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

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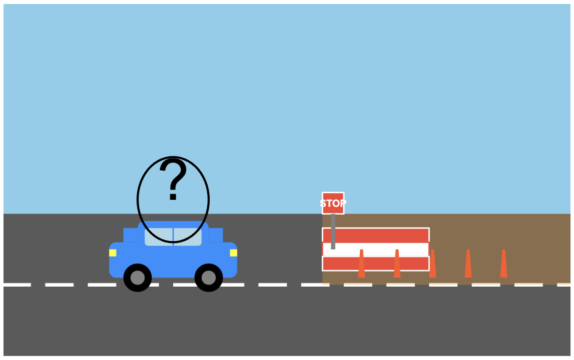


Fig. 1: What a current AV might do in this situation?

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.

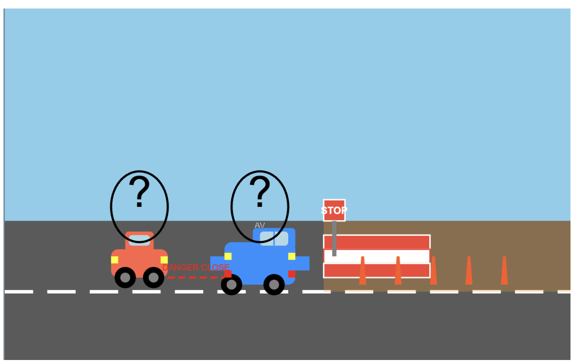


Fig. 2: Lack of communication between vehicles may lead to a potential accident.

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.

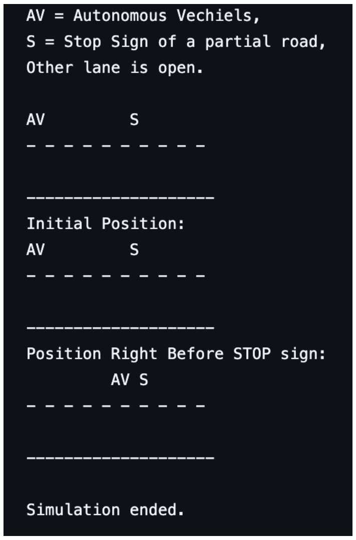
III. Preliminary

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)

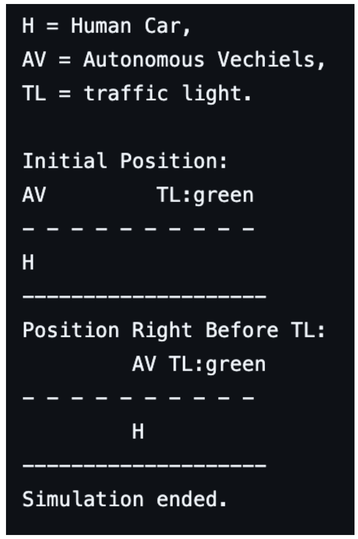
Fig. 3: Selected Models for the Experimentation

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

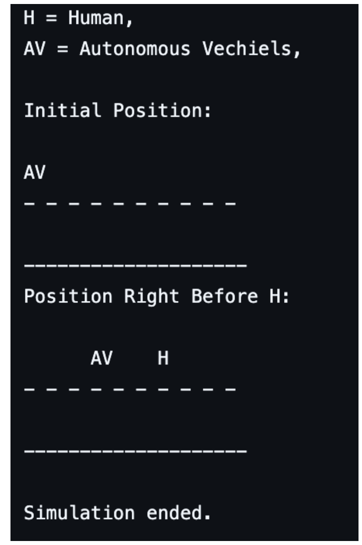
[1]https://huggingface.co/
[2]https://lmstudio.ai/



(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/

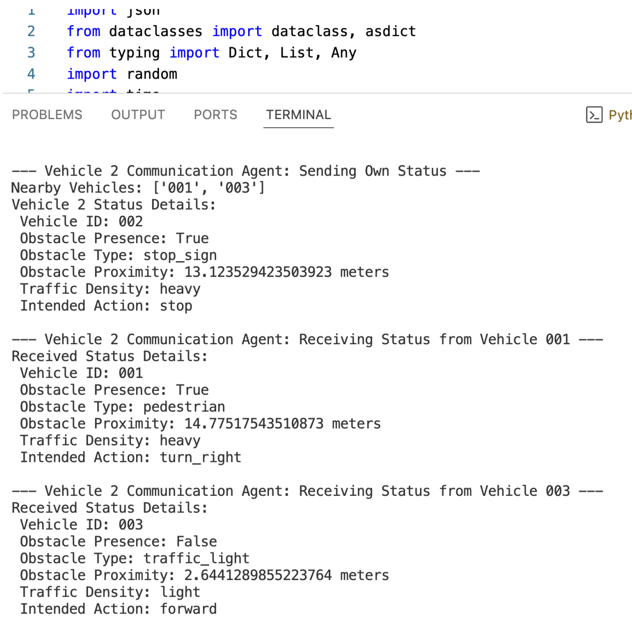


Fig. 5: An illustration of Communication Agent

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

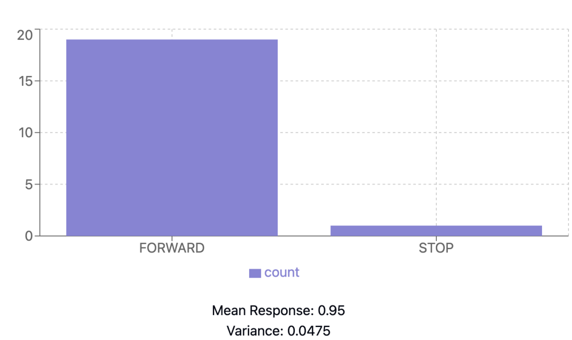


Fig. 6: LLM Model Consistency on the Tested Scenario

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.

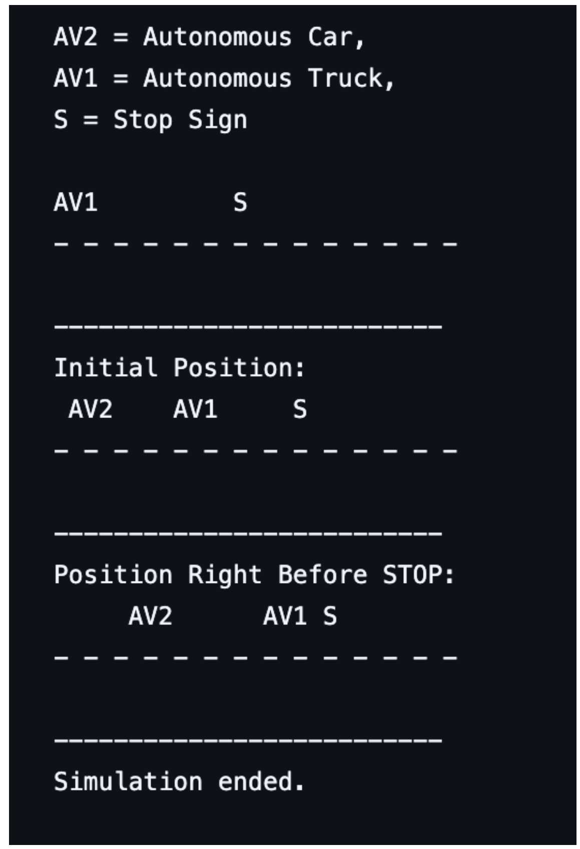


Fig. 7: Extended Traffic Scenario with V2V Communication

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

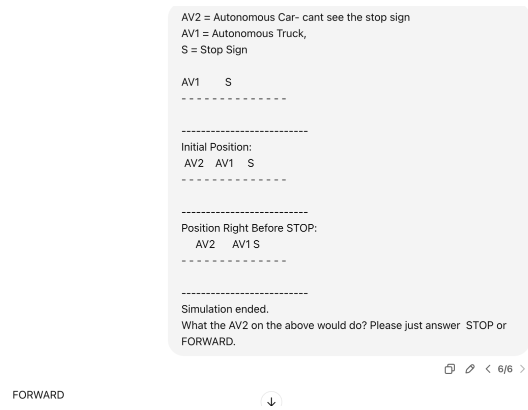


Fig. 8: LLM Model response without Communication agent's information (GPT-4 Turbo)

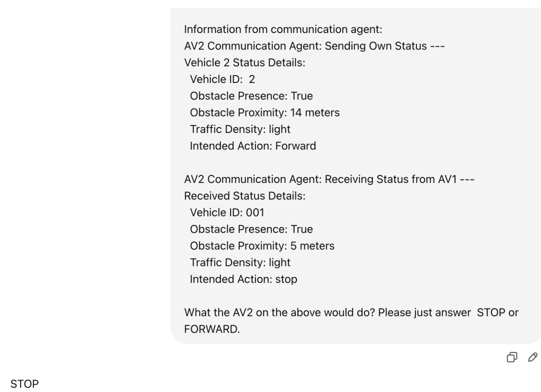


Fig. 9: LLM Model response with Communication agent's information (GPT-4 Turbo)

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.

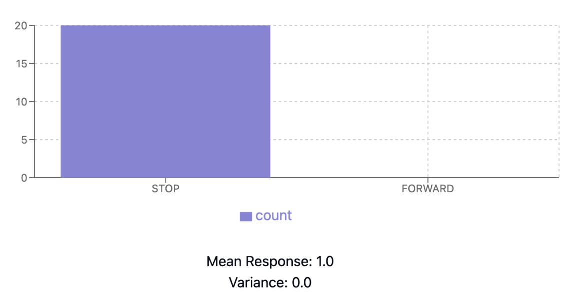


Fig. 10: LLM Model Consistency with V2V Communication support (GPT-4 Turbo)

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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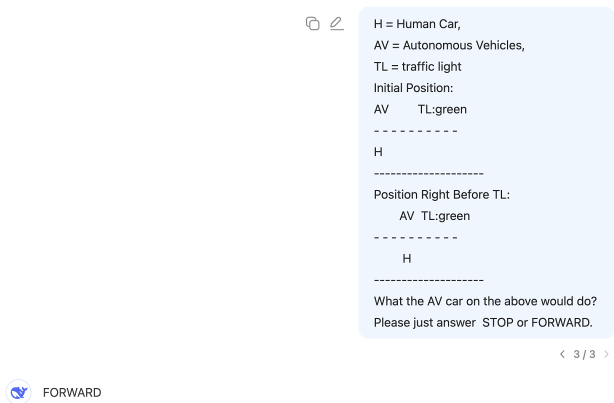
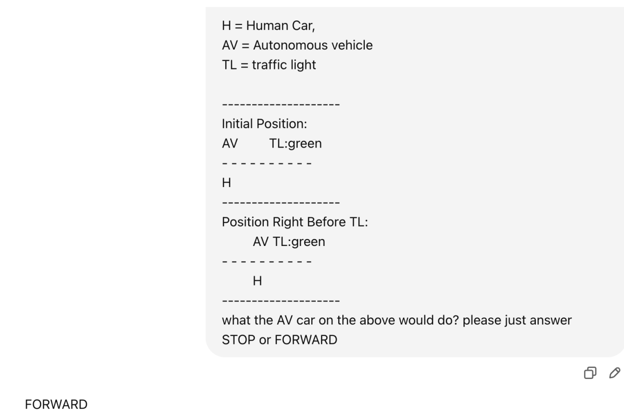
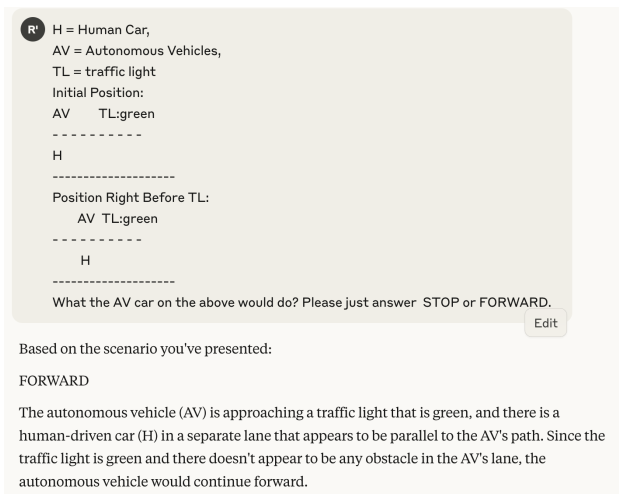


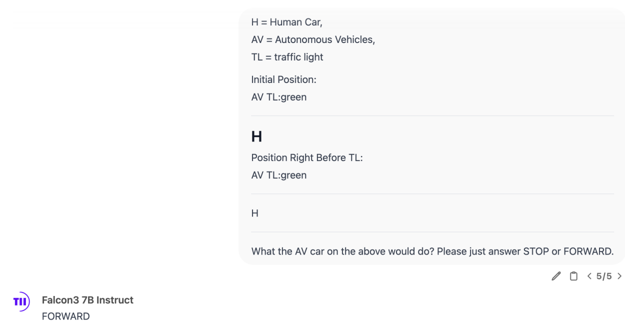
(a) Output from DeepSeek-V3



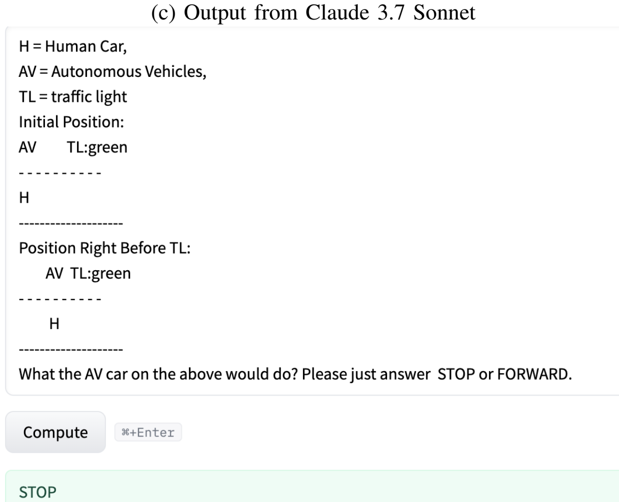
(b) Output from GPT-4 turbo



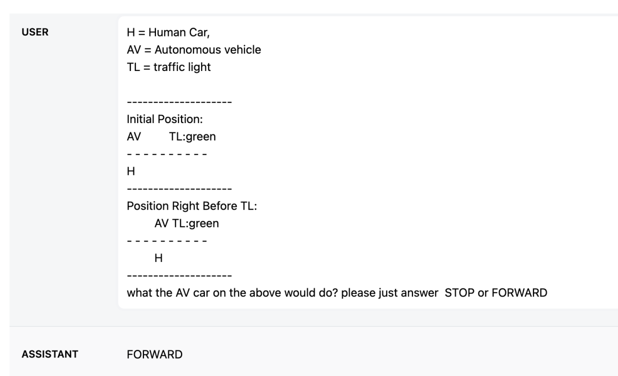
(c) Output from Claude 3.7 Sonnet



(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