improve decision-making reliability, we created a simulation where an AVs view was blocked. In this setup, an autonomous car (AV2) is driving behind an autonomous truck (AV1). There is a stop sign ahead, but AV2 could not see the sign because the truck in front is blocking its view, as shown in Figure 4.6. This kind of situation is common and dangerous in real-world driving, as it can lead to accidents if the car behind does not know why the car in front is stopping. This challenge will become more significant in mixed traffic environments where both human-driven and autonomous vehicles will share the road, each with different driving decision-making mechanisms and behaviors.

In this experiment, we investigated Whether the **Decision Agent** can improve its situational awareness by incorporating additional context shared through

```
AV2 = Autonomous Car(Can not see the stop sign),
AV1 = Autonomous Truck,
S = Stop Sign

AV2       AV1 S
- - - - - - - - - -
--------------------
Initial Position:
AV2       AV1 S
- - - - - - - - - -
--------------------
Position Right Before STOP:
     AV2  AV1 S
- - - - - - - - - -
--------------------
Simulation ended.
```

FIGURE 4.6: Extended Traffic Scenario with V2V Communication

a **Communication Agent**. The Communication Agent enables AV2 to receive status updates directly from AV1, extending its perception beyond its own local sensors. The data format included obstacle detection, proximity, and the intended action of AV1,

Information received by AV2 Communication Agent:

- Vehicle ID: 001
- Obstacle Presence: `True`
- Obstacle Type: `Stop sign`
- Obstacle Proximity: `15 meters`
- Intended Action: `stop`

4.4.1 Decision Agents Response: Without V2V Communication Data

First, the scenario was presented to the LLMs. For initial testing, we chose the model GPT-4 Turbo, without any V2V communication data. Based on that perception, the model responded with **FORWARD**, which means the car would continue to go forward shown in Figure 4.7.

> **Prompt:** "What would the AV above do? Just answer STOP or FORWARD."
>
> **Model (GPT-4 Turbo) Response:** FORWARD

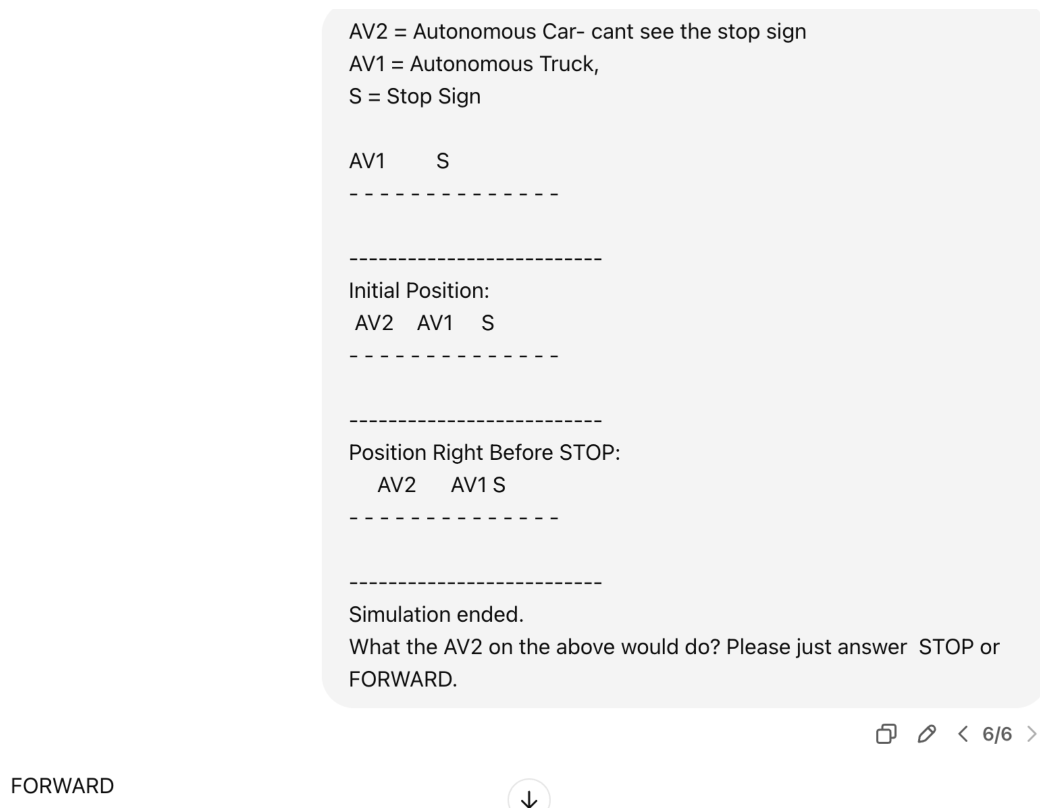
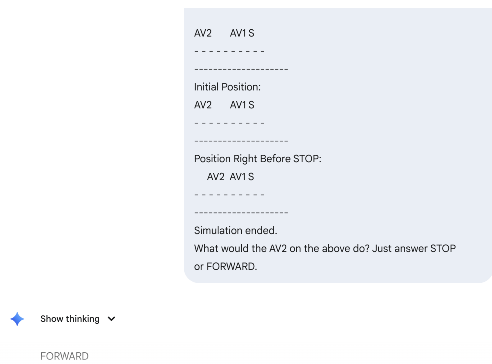
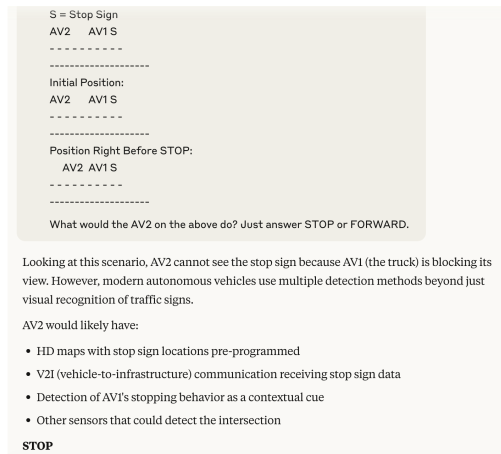


FIGURE 4.7: LLM Model Response without Communication agent's information (GPT-4 Turbo)

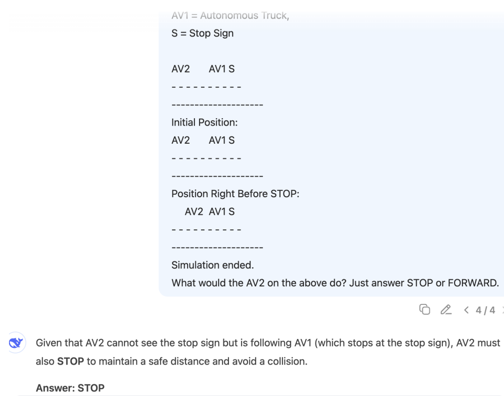
The same unsafe response, FORWARD, was also responded by Gemini 2.5 Flash. Although Claude 3.5 and DeepSeek responded correctly with STOP, as shown in Figure 4.8. However, both Claude and DeepSeek included additional explanations, despite the fact that the prompt clearly asked for a one-word answer. This inconsistency highlights a key issue: even advanced models can behave unpredictably when relying solely on their own perception. Without a complete environmental context, such as shared contextual information, they may make unsafe decisions or fail to follow important instructions.



(A) Response from Gemini 2.5 Flash



(B) Response from Claude 3



(C) Response from Deep

FIGURE 4.8: LLM Model Response without V2V Communication support on Experiment-2

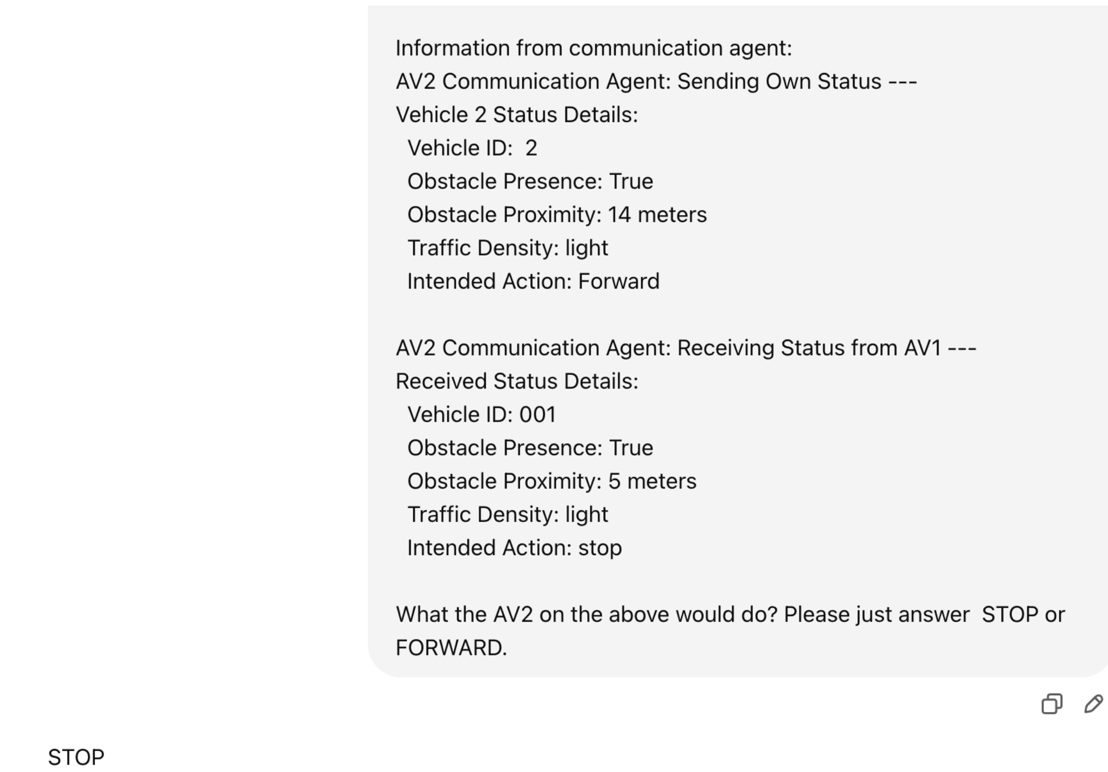
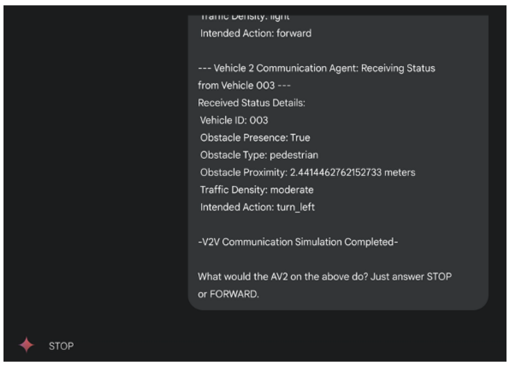


FIGURE 4.9: LLM Model Response with V2V Communication support (GPT-4 Turbo)

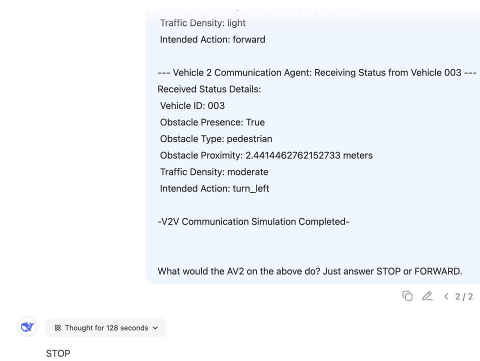
4.4.2 Decision Agents Response: With V2V Communication Data

We then again tested the same situation and examined whether the incorporation of V2V data improves the accuracy of the decisions and enables AVs to make more precise and context-aware decisions. By enabling the Communication Agent, AV1 shares its intended action and information about the obstacle ahead with AV2. These data are structured and passed as additional input presented to the model, as shown in Figure 4.9. For this case, we used GPT-4 Turbo. With access to this contextual information, the model responds with **STOP**, even without direct visual confirmation of the traffic sign in the case where GPT-4 Turbo was used. Now, with access to this extra context, the model made a safer decision, even though AV2 could not see the stop sign itself. This shows how V2V communication improves the accuracy of LLM decision-making. Unlike the first run (without communication), where the model chose to go forward and risked a collision, the shared information helped it choose a more context-aware and safe action.

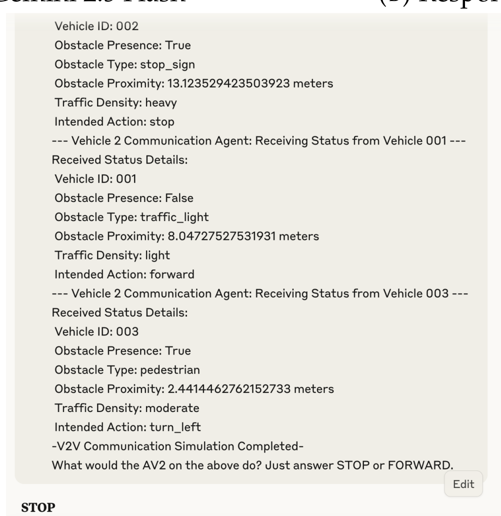
We also tested the same scenario with V2V communication using other popular commercial models, Gemini 2.5 Flash[4], Claude 3.5, and DeepSeek[5]. All of these models gave the correct response **STOP** after receiving the information shared by the Communication Agent shown in Figure 4.10. This shows that when models have access to extra context from V2V data, they can make safer and more reliable decisions.



(A) Response from Gemini 2.5 Flash



(B) Response from Claude 3



(C) Response from Deep

FIGURE 4.10: LLM Model Response with V2V Communication support on Experiment-2

[4]https://gemini.google.com/
[5]https://chat.deepseek.com/a/chat

4.5 Consistency test Of Decision Agent: Experiment 2

To confirm that V2V communication also resolves the consistency issue, we selected the model GPT-4 Turbo for further testing. We used the scenario previously described in Figure 4.6, where an autonomous car (AV2) follows a truck (AV1) that sees a stop sign, but AV2 cannot see it due to visual obstruction. We enabled the Communication Agent, which provided AV2 with structured V2V data from AV1, specifically, AV1's perception of the stop sign and its intention to stop. The prompt was executed 20 times and the responses were mapped as STOP = 1 (the correct and safe action) and FORWARD = 0 (an incorrect and unsafe action). We then calculated the mean and variance of the responses to evaluate consistency. As shown in Figure 4.11, the model responded with STOP in all 20 trials. This resulted in a mean of 1 and a variance of 0, indicating perfect consistency. These results confirm that incorporating V2V information through our multi-agent framework not only improves decision-making accuracy in complex scenarios but also eliminates the variability observed in single-agent systems.

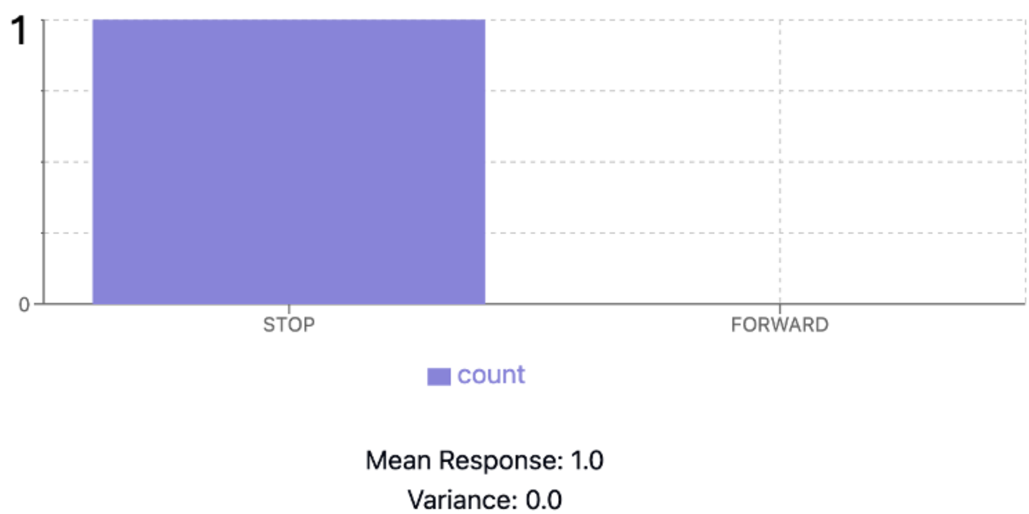


FIGURE 4.11: LLM Model Consistency with V2V Communication support(GPT4-Turbo)

4.6 Discussion

The results from these experiments clearly show both the potential and the current limitations of using Large Language Models (LLMs) as a decision agent in autonomous vehicles.

In Experiment 1, we observed that LLMs demonstrated strong capabilities in understanding and responding to traffic situations using rule-following and common-sense reasoning. However, a major limitation is inconsistent behavior when used without additional context. During consistency evaluation, we tested OpenHermes-2.5-Mistral-7B on the same driving scenario 20 times. The model responded correctly in 19 of 20 trials (mean response = 0.95), but made an incorrect decision, choosing **STOP** when the correct action was **FORWARD.** As illustrated in Figure 4.5, this variation is a critical safety concern, even a single incorrect decision in real-world driving can result in dangerous consequences that could cause rear-end collisions.

In Experiment 2, we introduced our multi-agent framework, which includes a Communication Agent responsible for sharing contextual Vehicle-to-Vehicle (V2V) data. When this enhanced contextual information version of the scenario was repeated for consistency, GPT-4 Turbo responded with correct action (STOP) in 20 of the trials. This resulted in a perfect mean of 1.0 and no variance, which confirmed the complete consistency of the decision.

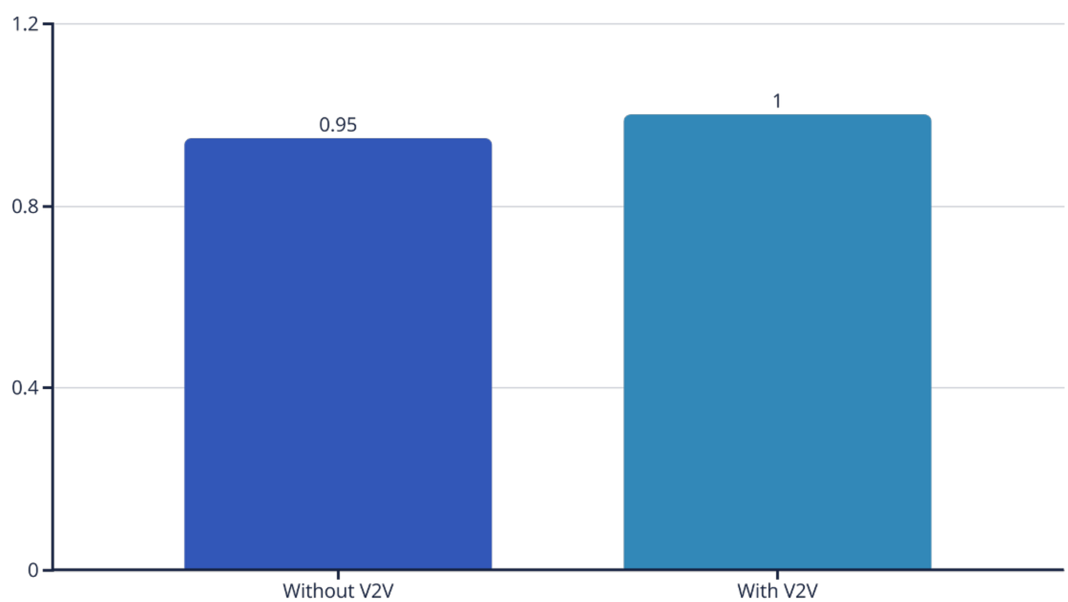


FIGURE 4.12: Comparison of Decision Consistency With and Without V2V Communication

The comparison between the two setups highlights an improvement. Without V2V communication, the LLM responded correctly most of the time with a variance (0.0475), showing somewhat inconsistent behavior that is unacceptable in safety-critical systems. However, when V2V data was introduced through our multi-agent framework, the model responded correctly in without any variance. As illustrated in Figure 4.12, this demonstrates how shared contextual information enables the LLM to make consistently accurate and safe decisions.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

We presented an approach for leveraging Large Language Models (LLMs) to enhance reasoning capabilities in uncertain traffic situations within a multi-agent framework for autonomous vehicles. We have investigated LLMs from Hugging Face, LM Studio, as well as major commercial services such as Claude, GPT-4, and Falcon. Their responses to basic traffic scenarios were analyzed, revealing varying levels of consistency and accuracy. Our results show that for RQ1, Large Language Models (LLMs) were able to make intelligent and safe decisions even in unfamiliar or novel traffic situations. They did not require specific training for each scenario and showed strong general reasoning skills, similar to how a human driver would respond to unexpected conditions. For RQ2, the use of multiple agents, such as a Decision Agent and a Communication Agent, improved the system performance compared to the single agent setup. When vehicles shared data such as speed, obstacles, and intentions through V2V communication, decisions became more accurate, consistent, and safer. This design also made the system more scalable and flexible for handling complex real-world traffic situations. These results reveal both the promise and the current limitations of this approach, highlighting the need for improved consistency in the model responses. The proposed approach aims at the realization of adaptive autonomous systems capable of human-like reasoning in unpredictable situations. By integrating contextual data derived from V2V communication with LLM reasoning, our goal is to bridge the critical gap in decision-making accuracy for autonomous vehicles.

5.2 Challenges and Future Work

- **Simulation Expansion:** Extend the simulation environment to include multilane roads and multiple vehicles, simulating more realistic traffic conditions with varying visibility and road complexity.

- **Increased the number of trails for Consistency Testing:** Run the same prompt more than 100 times per scenario per LLM to obtain a stronger statistical basis to evaluate the consistency of the decision.
- **Offline Evaluation of Local LLMs:** Test the effectiveness of local LLMs in disconnected environments to assess their viability in real-world AV applications.
- **Emergency Broadcasting via Communication Agent:**
  - Implement dynamic emergency messaging (e.g., broadcast STOP to nearby vehicles).
  - Evaluate radius-based alerts: Determine what warnings should be sent to the following vehicles based on proximity and shared intent.
- **Limited Scenario Diversity:** The simulation environment includes a limited range of traffic scenarios, which may restrict the system's ability to generalize to real-world driving conditions.
- **Lack of Fail-Safe Mechanisms:** No fail-safe or redundancy systems to handle incorrect LLM outputs or real-time error detection to ensure safety.
- **Unaddressed V2V Communication Constraints:** This study assumes ideal communication conditions, without evaluating real-world issues such as network congestion, signal interference or latency, especially in dense traffic scenarios.

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Publications

International Conference

Toward a Multi Agent Approach for LLM-Based Dynamic Vehicle Control and Communication in Accidental Condition

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***Abstract*—In autonomous vehicles (AVs), making the right decision in unknown traffic situations remains a challenge. Traditional AVs rely on pre-trained models, which often struggle in such cases where human-like reasoning is required. In this paper, we examine how Large Language Models (LLMs) act as a decision agent responding to scenario-specific text prompts derived from real-world traffic situations. In addition, we propose a Communication Agent that enables vehicle-to-vehicle (V2V) information sharing, such as speed, obstacles, and future intentions, in a structured format to provide contextual support for the decision agent. This paper proposes a preliminary approach to assess whether LLMs within a multi-agent framework, when provided with structured prompts and contextual data, can support consistent and human-like decision making.**

***Index Terms*—autonomous vehicles, large language models (LLMs), multi-agent, vehicle-to-vehicle (V2V) communication, decision making agent, communication agent.**

I. Introduction

This paper explores the potential of integrating Large Language Models (LLMs) [1] into a multi-agent framework [2] to improve decision making in autonomous vehicles (AVs), particularly in unknown and unsafe traffic situations. Our main concern would be to explore the use of LLMs for autonomous driving systems (ADS) as the main decision-making agent within a multi-agent framework to evaluate its reasoning ability [3] to handle uncertain traffic situations. Our goal is to contribute to the development of safer and more reliable Level 5 [4] autonomous vehicles. We aim to contribute to Level 5 (complete automation [5]). There are numerous instances in which traditional autonomous vehicles are capable of making effective decisions in familiar scenarios using pre-trained models. However, they may have trouble facing new or unusual situations where their programmed knowledge is not directly covered in such situations. Human drivers can use common sense and past experiences to handle unexpected events, such as knowing that traffic cones on a moving truck are not dangerous. However, current AV systems, even those that use rule-based approaches or reinforcement learning (RL [6]), will struggle in these scenarios. This limitation is especially evident in what we call unknown-unsafe domain situations where the correct action is not immediately clear [7]. During this investigation with various LLMs, we proceed under two assumptions: 1) certain AI systems can transform real-world situations into text-based explanations, which are later used as input for the LLMs, and 2) the outputs generated by the LLMs can be translated into actual decisions made by the AV's decision agent by interpreting the responses from the LLMs. We are investigating the effectiveness of various LLMs for use as decision-making agents in autonomous driving systems. Our initial objective is to answer the research question (Research Question 1): Can an agent make decisions with the help of an LLM without undergoing a specific learning process for each new situation? In our research, we will assume that vehicle-to-vehicle (V2V) communication has been achieved through a standardized networking protocol, such as LAN-based direct communication or a low-latency wireless system. Under this assumption, each vehicle can communicate with other vehicles within a defined radius (e.g., 10 meters). When a vehicle enters the information sharing radius of another vehicle, it can exchange data regarding their current status, such as obstacle detection, traffic conditions, direction, and future intended actions. To evaluate the impact of V2V communication on autonomous decision-making, we will investigate how LLMs process and utilize this information. Specifically, we will examine whether the incorporation of V2V exchanged data improves decision accuracy and enables AVs to make more precise and context-aware decisions. However, V2V communication introduces a critical question, (Research Question 2): Is a single centralized decision-making agent sufficient to process all incoming V2V data and make autonomous driving decisions, or is a multi-agent system required for improved efficiency and scalability? In this paper, we investigate the answers to these two research questions.

II. Motivation and Background

Imagine a traffic situation, where a road is partially blocked due to construction, with traffic cones and a 'STOP' sign indicating a partial road block. A typical autonomous vehicle (AV) might see the 'STOP' sign and interpret it as a complete

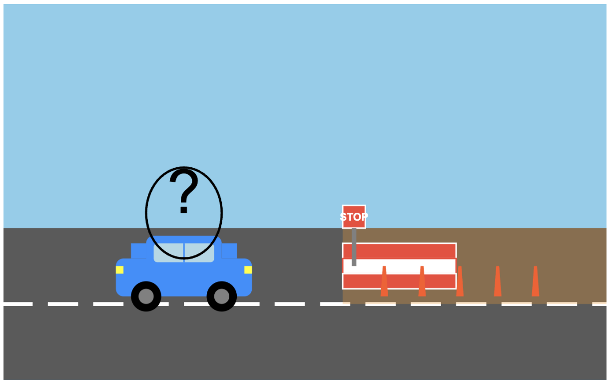


Fig. 1: What a current AV might do in this situation?

road closure, coming to a complete stop because that is what its pre-programmed data tell it to do. However, a human driver in the same situation might use common sense, realize that the road is only partially closed, and safely continue through the open section.

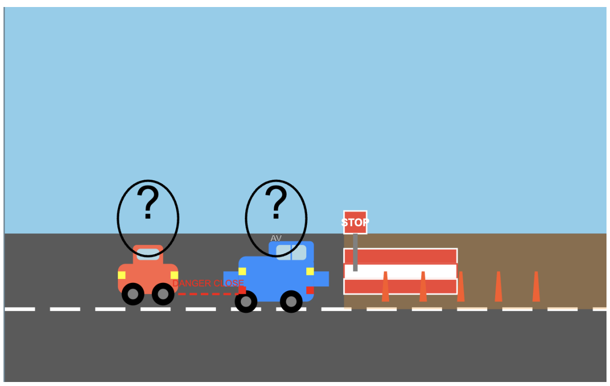


Fig. 2: Lack of communication between vehicles may lead to a potential accident.

Now imagine a more complicated situation where an autonomous truck comes to a sudden stop when it sees the 'STOP' sign. There is another car, driven by a human or another AV, right behind it. This sudden stop could easily cause a crash. Now imagine a human driver encountering a partially blocked road. To navigate safely, the driver would shift into the adjacent open lane, relying on instinct, experience, and situational awareness. Anticipating the possibility of an oncoming vehicle from the opposite direction or from behind, the driver would proactively slow down, assessing the risk, and would take the necessary precautions to avoid a collision. In contrast, a traditional AV, which lacks human-like reasoning and predictive thinking, may not recognize the potential danger. Without contextual understanding, it can continue at its normal speed, assuming the lane is clear, increasing the risk of a head-on collision.

However, if the AV had better reasoning abilities, it might recognize that the road is only partially closed and proceed safely through the open part. And if the AV could communicate with the vehicle behind it, it could alert the other driver about its intended actions, particularly if the lane were to close suddenly, helping to prevent a potential accident. A fundamental challenge in traditional autonomous vehicles (AVs) is to prepare for all truly unknown situations [8]. Any scenario we create is technically 'known' to us, even if it feels unfamiliar to the AVs, making it difficult to test how AVs handle truly unknown-unsafe situations. In addition, it is difficult to recreate complex real-world scenarios in simulation environments. For example, it is difficult to accurately simulate unpredictable human actions or complicated environmental conditions. In real life, there could be countless unexpected situations that are nearly impossible to include in training data sets for traditional autonomous driving systems (ADS) to avoid accidents. Human drivers use common sense to deal with these situations, so through this paper we will explore whether LLMs can also show human-like reasoning to handle them effectively or not.

To address these challenges, we propose a possible approach for integrating LLMs into a multi-agent framework for autonomous driving control system. LLMs have the potential to provide common sense or reasoning ability that traditional systems lack, helping AVs better understand the context of complex real-world scenarios. Incorporating Vehicle-to-Vehicle communication using multi-agent, which will allow vehicles to exchange information with other vehicles. This capability is also essential for creating realistic and complex driving scenarios.

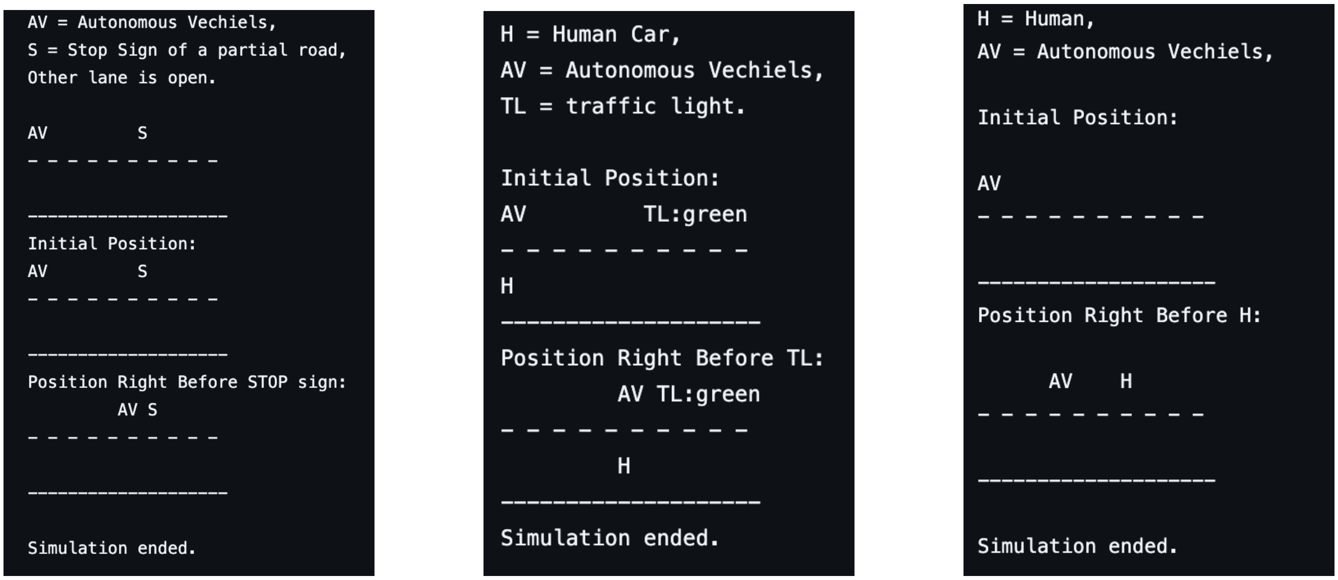
III. Preliminary

Recommendation	Model Name	Benchmark Performance
LM Studio Recommended Models	Mistral 7B	74.6% (MMLU), 83.5% (GSM8K)
	OpenHermes 2.5	72.1% (MMLU), 79.2% (BIG-bench)
	DeepSeek 7B	76.3% (MMLU), 85.4% (GSM8K)
Hugging Face Open-Source Models	LLaMA 2 13B	75.8% (MMLU), 80.7% (BIG-bench)
	Mixtral 8x7B	78.2% (MMLU), 88.1% (GSM8K)
Top Commercial Services	Claude 3 Sonnet	82.3% (MMLU), 90.2% (BIG-bench)
	GPT-4 Turbo	85.6% (MMLU), 92.4% (GSM8K)
	Falcon 7B/40B	73.4% (MMLU), 78.9% (BIG-bench)

Fig. 3: Selected Models for the Experimentation

To investigate the use of LLMs as a decision agent in AVs, we have utilized open-source and local deployment platforms. Hugging Face[1] offers a wide range of open-source pre-trained models, while LM Studio[2] integrates LLM models from Hugging Face into a local system, even without powerful GPUs. Now, the question is what factors were considered in the selection of LLMs for this study? One key factor in

[1]https://huggingface.co/
[2]https://lmstudio.ai/



(a) Stop sign on Partial road (b) Traffic Light (c) Human suddenly crossing road

Fig. 4: Illustration of real life traffic scenarios

our model selection was quantization, which optimizes model performance while reducing computational requirements. This research [9] indicates that 8-bit quantization enables the majority of LLMs to maintain a performance level comparable to their nonquantized equivalents, regardless of model size (e.g. 7B to 70B parameters). Moreover, LLMs that are quantized to 4 bits can also uphold similar performance to their non-quantized versions across most benchmarks. This approach achieves memory reduction of 50 to 75% while preserving precision in complex tasks such as reasoning, decision making, and domain-specific applications. The models chosen for this investigation were selected using a structured approach based on three key factors: popularity and performance in text-to-text generation, LM Studio recommendations for optimized accuracy, and comparative evaluations of the top commercial services. Specifically, 1) Some models were chosen based on the highest number of downloads from Hugging Face, ensuring widespread adoption and benchmark effectiveness. 2) Models suggested by LM Studio were included due to their strong performance and compatibility with local inference environments. 3) The best commercial services were selected based on their comparative performance with open-source counterparts, prioritizing accuracy, interpretability, and real-time inference. The selected models are shown in Fig. 3. However, not all Hugging Face models are fully compatible with the LM Studio runtime. As a result, some models were tested directly on the Hugging Face interface to avoid compatibility issues. Furthermore, while models such as OpenAI's o1, DeepSeek R1, and Llama 3.1 405B have demonstrated strong benchmark performance, they were not included in this study due to limited quantization support, lack of local deployment feasibility, and restricted open-source availability.

To test these selected models, we have prepared a set of simple text-based simulation scenarios using Python, as illustrated in Fig. 4. These scenarios are designed to cover situations that require logical reasoning or the application of common rules knowledge, such as recognizing a red traffic light and stopping accordingly. These scenarios will be used as input for various LLMs to assess how effectively they handle both types of challenges. The experiments will be conducted using the LLM selected in Fig.3.

IV. Our Approach

The main phase of this research focuses on using the shared data of the communication agent within our proposed multi-agent framework. The Communication Agent ensures that vehicles share critical information, including obstacle detection, traffic conditions, speed, and intended actions, in a standardized format within a defined radius, the expected format is demonstrated in Fig. 5. This structured data exchange is expected to significantly improve the accuracy of Decision Agent by providing a more comprehensive contextual understanding of the driving environment. For initial testing, we selected a basic traffic scenario involving an autonomous vehicle (AV) approaching a green traffic light, as illustrated in Fig. 4(b), and presented it to various language models to evaluate their decision-making behavior. The scenario was communicated through the prompt: 'What would the AV on the above do? Please just answer STOP or FORWARD.' The selected models included Claude[3] 3.7 Sonnet, GPT[4]-4 Turbo, Falcon[5] 3 7B and open-source alternatives such as OpenHermes-2.5-Mistral-7B and google/flan-t5-large. The responses of these models, sourced from Hugging Face, LM

[3] https://claude.ai/chats
[4] https://chat.openai.com/
[5] https://chat.falconllm.tii.ae/

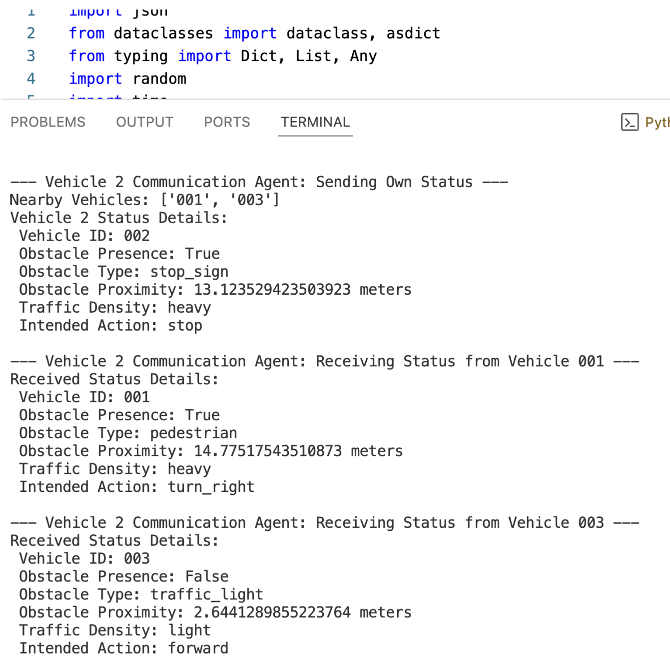


Fig. 5: An illustration of Communication Agent

Studio, and commercial providers, are shown in Fig. 11. GPT-4 Turbo and Falcon provided direct and expected responses 'FORWARD', which aligns with the logic of the situation. However, Claude deviated from the expected format by including an explanatory response, despite the prompt requesting a one-word answer. OpenHermes-2.5 responded with a clear 'FORWARD', demonstrating alignment with the input instructions. Surprisingly, the google/flan-t5-large output differed from all others by responding 'STOP', contradicting the intended logic of the scenario.

A major consideration was consistency. The subresearch question, 'Does repeated querying of LLMs on the same scenario lead to variations in decision-making outcomes?' will be one of such investigations of consistency. To test this, each scenario was submitted to the models multiple times for regenerating the outputs. This approach allowed us to observe whether the models produced stable and repeatable responses

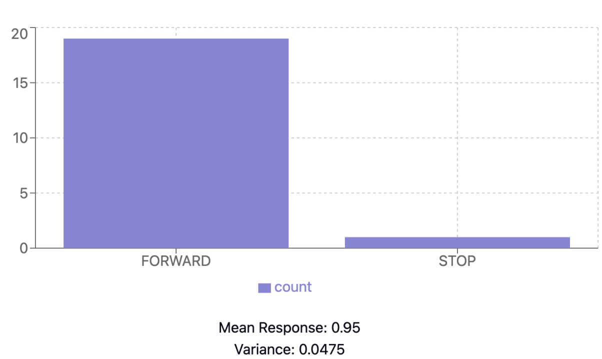


Fig. 6: LLM Model Consistency on the Tested Scenario

or if their decisions varied unpredictably. Consistency is especially critical in autonomous vehicle (AV) applications, where uncertain output can cause serious safety concerns.

For giving an example of this analysis, we ran the prompt at least 20 times on OpenHermes-2.5-Mistral-7B, and the consistency results are presented in Fig. 6. Consistency was calculated by mapping 'FORWARD' = 1 and 'STOP' = 0. 'FORWARD' mean is closer to 1, it indicates that the output is having greater consistency with the expected response.

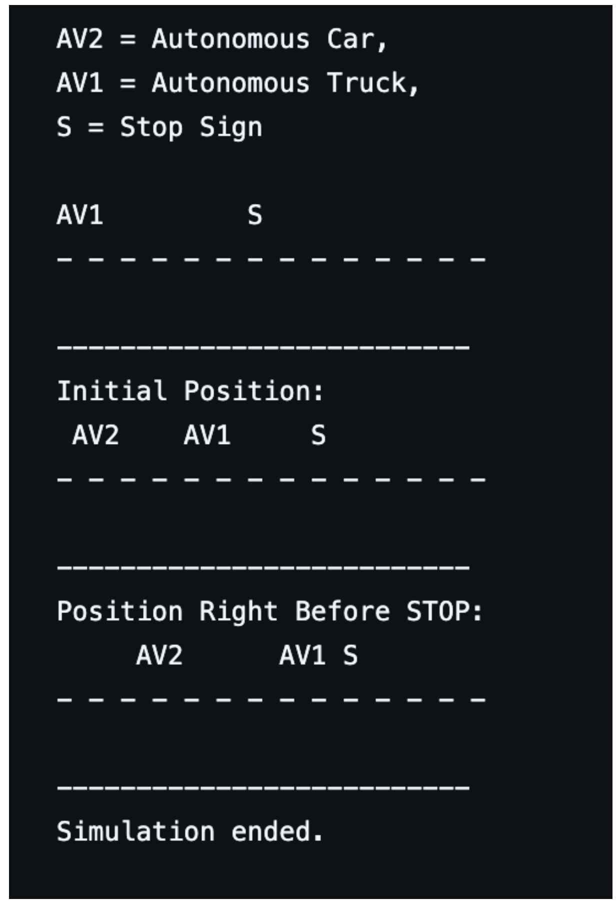


Fig. 7: Extended Traffic Scenario with V2V Communication

To investigate the impact of V2V communication on autonomous decision-making, we extended our simulation to a more complex traffic scenario. In this extended scenario, AV2 (an autonomous car) follows AV1 (an autonomous truck), with a stop sign ahead that AV2 cannot see because its line of sight is blocked by AV1, as shown in Fig. 7. To investigate how LLMs process and utilize this information, this scenario was presented to the LLM with the same prompt: 'What would the AV on the above do? Please, just answer STOP or FORWARD'. The model responded with 'FORWARD', as shown in Fig. 8, for the case of using GPT-4 Turbo. This decision could potentially lead to an accident. We then examine whether the incorporation of V2V exchanged data improves the accuracy of the decisions and enables AVs to make more precise and context-aware decisions. By enabling

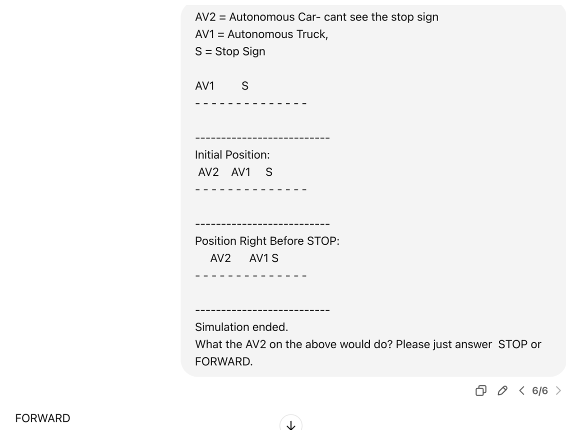


Fig. 8: LLM Model response without Communication agent's information (GPT-4 Turbo)

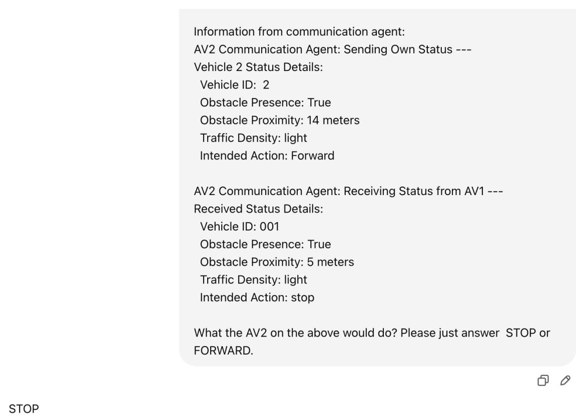


Fig. 9: LLM Model response with Communication agent's information (GPT-4 Turbo)

the Communication Agent, AV1 shares its intended action and information about the obstacle ahead with AV2. These data are structured and passed as additional input presented to the model, as shown in Fig. 9, for the case of using GPT-4 Turbo. With access to this contextual information, the model responds with 'STOP', even without direct visual confirmation of the traffic sign in the case where GPT-4 Turbo was used.

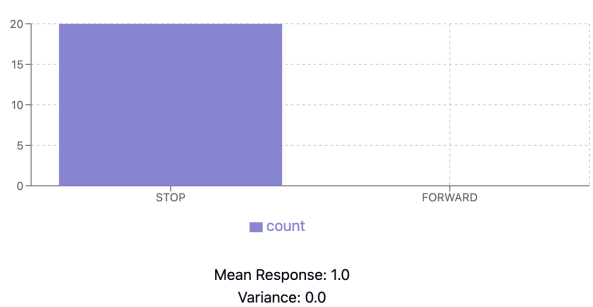


Fig. 10: LLM Model Consistency with V2V Communication support (GPT-4 Turbo)

To evaluate the consistency of the model decision, we ran the same prompt 20 times. The consistency was calculated by mapping 'FORWARD' = 1 and 'STOP' = 0. The resulting mean value of 1 for 'STOP' indicates that the output is having greater consistency with the expected response. The consistency of GPT-4 Turbo's responses with V2V support is shown in Fig. 10, which confirms that communication agent inputs help LLMs generate more accurate decisions in critical traffic environments.

V. Conclusion

We presented an approach for utilizing Large Language Models (LLMs) to enhance reasoning capabilities in uncertain traffic situations within a multi-agent framework for autonomous vehicles. We have investigated LLMs from Hugging Face, LM Studio, as well as major commercial services such as Claude, GPT-4 Turbo, and Falcon. Their responses to basic traffic scenarios were analyzed, revealing varying levels of consistency and accuracy. These results revealed both the promise and the current limitations of this approach, highlighting the need for improved consistency in the model responses. The proposed approach aims at the realization of adaptive autonomous systems capable of human-like reasoning in unpredictable situations. By integrating contextual data derived from V2V communication with LLM reasoning, we can have further investigations to bridge the critical gap in decision-making accuracy for autonomous vehicles.

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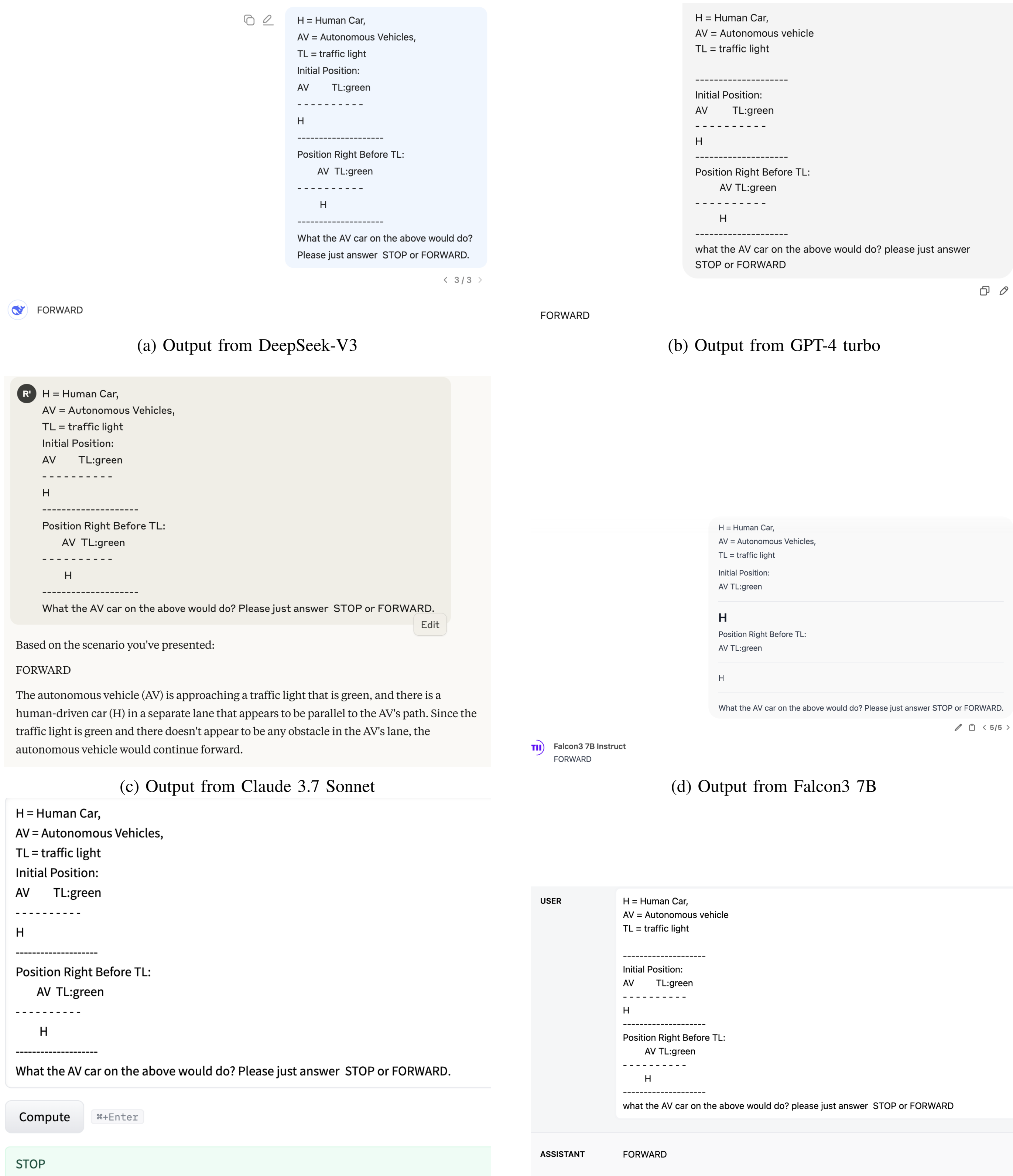

(a) Output from DeepSeek-V3

(b) Output from GPT-4 turbo

(c) Output from Claude 3.7 Sonnet

(d) Output from Falcon3 7B

(e) Output from google/flan-t5-large

(f) Output from OpenHermes-2.5-Mistral-7B

Fig. 11: Responses from different LLMs

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Hamamatsu, Japan
July 21, 2025
Rafi Md Ashifujjman

Chapter 6

Simulation Source Code

6.1 Scenario 1: Traffic Light Recognition Simulation - Autonomous Vehicle Approaching Green Traffic Light

CODE LISTING 6.1: Scenario 1: Traffic Light Recognition Simulation - Autonomous Vehicle Approaching Green Traffic Light

```
# This code simulates a road with three lanes: top (AV), middle (divid
# The AV moves forward in the top lane, the human moves forward in the
# and the traffic light is in the middle-right.
# The code writes the road state to a file and moves the vehicles forw
# The simulation ends when the AV is close to the traffic light.

import time
class RoadCollisionSimulator:
    def __init__(self, road_length):
        # Initialize the road with 3 lanes: top (AV), middle (divider,
        self.road = [[' ' for _ in range(road_length)] for _ in range(

        # Initial positions
        self.av_position = 0
        # AV starts at the beginning of the top lane
        self.human_position = 0
        # Human starts at the beginning of the bottom lane
        self.traffic_light_position = road_length // 2 + 2
        # Traffic light in the middle-right

        # Place vehicles and traffic light in initial positions
        self.road[0][self.av_position] = 'AV'
        # Place AV in the top lane
        self.road[0][self.traffic_light_position] = 'TL:green'
        # Place traffic light in top lane
```

```
        self.road[2][self.human_position] = 'H'
        # Place Human in the bottom lane

        # Lane divider setup (alternating '-' and ' ')
        self.road[1] = ['-' if i % 2 == 0 else '␣' for i in range(roac

        # Open a file to write the simulation output
        self.output_file = open("TrafficLightRecog.txt", "w")

    def write_road_to_file(self, description):
        # Write the description and road state to the file
        self.output_file.write(description + "\n")
        for lane in self.road:
            road_line = ''.join(lane)
            self.output_file.write(road_line + "\n")
            # Write each lane to the file
        self.output_file.write('-' * len(self.road[0]) + "\n")
        # Separator line
        self.output_file.flush()
        # Ensure data is written to the file

    def move_av(self):
        # Move AV forward in the top lane
        if self.av_position < self.traffic_light_position - 2:
            self.road[0][self.av_position] = '␣'
            # Remove AV from current position
            self.av_position += 1
            # Move AV forward
            self.road[0][self.av_position] = 'AV'
            # Place AV in the new position

    def move_human(self):
        # Move Human forward in the bottom lane
        if self.human_position < len(self.road[2]) - 1:
            self.road[2][self.human_position] = '␣'
            # Remove Human from current position
            self.human_position += 1
            # Move Human forward
            self.road[2][self.human_position] = 'H'
            # Place Human in the new position

    def simulate(self):
        # Step 1: Initial position
        self.write_road_to_file("AV␣=␣Autonomous␣Vehicle,\nH␣=␣Human,\
```

```
        self.write_road_to_file("Initial Position:")

        # Move vehicles until AV is close to traffic light
        while self.av_position < self.traffic_light_position - 2:
            self.move_av()
            self.move_human()
            time.sleep(0.3)

        # Step 2: Position right before traffic light
        self.write_road_to_file("Position Right Before TL:")

        # Step 3: Final movement
        self.move_av()
        self.move_human()

        # Step 3: Final position
        self.write_road_to_file("Final Position:")

        self.output_file.write("Simulation ended.\n")
        # Write simulation end message
        self.output_file.close()
        # Close the file after simulation ends

# Simulation parameters
road_length = 20

# Create an instance of the RoadCollisionSimulator
simulator = RoadCollisionSimulator(road_length)

# Run the simulation
simulator.simulate()
```

6.2 Scenario 2: Stop Sign Detection Simulation - Autonomous Vehicle Approaching Stop Sign on Partial Road

CODE LISTING 6.2: Scenario 2: Stop Sign Detection Simulation - Autonomous Vehicle Approaching Stop Sign on Partial Road

```
# This code simulates a road with two lanes: top (AV and Stop Sign),
# The AV moves forward in the top lane, the stop sign is in the middl
# and the divider is in the bottom lane.
```

```
# The code writes the road state to a file and moves the vehicles forw
# The simulation ends when the AV is close to the stop sign.

import time

class RoadCollisionSimulator:
    def __init__(self, road_length):
        # Initialize the road with 2 lanes: top (AV and Stop Sign), bo
        self.road = [[' ' for _ in range(road_length)] for _ in range(

        # Initial positions
        self.av_position = 0
        # AV starts at the beginning of the top lane
        self.stop_sign_position = road_length // 2
        # Stop sign in the middle of top lane

        # Place AV and stop sign in initial positions
        self.road[0][self.av_position] = 'AV'
        # Place AV in the top lane
        self.road[0][self.stop_sign_position] = 'S'
        # Place stop sign in top lane

        # Lane divider setup (alternating '-' and ' ') - represents th
        self.road[1] = ['-' if i % 2 == 0 else ' ' for i in range(road

        # Open a file to write the simulation output
        self.output_file = open("StopSign.txt", "w")

    def write_road_to_file(self, description):
        # Write the description and road state to the file
        self.output_file.write(description + "\n")
        for lane in self.road:
            road_line = ''.join(lane)
            self.output_file.write(road_line + "\n")
            # Write each lane to the file
        self.output_file.write('-' * len(self.road[0]) + "\n")
        # Separator line
        self.output_file.flush()
        # Ensure data is written to the file

    def move_av(self):
        # Move AV forward in the top lane towards stop sign
        if self.av_position < self.stop_sign_position - 1:
            self.road[0][self.av_position] = ' '
```

```
            # Remove AV from current position
            self.av_position += 1
            # Move AV forward
            self.road[0][self.av_position] = 'AV'
            # Place AV in the new position

    def simulate(self):
        # Header information
        self.write_road_to_file("AV␣=␣Autonomous␣Vehicles,\nS␣=␣Stop␣S

        # Step 1: Initial position
        self.write_road_to_file("Initial␣Position:")

        # Move AV until it's right before the stop sign
        while self.av_position < self.stop_sign_position - 1:
            self.move_av()
            time.sleep(0.3)

        # Step 2: Position right before stop sign
        self.write_road_to_file("Position␣Right␣Before␣STOP␣sign:")

        self.output_file.write("Simulation␣ended.\n")
        # Write simulation end message
        self.output_file.close()
        # Close the file after simulation ends

# Simulation parameters
road_length = 15

# Create an instance of the RoadCollisionSimulator
simulator = RoadCollisionSimulator(road_length)

# Run the simulation
simulator.simulate()
```

6.3 Scenario 3: Sudden Human Crossing Detection Simulation - Autonomous Vehicle Encountering Unexpected Pedestrian

CODE LISTING 6.3: Scenario 3: Sudden Human Crossing Detection Simulation - Autonomous Vehicle Encountering Unexpected Pedestrian

```
# This code simulates a road with two lanes: top (AV and Human), botto
# The AV moves forward in the top lane, the human appears suddenly in
# and the divider is in the bottom lane.
# The code writes the road state to a file and moves the vehicles forw
# The simulation ends when the AV is close to where the human will ap

import time

class RoadCollisionSimulator:
    def __init__(self, road_length):
        # Initialize the road with 2 lanes: top (AV and Human), bottom
        self.road = [['␣' for _ in range(road_length)] for _ in range(

        # Initial positions
        self.av_position = 0
        # AV starts at the beginning of the top lane
        self.human_position = road_length // 2 + 1
        # Human will appear later in the middle-right

        # Place AV in initial position
        self.road[0][self.av_position] = 'AV'
        # Place AV in the top lane

        # Lane divider setup (alternating '-' and ' ')
        self.road[1] = ['-' if i % 2 == 0 else '␣' for i in range(roac

        # Open a file to write the simulation output
        self.output_file = open("Suddenhumancrossing.txt", "w")

    def write_road_to_file(self, description):
        # Write the description and road state to the file
        self.output_file.write(description + "\n")
        for lane in self.road:
            road_line = ''.join(lane)
            self.output_file.write(road_line + "\n")
            # Write each lane to the file
        self.output_file.write('-' * len(self.road[0]) + "\n")
        # Separator line
        self.output_file.flush()
        # Ensure data is written to the file
```

```
    def move_av(self):
        # Move AV forward in the top lane
        if self.av_position < len(self.road[0]) - 1:
            self.road[0][self.av_position] = '␣'
            # Remove AV from current position
            self.av_position += 1
            # Move AV forward
            if self.road[0][self.av_position] != 'H':
                # Don't overwrite Human
                self.road[0][self.av_position] = 'AV'
                # Place AV in the new position

    def add_human(self):
        # Human suddenly appears in the road
        self.road[0][self.human_position] = 'H'

    def simulate(self):
        # Header information
        self.write_road_to_file("H␣=␣Human,\nAV␣=␣Autonomous␣Vehicles,

        # Step 1: Initial position (only AV visible)
        self.write_road_to_file("Initial␣Position:")

        # Move AV until it's close to where human will appear
        while self.av_position < self.human_position - 2:
            self.move_av()
            time.sleep(0.3)

        # Human suddenly crosses - add human to the scene
        self.add_human()

        # Step 2: Position right before Human (human has suddenly app
        self.write_road_to_file("Position␣Right␣Before␣H:")

        self.output_file.write("Simulation␣ended.\n")
        # Write simulation end message
        self.output_file.close()
        # Close the file after simulation ends

# Simulation parameters
road_length = 15

# Create an instance of the RoadCollisionSimulator
simulator = RoadCollisionSimulator(road_length)
```

```
# Run the simulation
simulator.simulate()
```

6.4 Scenario 4: Multi-Vehicle Collision Simulation - Autonomous Truck and Car Approaching Stop Sign with Possible Road Collision Simulation

CODE LISTING 6.4: Scenario 4: Multi-Vehicle Collision Simulation - Autonomous Truck and Car Approaching Stop Sign with Possible Road Collision Simulation

```
# This code simulates a road with two lanes: top (AVs), bottom (divide
# The AV1 truck moves forward in the top lane, the AV2 car moves forwa
# and the stop sign is in the middle of the top lane.
# The code writes the road state to a file and moves the vehicles forw
# The simulation ends when the AV1 truck hits the stop sign.

import time

class RoadCollisionSimulator:
    def __init__(self, road_length):
        # Initialize the road with 2 lanes: top (AVs), bottom (divider
        self.road = [[' ' for _ in range(road_length)] for _ in range(
        self.road[0][road_length // 2] = 'S'
        # Stop sign in the top lane (initially at the middle)

        # Position AV1 (truck) closer to stop sign, AV2 (car) further
        self.av1_position = road_length // 2 - 2
        # AV1 truck starts 2 positions before stop sign
        self.av2_position = 0
        # AV2 car starts at the beginning of the top lane

        self.road[0][self.av1_position] = 'AV1'
        # Place AV1 truck in the top lane
        self.road[0][self.av2_position] = 'AV2'
        # Place AV2 car in the top lane

        self.collision_occurred = False
        # Track if a collision occurred

        # Lane divider setup (alternating '-' and ' ')
```

```
        self.road[1] = ['-' if i % 2 == 0 else '␣' for i in range(road

        # Open a file to write the simulation output
        self.output_file = open("ExtendedScenario.txt", "w")

    def write_road_to_file(self, description):
        # Write the description and road state to the file
        self.output_file.write(description + "\n")
        for lane in self.road:
            road_line = ''.join(lane)
            self.output_file.write(road_line + "\n")
            # Write each lane to the file
        self.output_file.write('-' * len(self.road[0]) + "\n")
        # Separator line
        self.output_file.flush()
        # Ensure data is written to the file

    def detect_collision(self):
        # Check if AV1 hits the stop sign in the top lane
        if self.road[0][self.av1_position] == 'S':
            # Collision detected, mark with X
            self.road[0][self.av1_position] = 'X'
            # Mark collision with 'X'
            self.collision_occurred = True
            return True
        return False

    def move_av2_car(self):
        # Move AV2 car forward in the top lane (only if no collision o
        if not self.collision_occurred and self.av2_position < self.av
            self.road[0][self.av2_position] = '␣'
            # Remove AV2 from current position
            self.av2_position += 1
            # Move AV2 forward
            if self.av2_position < len(self.road[0]):
                self.road[0][self.av2_position] = 'AV2'
                # Place AV2 in the new position

    def move_av1_truck(self):
        # Move AV1 truck forward in the top lane
        if not self.collision_occurred:
            self.road[0][self.av1_position] = '␣'
            # Remove AV1 from current position
            self.av1_position += 1
```

```
            # Move AV1 forward
            if self.av1_position < len(self.road[0]):
                if self.road[0][self.av1_position] == 'S':
                    # Do not update AV1 to 'X' here; collision detecti
                    pass
                else:
                    self.road[0][self.av1_position] = 'AV1'
                    # Place AV1 in the new position

    def simulate(self):
        # Step 1: Initial position
        self.write_road_to_file("AV2␣=␣Autonomous␣Car,\nAV1␣=␣Autonom
        self.write_road_to_file("Initial␣Position:")

        # Step 2: Move to position right before STOP
        # Move vehicles until AV1 is one step away from stop sign
        stop_sign_position = len(self.road[0]) // 2
        while self.av1_position < stop_sign_position - 1:
            self.move_av2_car()
            self.move_av1_truck()
            time.sleep(0.5)
            # Simulate movement delay

        # Write the "Position Right Before STOP" state
        self.write_road_to_file("Position␣Right␣Before␣STOP:")

        # Step 3: Final move - AV1 hits the stop sign
        self.move_av2_car()
        self.move_av1_truck()

        # Detect collision and mark with X
        self.detect_collision()

        # Write final position
        self.write_road_to_file("Final␣Position:")

        self.output_file.write("Simulation␣ended.\n")
        # Write simulation end message
        self.output_file.close()
        # Close the file after simulation ends

# Simulation parameters
road_length = 20
```

```
# Create an instance of the RoadCollisionSimulator
simulator = RoadCollisionSimulator(road_length)

# Run the simulation
simulator.simulate()
```

6.5 Scenario 5: Multi-Agent Coordination Simulation - Three Autonomous Vehicles Coordinating Movement Around Human Obstacle

CODE LISTING 6.5: Scenario 5: Multi-Agent Coordination Simulation - Three Autonomous Vehicles Coordinating Movement Around Human Obstacle

```
# This code simulates a road with three lanes: top (AV1, H), middle (
# The AV1 moves forward in the top lane, the human moves forward in th
# and the AV2 moves forward in the bottom lane.
# The code writes the road state to a file and moves the vehicles forw
# The simulation ends when the AV1 is close to the human.

import time

class RoadCollisionSimulator:
    def __init__(self, road_length):
        # Initialize the road with 3 lanes: top (AV1, H), middle (divi
        self.road = [['␣' for _ in range(road_length)] for _ in range(

        # Initial positions
        self.av1_position = 0
        # AV1 starts at the beginning of the top lane
        self.human_position = road_length // 2 + 2
        # Human starts in the middle-right of top lane
        self.av2_position = 0
        # AV2 starts at the beginning of the bottom lane
        self.av3_position = 0
        # AV3 will appear later in the top lane

        # Place vehicles in initial positions
        self.road[0][self.av1_position] = 'AV1'
        # Place AV1 in the top lane
        self.road[0][self.human_position] = 'H'
        # Place Human in the top lane
```

```
        self.road[2][self.av2_position] = 'AV2'
        # Place AV2 in the bottom lane

        # Lane divider setup (alternating '-' and ' ')
        self.road[1] = ['-' if i % 2 == 0 else '␣' for i in range(roac

        # Open a file to write the simulation output
        self.output_file = open("NextStep.txt", "w")

    def write_road_to_file(self, description):
        # Write the description and road state to the file
        self.output_file.write(description + "\n")
        for lane in self.road:
            road_line = ''.join(lane)
            self.output_file.write(road_line + "\n")
            # Write each lane to the file
        self.output_file.write('-' * len(self.road[0]) + "\n")
        # Separator line
        self.output_file.flush()
        # Ensure data is written to the file

    def move_av1(self):
        # Move AV1 forward in the top lane
        if self.av1_position < len(self.road[0]) - 1:
            self.road[0][self.av1_position] = '␣'
            # Remove AV1 from current position
            self.av1_position += 1
            # Move AV1 forward
            if self.road[0][self.av1_position] != 'H':
                # Don't overwrite Human
                self.road[0][self.av1_position] = 'AV1'
                # Place AV1 in the new position

    def move_av2(self):
        # Move AV2 forward in the bottom lane
        if self.av2_position < len(self.road[2]) - 1:
            self.road[2][self.av2_position] = '␣'
            # Remove AV2 from current position
            self.av2_position += 1
            # Move AV2 forward
            self.road[2][self.av2_position] = 'AV2'
            # Place AV2 in the new position

    def add_av3(self):
```

```
        # Add AV3 to the top lane at the beginning
        self.av3_position = 0
        self.road[0][self.av3_position] = 'AV3'

    def simulate(self):
        # Step 1: Initial position
        self.write_road_to_file("H = Human,\nAV1,AV2,AV3 = Autonomous
        self.write_road_to_file("Initial Position:")

        # Move vehicles until AV1 is close to Human
        while self.av1_position < self.human_position - 2:
            self.move_av1()
            self.move_av2()
            time.sleep(0.3)

        # Step 2: Position right before Human
        self.write_road_to_file("Position Right Before Human:")

        # Step 3: Final movements and add AV3
        self.move_av1()
        self.move_av2()
        self.add_av3()
        # AV3 appears in the final position

        # Step 3: Final position
        self.write_road_to_file("Final Position:")

        self.output_file.write("Simulation ended.\n")
        # Write simulation end message
        self.output_file.close()
        # Close the file after simulation ends

# Simulation parameters
road_length = 20

# Create an instance of the RoadCollisionSimulator
simulator = RoadCollisionSimulator(road_length)

# Run the simulation
simulator.simulate()
```

6.6 Scenario 6: Vehicle-to-Vehicle (V2V) Communication System - Multi-Agent Information Sharing and Status Broadcasting

CODE LISTING 6.6: Scenario 6: Vehicle-to-Vehicle (V2V) Communication System - Multi-Agent Information Sharing and Status Broadcasting

```
import json
from dataclasses import dataclass, asdict
from typing import Dict, List, Any
import random
import time
import math

@dataclass
class VehicleStatus:
    # Comprehensive vehicle status data structure
    vehicle_id: str
    timestamp: float

    # Obstacle Detection
    obstacle_presence: bool
    obstacle_type: str
    obstacle_proximity: float
    # 0-15 meters

    # Traffic Conditions
    traffic_density: str
    # light, moderate, heavy
    road_conditions: str
    # normal, wet, construction, etc.

    # Vehicle Dynamics
    current_speed: float
    direction: str
    # forward, backward, stationary

    # Intended Action
    intended_action: str
    # forward, stop, turn_left, turn_right

    # Position for distance calculation
```

```
    x_coordinate: float
    y_coordinate: float

class V2VCommunicationSystem:
    def __init__(self, communication_radius: float = 50.0):
        self.communication_radius = communication_radius
        self.vehicles = {}

    def add_vehicle(self, vehicle_id: str, x: float, y: float):
        # Add a vehicle to the communication system
        self.vehicles[vehicle_id] = {
            'position': (x, y),
            'status': None
        }

    def calculate_distance(self, vehicle1_id: str, vehicle2_id: str) -
        # Calculate distance between two vehicles
        pos1 = self.vehicles[vehicle1_id]['position']
        pos2 = self.vehicles[vehicle2_id]['position']
        return math.sqrt((pos1[0] - pos2[0])**2 + (pos1[1] - pos2[1])*

    def get_nearby_vehicles(self, vehicle_id: str) -> List[str]:
        # Find nearby vehicles within communication radius
        nearby_vehicles = []
        for other_id in self.vehicles.keys():
            if other_id != vehicle_id:
                distance = self.calculate_distance(vehicle_id, other_i
                if distance <= self.communication_radius:
                    nearby_vehicles.append(other_id)
        return nearby_vehicles

class Vehicle2CommunicationAgent:
    def __init__(self, v2v_system: V2VCommunicationSystem):
        self.vehicle_id = "002"
        # Vehicle 2 (Sender)
        self.v2v_system = v2v_system

        # Position Vehicle 2 at (10, 10)
        self.v2v_system.add_vehicle(self.vehicle_id, 10, 10)

        # Tracking received statuses
        self.received_statuses = {}
        self.nearby_vehicles = []
```

```
        # Open output file for writing
        self.output_file = open("v2v_communication_output.txt", "w")

    def write_to_file(self, message):
        # print(message)
        self.output_file.write(message + "\n")
        self.output_file.flush()

    def send_own_status(self):
        # Generate and send Vehicle 2's own status with specific deta
        self.write_to_file("\n---␣Vehicle␣2␣Communication␣Agent:␣Sendi

        # Scan for nearby vehicles
        self.nearby_vehicles = self.v2v_system.get_nearby_vehicles(sel
        self.write_to_file(f"Nearby␣Vehicles:␣{self.nearby_vehicles}")

        # Create status with specific requirements
        vehicle_2_status = VehicleStatus(
            vehicle_id="002",
            timestamp=time.time(),

            # Obstacle Detection with stop sign
            obstacle_presence=True,
            obstacle_type="stop_sign",
            obstacle_proximity=13.123529423503923,

            # Traffic Conditions
            traffic_density="heavy",
            road_conditions=random.choice(['normal', 'wet', 'construct

            # Vehicle Dynamics
            current_speed=random.uniform(0, 60),
            direction='forward',

            # Intended Action
            intended_action='stop',

            # Position
            x_coordinate=10,
            y_coordinate=10
        )

        # Store status in V2V system
        self.v2v_system.vehicles[self.vehicle_id]['status'] = asdict(v
```

```
            self.write_to_file("Vehicle 2 Status Details:")
            self.write_to_file(f" Vehicle ID: {vehicle_2_status.vehicle_id
            self.write_to_file(f" Obstacle Presence: {vehicle_2_status.ob
            self.write_to_file(f" Obstacle Type: {vehicle_2_status.obstacl
            self.write_to_file(f" Obstacle Proximity: {vehicle_2_status.o
            self.write_to_file(f" Traffic Density: {vehicle_2_status.traff
            self.write_to_file(f" Intended Action: {vehicle_2_status.inten

            return vehicle_2_status

        def receive_vehicle_status(self, sender_vehicle_id: str):
            # Receive status from another vehicle
            self.write_to_file(f"\n--- Vehicle 2 Communication Agent: Rec

            # Simulate receiving status from the sender vehicle
            sender_status = self.v2v_system.vehicles[sender_vehicle_id]['s

            self.write_to_file("Received Status Details:")
            self.write_to_file(f" Vehicle ID: {sender_status['vehicle_id']
            self.write_to_file(f" Obstacle Presence: {sender_status['obsta
            self.write_to_file(f" Obstacle Type: {sender_status.get('obsta
            self.write_to_file(f" Obstacle Proximity: {sender_status['obs
            self.write_to_file(f" Traffic Density: {sender_status['traffic
            self.write_to_file(f" Intended Action: {sender_status['intende

            # Store received status
            self.received_statuses[sender_vehicle_id] = sender_status

        def close_file(self):
            # Close the output file
            self.output_file.close()

    def simulate_v2v_communication():
        # Simulate V2V communication from Vehicle 2's perspective
        # Create V2V communication system
        v2v_system = V2VCommunicationSystem(communication_radius=50.0)

        # Create other vehicles
        v2v_system.add_vehicle("001", 5, 5)
        # Vehicle 1 close to Vehicle 2
        v2v_system.add_vehicle("003", 20, 20)
        # Vehicle 3 at (20, 20)
```

```
# Create Vehicle 2's Communication Agent
vehicle_2_comm = Vehicle2CommunicationAgent(v2v_system)

# Vehicle 2 sends its own status
vehicle_2_status = vehicle_2_comm.send_own_status()

# Simulate sending status to other vehicles
# (In a real system, this would be a broadcast)
v2v_system.vehicles["001"]['status'] = {
    'vehicle_id': "001",
    'timestamp': time.time(),
    'obstacle_presence': random.choice([True, False]),
    'obstacle_type': random.choice(['traffic_light', 'pedestrian',
    'obstacle_proximity': random.uniform(0, 15),
    'traffic_density': random.choice(['light', 'moderate', 'heavy
    'road_conditions': random.choice(['normal', 'wet', 'constructi
    'current_speed': random.uniform(0, 120),
    'direction': random.choice(['forward', 'stationary']),
    'intended_action': random.choice(['forward', 'stop', 'turn_le
    'x_coordinate': 5,
    'y_coordinate': 5
}

v2v_system.vehicles["003"]['status'] = {
    'vehicle_id': "003",
    'timestamp': time.time(),
    'obstacle_presence': random.choice([True, False]),
    'obstacle_type': random.choice(['traffic_light', 'pedestrian',
    'obstacle_proximity': random.uniform(0, 15),
    'traffic_density': random.choice(['light', 'moderate', 'heavy
    'road_conditions': random.choice(['normal', 'wet', 'constructi
    'current_speed': random.uniform(0, 120),
    'direction': random.choice(['forward', 'stationary']),
    'intended_action': random.choice(['forward', 'stop', 'turn_le
    'x_coordinate': 20,
    'y_coordinate': 20
}

# Vehicle 2 receives statuses from Vehicle 1 and Vehicle 3
vehicle_2_comm.receive_vehicle_status("001")
vehicle_2_comm.receive_vehicle_status("003")

# Write simulation completion message
vehicle_2_comm.write_to_file("\n--V2V Communication Simulation Com
```

```
        # Close the output file
        vehicle_2_comm.close_file()

    # Run the simulation
    if __name__ == "__main__":
        simulate_v2v_communication()
```

6.7 Scenario 7: LLM Decision Consistency Analysis - Statistical Evaluation of Language Model Decision Patterns in Autonomous Driving Scenarios

CODE LISTING 6.7: Scenario 7: LLM Decision Consistency Analysis - Statistical Evaluation of Language Model Decision Patterns in Autonomous Driving Scenarios

```
import numpy as np
import matplotlib.pyplot as plt

# Response data (1 = FORWARD, 0 = STOP)
responses = [1] * 20
# All 20 responses were FORWARD
# Calculate statistics
mean_response = np.mean(responses)
variance_response = np.var(responses)
std_dev = np.std(responses)
# Create visualization
plt.figure(figsize=(8, 5))

# Bar plot for mean
plt.bar(['Mean'], [mean_response], color='skyblue', label=f'Mean: {me

# Add error bar showing standard deviation
plt.errorbar(['Mean'], [mean_response], yerr=[std_dev],
             fmt='none', ecolor='red', capsize=10, label=f'Std Dev: {st

# Customize plot
plt.title('LLM Decision Tendency (FORWARD=1, STOP=0)', pad=20)
plt.ylim(0, 1.2)
plt.ylabel('Response Value')
plt.legend()
plt.grid(axis='y', alpha=0.3)
```

```
    # Annotate important values
    plt.text(0, mean_response+0.05, f'Variance:␣{variance_response:.2f}',
            ha='center', va='bottom', fontsize=10)

plt.show()
```