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

PRESENTER - RAFI MD ASHIFUJJMAN, ID - 71330708

SUPERVISOR- NAOKI FUKUTA

DEPARTMENT OF INFORMATICS

GRADUATE SCHOOL OF INTEGRATED SCIENCE AND TECHNOLOGY,

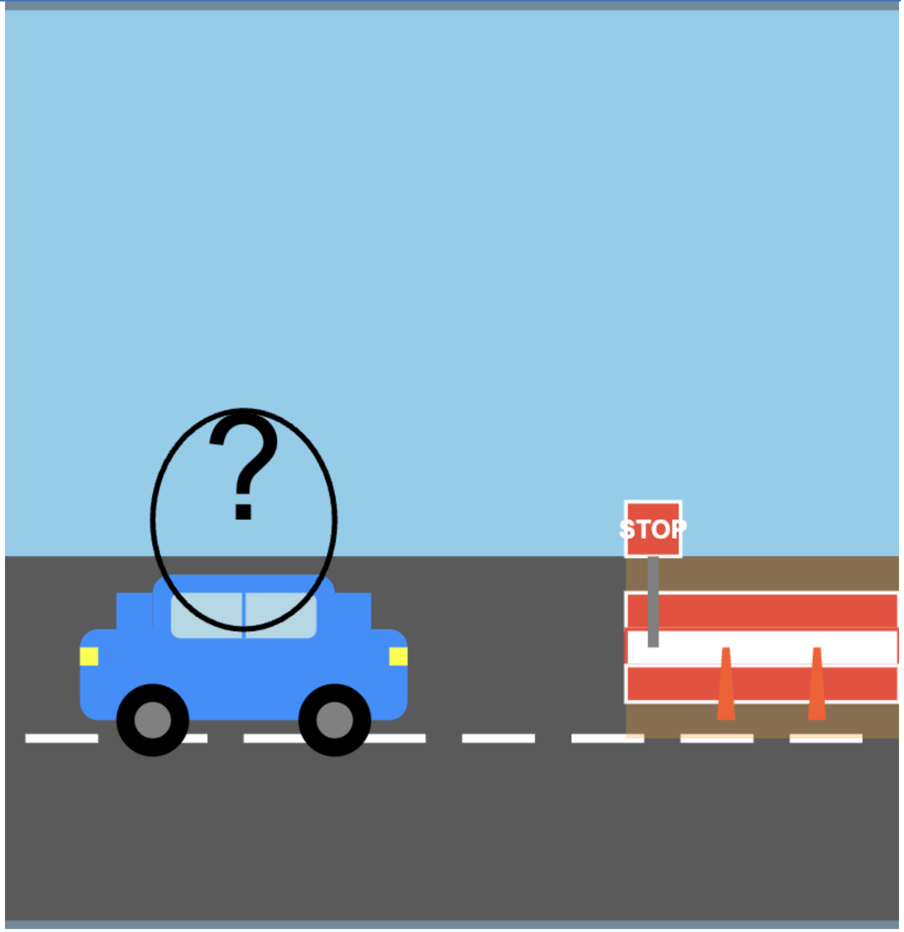
SHIZUOKA UNIVERSITY.

Research Background:

- This appears to be a case of partial road construction or maintenance, that I often I see in Road. **What traditional AV might do in this situation?**

- Traditional AV sees "STOP" sign and completely halts
- Human driver uses common sense to navigate partially blocked road

➢ **Absence of common-sense, human like reasoning!**



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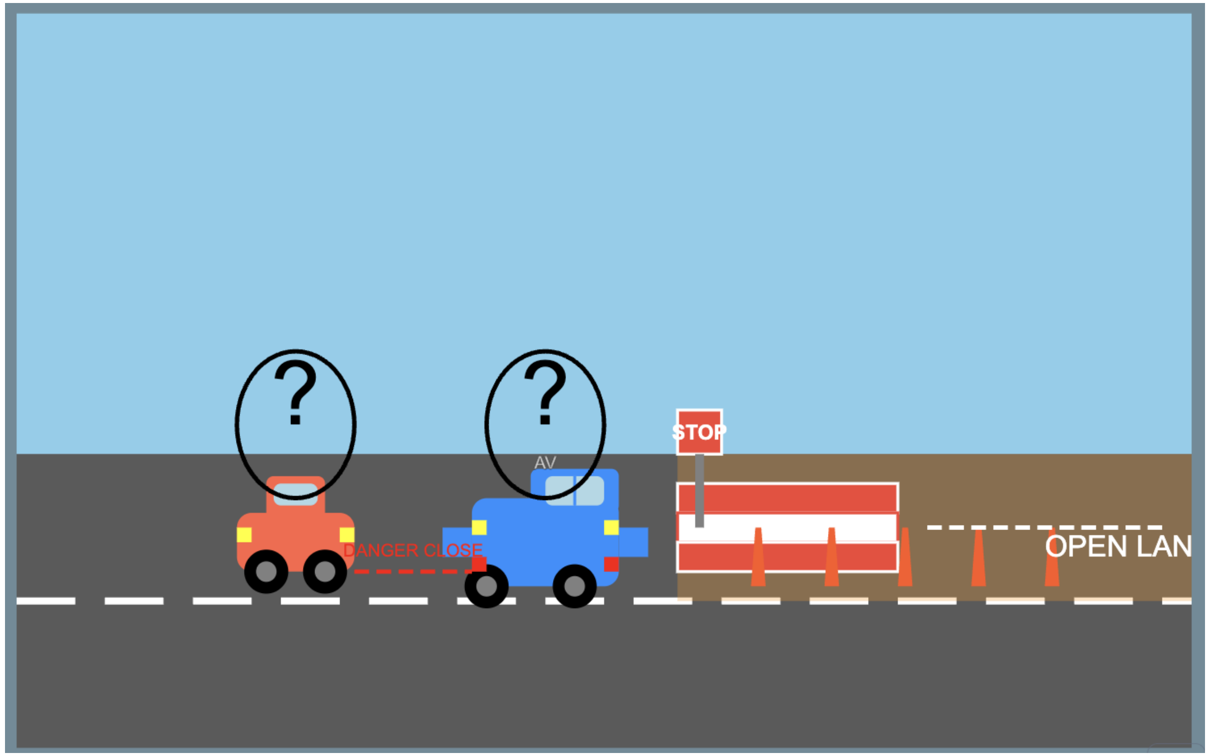
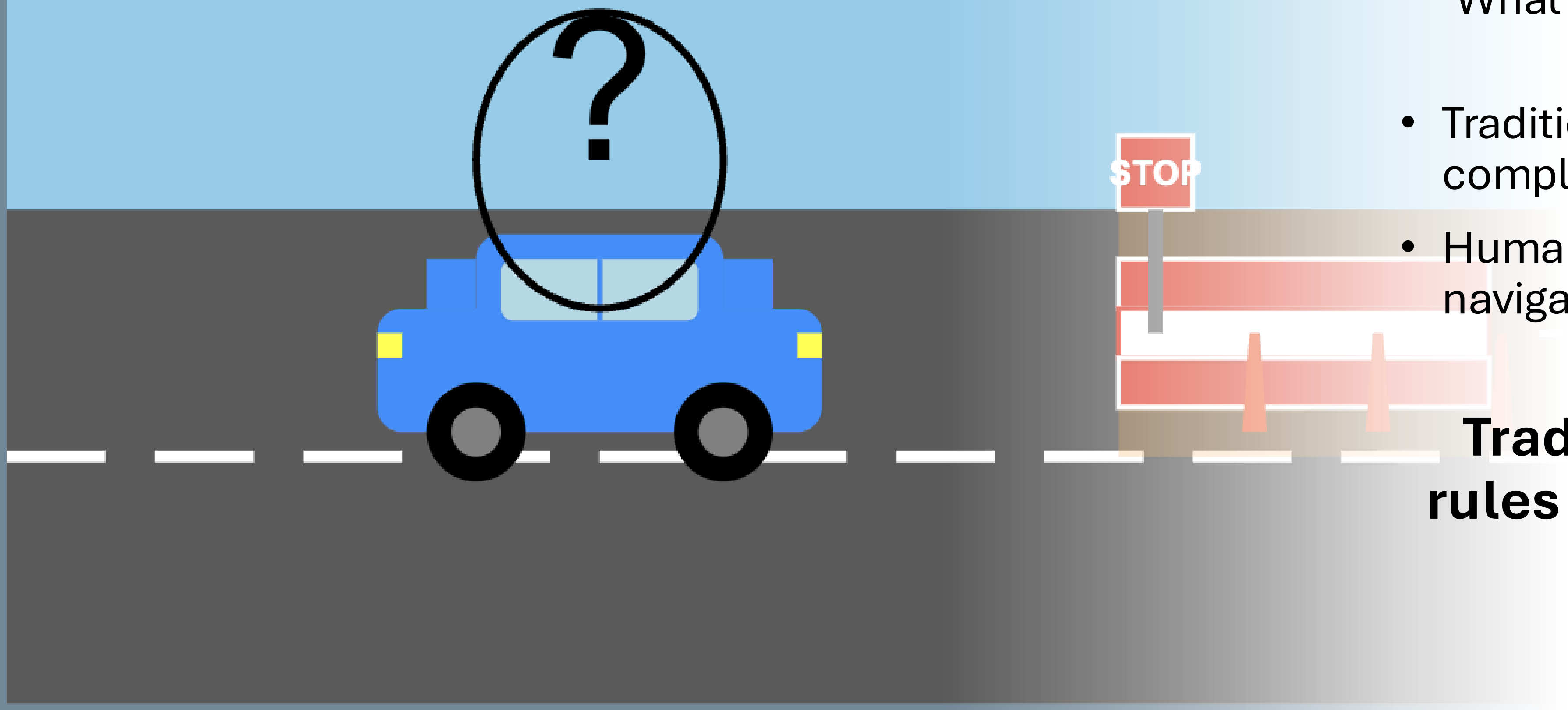


- First AV1 Encounters stop sign Comes to complete stop on a partially blocked road
- Following AV2 Approaches behind AV1 Can’t see stop sign, Different decision-making logic may not stop completely

What is missing ?

- ➢ No inter-vehicle communication
- ➢ **Multi-Agent framework could be a potential solution for this.**



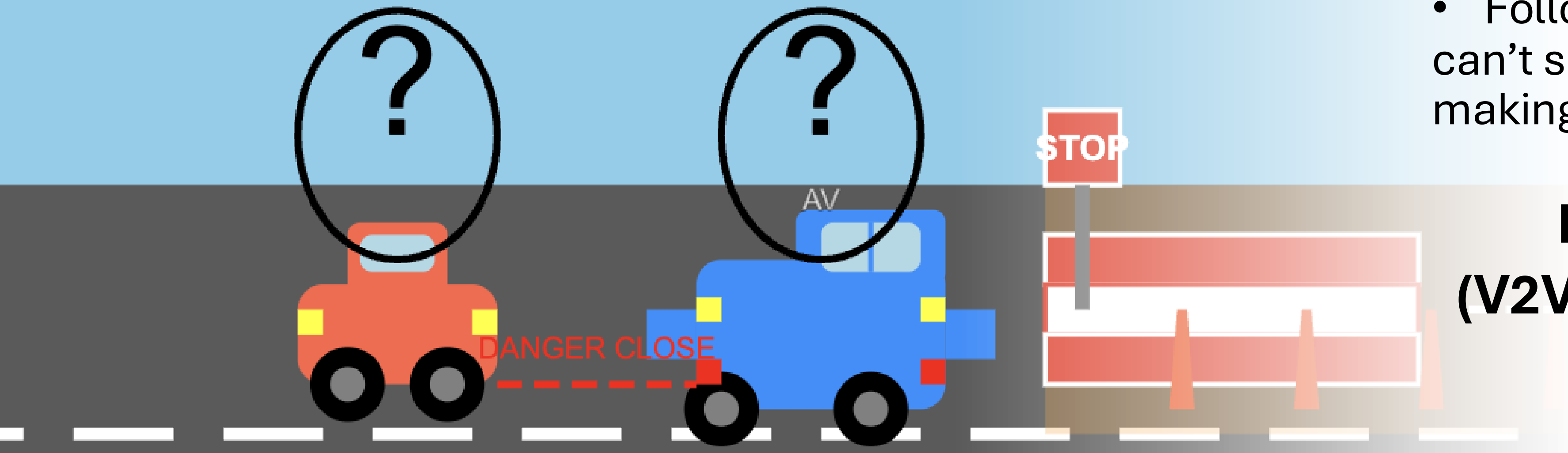
Traditional AVs Limitations

- This appears to be a case of partial road construction or maintenance, that I often we see in Road.

What traditional AV might do in this situation?

- Traditional AV sees "STOP" sign and completely halts
- Human driver uses common sense to navigate partially blocked road

Traditional AVs follow rigid rules without common sense or reasoning.



Traditional AVs Limitations

- First AV1 Encounters stop sign Comes to complete stop on a partially blocked road

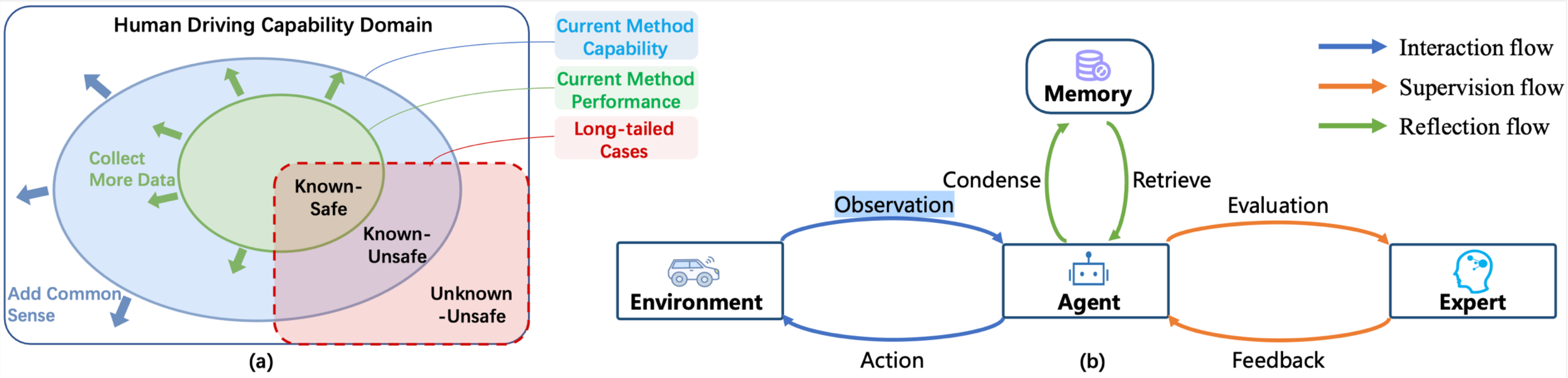
- Following AV2 Approaches behind AV1 can't see stop sign, Different decision-making logic may not stop completely

Lack of vehicle-to-vehicle (V2V) communication can lead to accidents

Research Question:

- Can LLMs effectively **enhance decision-making** for AVs in **Unknown-Unsafe domains** within a **multi-agent framework** compared to current mechanisms?

Research Background



- The domain (a) is divided into Known-Safe, Known-Unsafe, and Unknown-Unsafe regions.
- Unknown-unsafe cases that humans can often solve with their experience and common sense.

Unknown-Unsafe: Challenging scenarios requiring human-like reasoning.

- Current AV System Architecture (b), consists of an Agent that interacts with the Environment, Condenses Observations, Retrieves Evaluations, and receives Feedback from an Expert.
- Without the incorporation of common sense, the model still fails to the long tailed cases. [Fu 2024]

Fu, D., Li, X., Wen, L., Dou, M., Cai, P., Shi, B., & Qiao, Y. (2024). Drive like a human: Rethinking autonomous driving with large language models. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision* (pp. 910-919).

Research Objective

- To explore the use of **Large Language Models(LLMs)** for autonomous driving systems(ADS) as the main decision-making agent within **a multi-agent framework** for evaluating its reasoning abilities in handling Unknown-Unsafe

Research Objective

Explore LLMs

Investigate large language models as primary decision agents

Evaluate Reasoning

Evaluating LLMs reasoning abilities in handling complex scenarios

Multi-Agent Framework

Implement vehicle-to-vehicle communication systems

Enhance Safety

Research Contribution :

- The main contribution of this research includes,
  - Investigating the **LLMs** as the main decision agent in ADS
  - Evaluating LLMs reasoning abilities in handling Unknown-Unsafe domain
  - Implementing a Multi-Agent Framework for V2V Communication

Why LLM as Decision Agent:

- This paper[Cui 2023] introduces DriveLLM, a decision-making framework that combines large language models (LLMs) with autonomous driving systems to enhance commonsense reasoning in complex driving scenarios.

- Combines LLMs with autonomous driving systems.
- Uses a cyber-physical feedback system for continuous learning.
- Outperforms traditional decision-making frameworks.

Cui, Y., Huang, S., Zhong, J., Liu, Z., Wang, Y., Sun, C., ... & Khajepour, A. (2023). Drivellm: Charting the path toward full autonomous driving with large language models. *IEEE Transactions on Intelligent Vehicles*.

Why Multiagent Approach:

- This paper [Ayache 2017] presents an autonomous vehicular system based on multi-agents to reduces the complexity of the autonomous system by splitting tasks between different agents, which in turn reduces execution time and allows for quicker intervention in complex scenarios. The proposed MAS can be applied to all vehicle brands, unlike existing systems that are dedicated to specific brands.

- Splits complex tasks across multiple specialized agents
- Enables more efficient system-wide processing
- Dramatically reduces overall execution time
- Compatible with all vehicle brands

Ayache, N., Yahyaouy, A., & Abdelouahed, S. M. (2017, April). An autonomous vehicular system based on muli-agents control: Architecture and behavior simulation. In *2017 Intelligent Systems and Computer Vision (ISCV)* (pp. 1-7). IEEE.

Related Work

- This paper [Hook 2021] presents experiments on learning decision-making policies in multi-agent environments for autonomous systems like connected autonomous vehicles. Agents were able to learn to navigate their environment and avoid collisions even in a partially observable setting with obstacles and other moving agents. However, Learning decision-making policies is challenging due to the non-stationary nature of the environment.

Hook, J., El-Sedky, S., De Silva, V., & Kondoz, A. (2021). Learning data-driven decision-making policies in multi-agent environments for autonomous systems. *Cognitive Systems Research*, *65*, 40-49.

- This study [Ananthajothi 2023] 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 enhance reliability and safety by enabling human-like reasoning and adaptability.

Ananthajothi, K., GS, S. S., & Saran, J. U. (2023, December). LLM's for Autonomous Driving: A New Way to Teach Machines to Drive. In *2023 3rd International Conference on Mobile Networks and Wireless Communications (ICMNWC)* (pp. 1-6). IEEE.

Our Approach

- During this investigation with various LLM, we proceed our investigation under two assumptions

➢ Certain AI can transform real-world situations into text-based explanations, which are subsequently used as input for the LLMs

➢ The outputs generated by the LLMs can be translated into actual decisions made by the decision agent of AV by interpreting the responses from the LLMs.

Our Approach

The factors were considered in the selection of LLM models for this study

- Quantization for Optimization
- Top downloaded models from Hugging Face
- LM Studio Recommendations, optimized accuracy and compatibility with local inference environments
- Top commercial LLMs with open-source counterparts for accuracy

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)

Our Approach

To test these selected model, we have prepared simple text-based scenarios.

- Logical Reasoning Scenarios: Complex situations requiring analytical thinking
- Common Knowledge Scenarios: Standard situational responses

```
H = Human Car,
AV = Autonomous vehicle
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
```

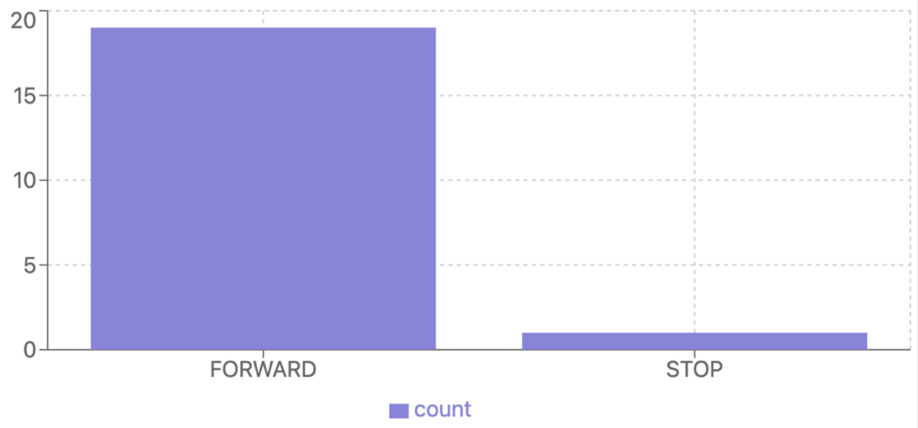
Our Approach

- We ran "*What would the AV do in this situation? Please, just answer STOP or FORWARD*" this same prompt at least 20 times in OpenHermes-2.5-Mistral 7B and analyzed the results.

USER

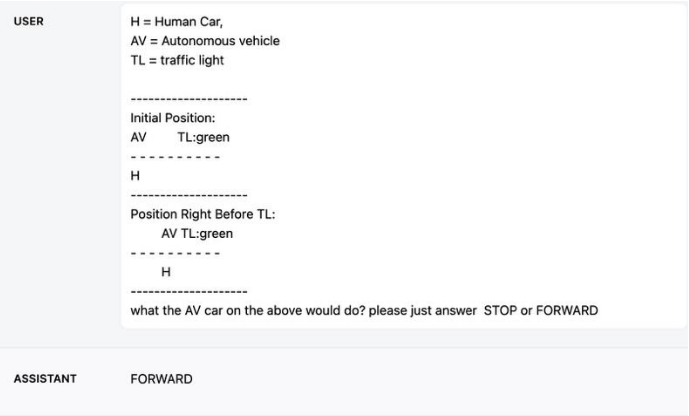
```
H = Human Car,
AV = Autonomous vehicle
TL = traffic light

--------------------
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
```

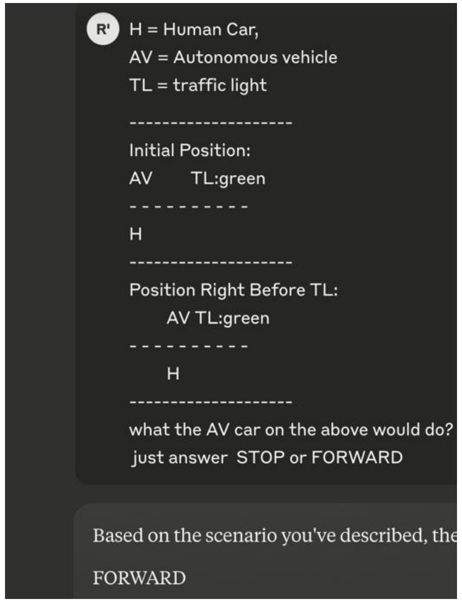
ASSISTANT FORWARD

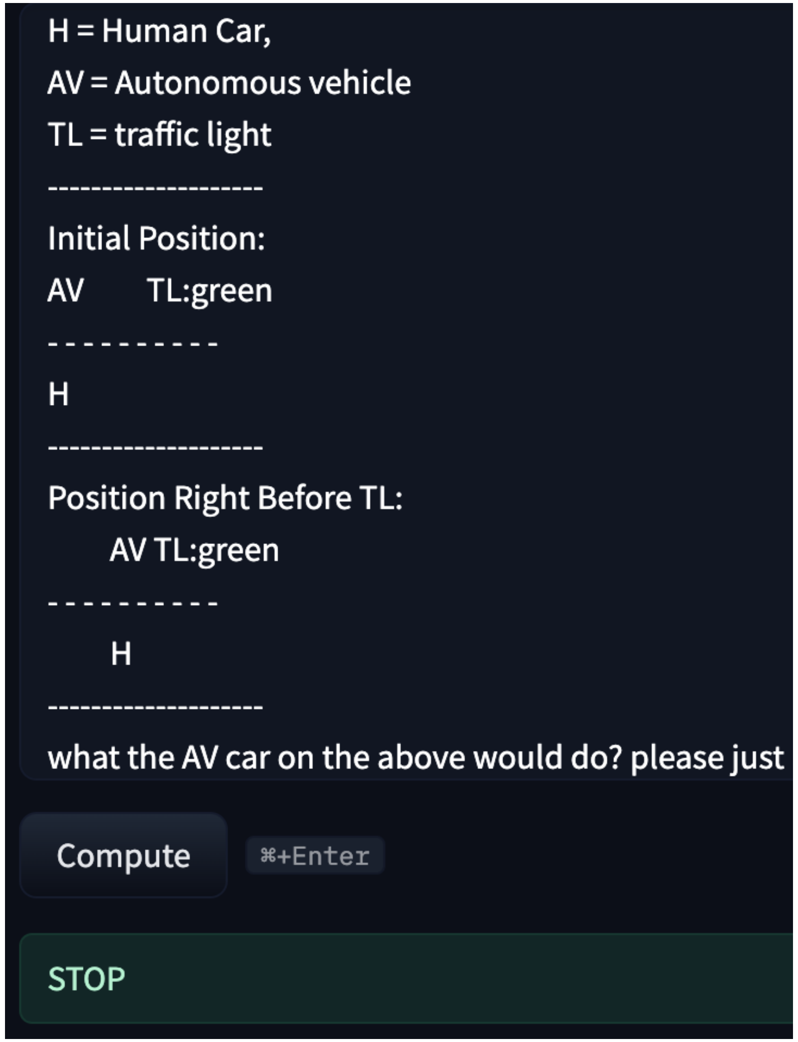


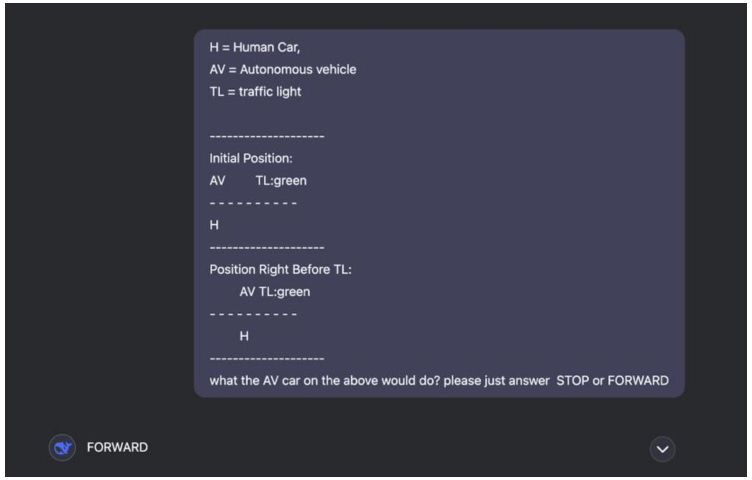
Mean Response: 0.95
Variance: 0.0475

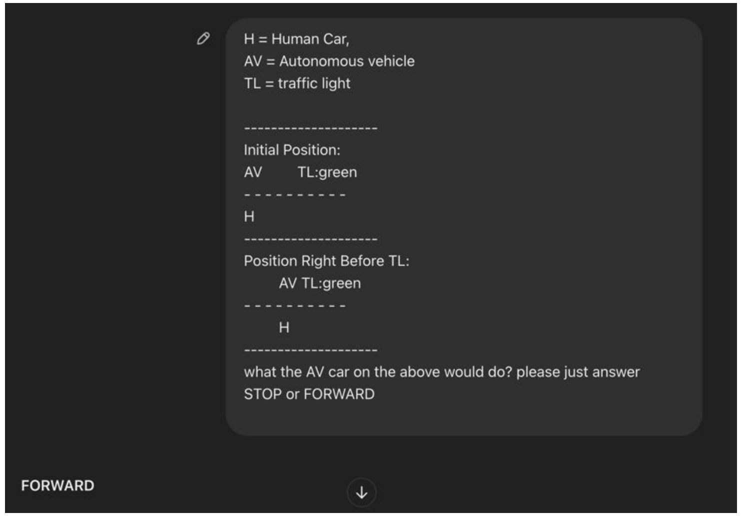
Response from Top Commercial LLM











Our Approach

We are also assuming that,

- V2V communication is already achieved and operational through a standardized networking protocol.(LAN-based, Low-latency wireless systems)
- Communication occurs within a fixed radius**(**When a vehicle enters the information sharing radius of another vehicle, they exchange.)

➢ **This assumption allows us to focus on how shared data affects autonomous decision-making**

Our Approach

- Multi-Agent Framework: Communication and Decision Agents
- Communication Agent
  - Responsible for transmitting & receiving V2V data.
  - Ensures structured information sharing in a fixed text data format.
- Decision Agent will use V2V-shared data as input for decision-making.

➢ **Examining how LLMs process and utilize V2V-exchanged data.**

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

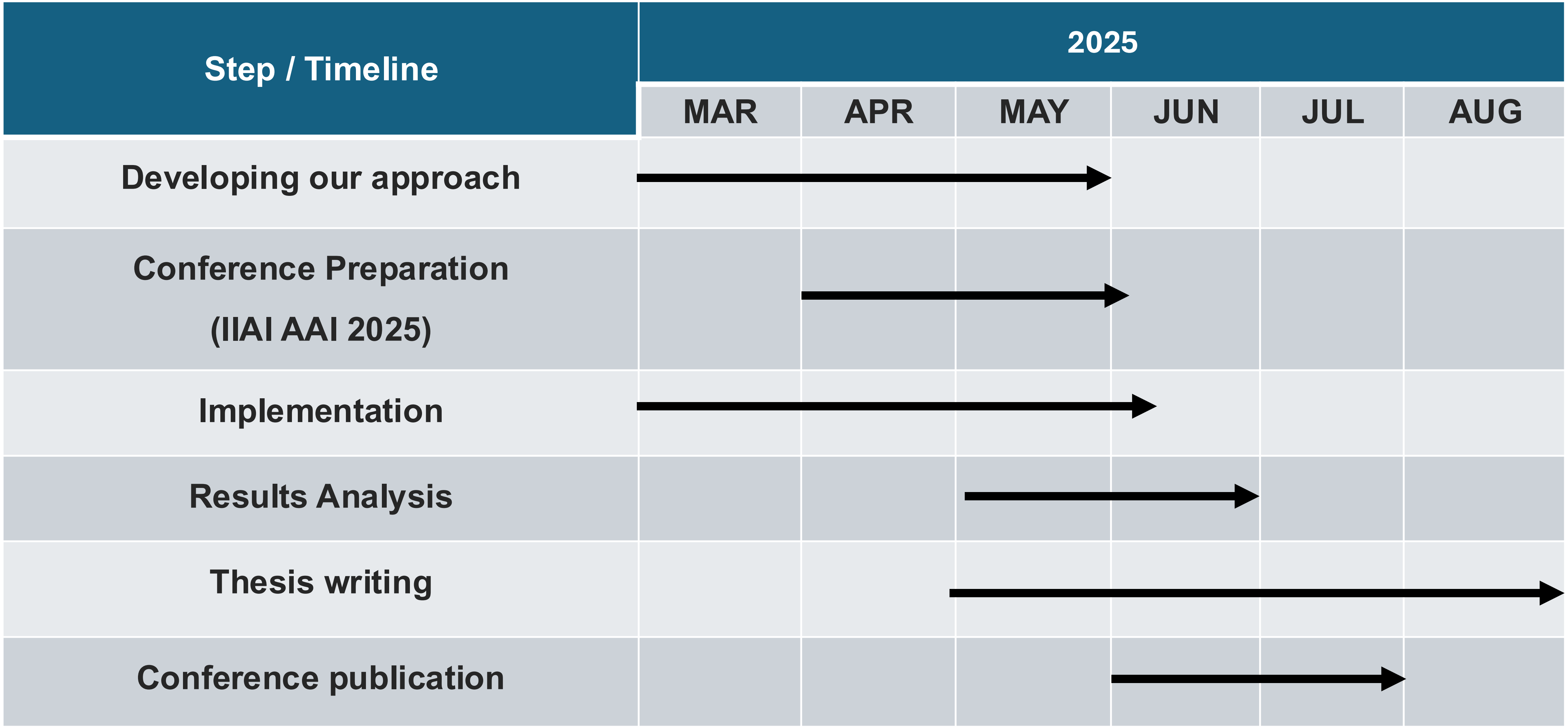
PROBLEMS OUTPUT PORTS TERMINAL Pyth

```
--- Vehicle 2 Communication Agent: Sending Own Status ---
Nearby Vehicles: ['001', '003']
Vehicle 2 Status Details:
 Vehicle ID: 002
 Obstacle Presence: True
 Obstacle Type: stop_sign
 Obstacle Proximity: 13.123529423503923 meters
 Traffic Density: heavy
 Intended Action: stop

--- Vehicle 2 Communication Agent: Receiving Status from Vehicle 001 ---
Received Status Details:
 Vehicle ID: 001
 Obstacle Presence: True
 Obstacle Type: pedestrian
 Obstacle Proximity: 14.77517543510873 meters
 Traffic Density: heavy
 Intended Action: turn_right

--- Vehicle 2 Communication Agent: Receiving Status from Vehicle 003 ---
Received Status Details:
 Vehicle ID: 003
 Obstacle Presence: False
 Obstacle Type: traffic_light
 Obstacle Proximity: 2.6441289855223764 meters
 Traffic Density: light
 Intended Action: forward
```

Current Challenges

- Can an agent make decisions with the help of an LLM without undergoing a specific learning process for each new situation?
- How may the different language affect the output?
- How will the GPU performance affect the time of decision making?
- How addition prompt engineering will affect the decision?

Research Timeline



Thank you