

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

PRESENTER - RAFI MD ASHIFUJMAN, ID - 71330708

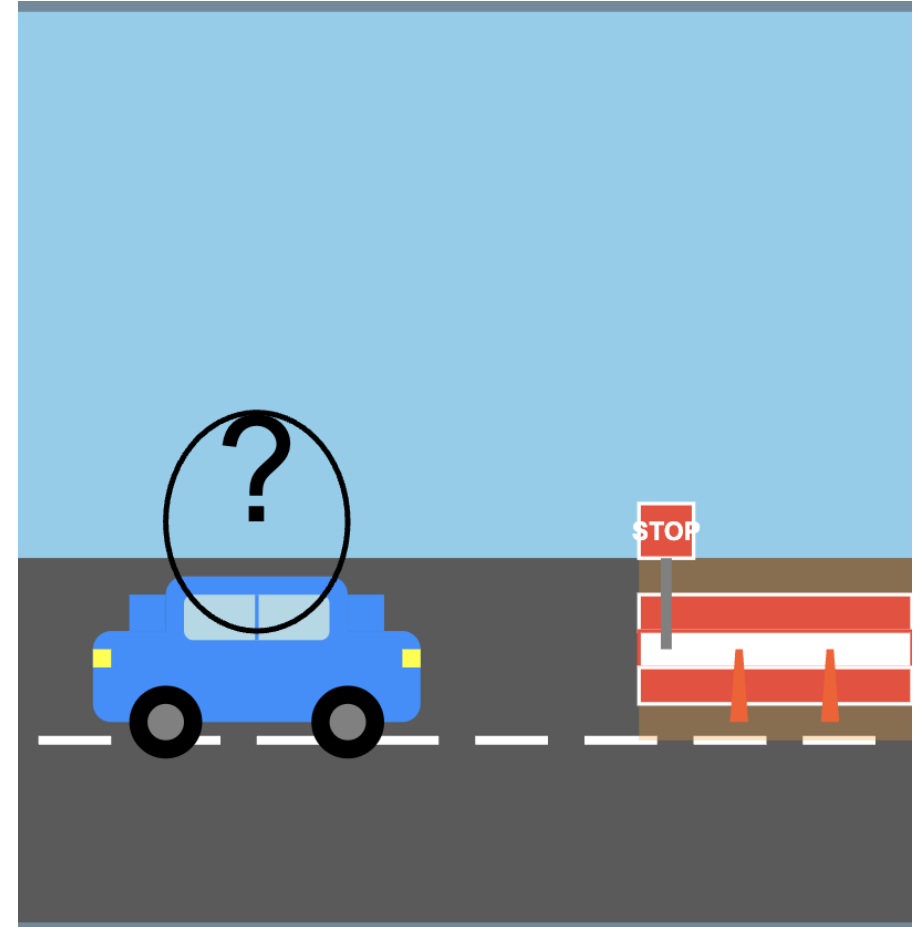
SUPERVISOR- NAOKI FUKUTA

DEPARTMENT OF INFORMATICS

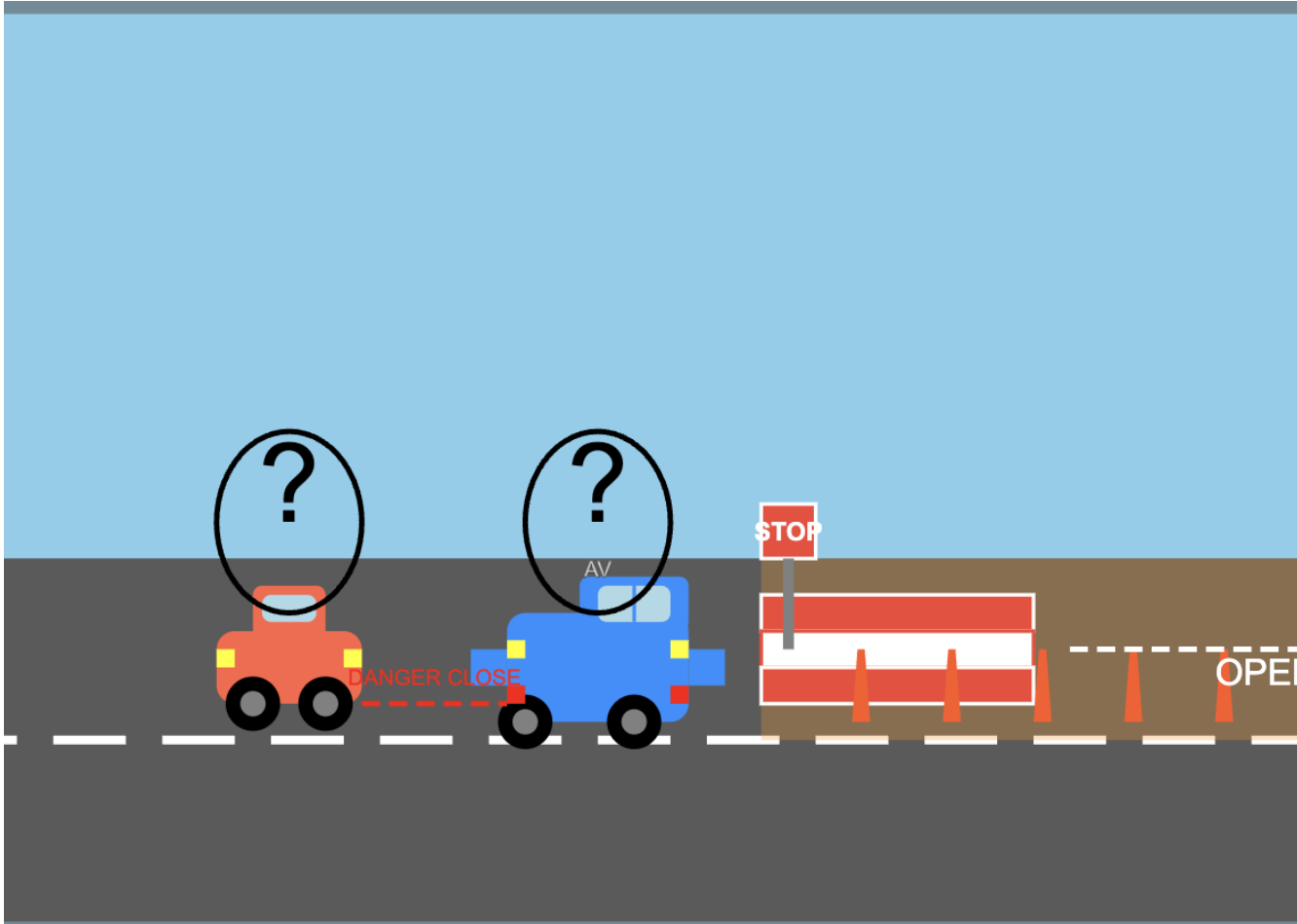
GRADUATE SCHOOL OF INTEGRATED SCIENCE AND TECHNOLOGY,
SHIZUOKA UNIVERSITY.

Research Background: Traditional AVs Limitations

- 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!**



Research Background: Traditional AVs Limitations

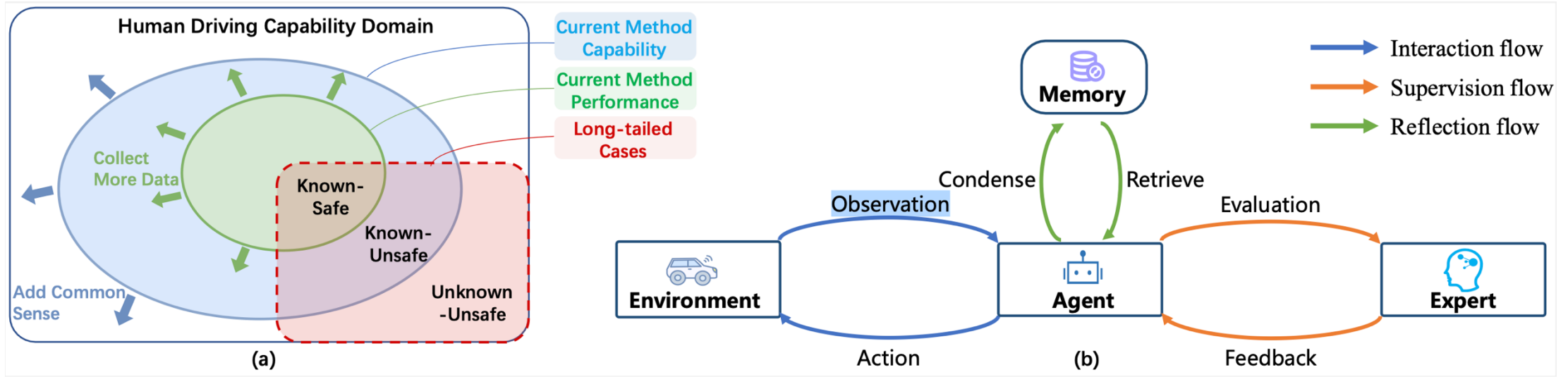


- First AV1 Encounters stop sign Comes to complete stop on a partially blocked road
- Following AV2 Approaches behind AV1 can't see stop sign, Different decision-making logic may not stop completely
- **Lack of vehicle-to-vehicle (V2V) communication can lead to accidents**

Research Question:

- Can an agent make decisions with the help of an LLM without undergoing a specific learning process for each new situation?
- 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?

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]

Research Background:

- **Unknown Situations:** Traditional systems struggle with truly unfamiliar scenarios that weren't included in training data.
 - **Simulation Limitations:** Difficulty recreating complex real-world conditions and unpredictable human behavior
 - **Infinite Scenarios:** Countless unexpected situations that are impossible to pre-program
-
- We going to investigate whether LLMs can provide common sense or reasoning that traditional systems lack, like how human drivers handle unexpected situations

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 LLMs 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.

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*.

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

Related Work

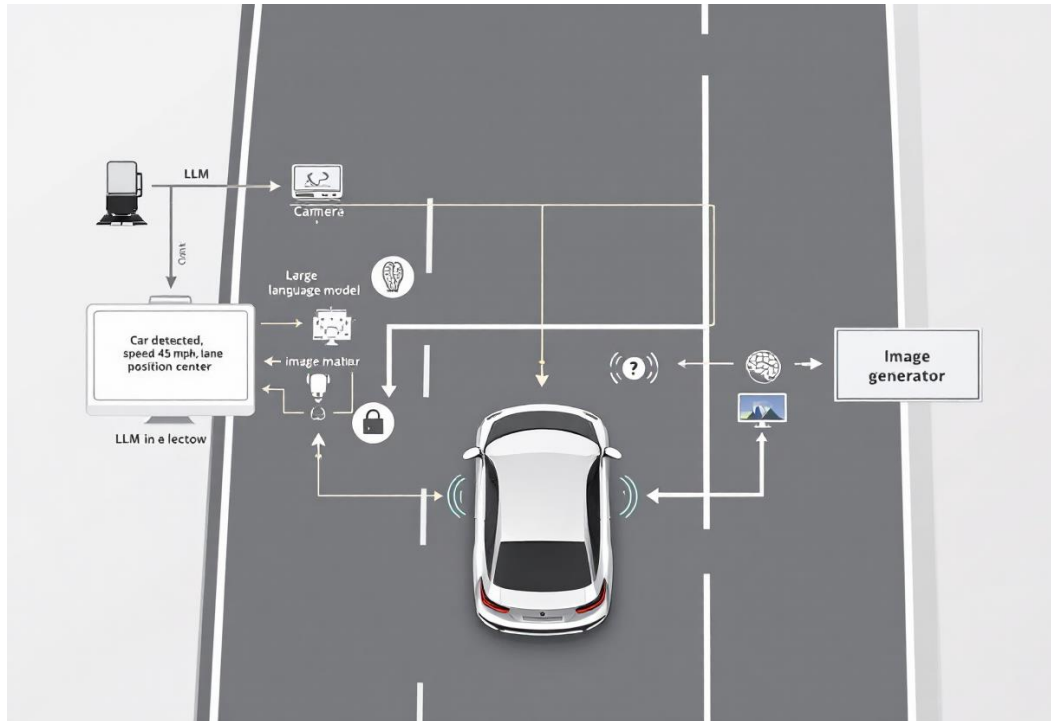
- This paper [Hook 2021] presents experiments on learning decision-making policies in multi-agent environments for autonomous systems like connected autonomous vehicles. Agents were able to learn to navigate their environment and avoid collisions even in a partially observable setting with obstacles 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., & Kondo, A. (2021). Learning data-driven decision-making policies in multi-agent environments for autonomous systems. *Cognitive Systems Research*, 65, 40-49.

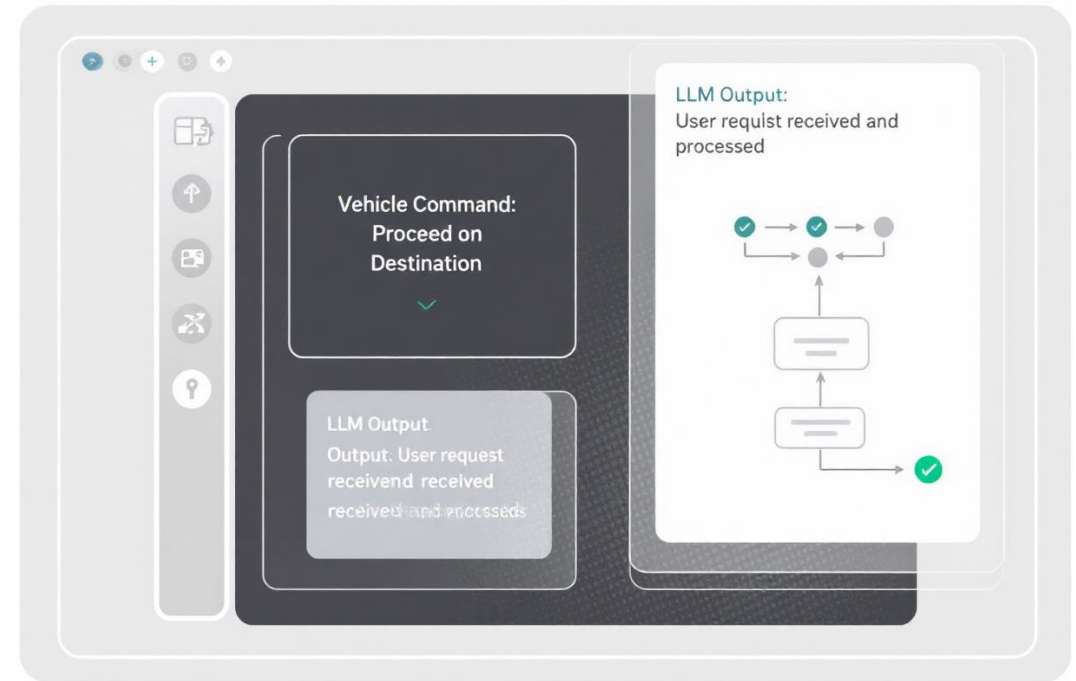
- This study [Ananthajothi 2023] looks to explore the ability of integrating LLMs into Autonomous driving (AD) structures to emulate human-like behavior . LLMs can use their memory to apply past experiences to future decision-making, improving adaptability and decision-making in AD systems. It can enhance 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 (ICMNBC)* (pp. 1-6). IEEE.

Our Approach: Research 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: Model Selection

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)

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

Our Approach: Environment Setup

- To test these selected models, we have prepared a set of simple text-based simulation of real-life traffic scenarios.
- We ran this same prompt “*What would the AV do in this situation? Please, just answer STOP or FORWARD*”.

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.

✎ 🗑 < 5/5 >

H = Human Car,
AV = Autonomous Vechiels,
TL = traffic light.

Initial Position:

AV TL:green

- - - - -

H

Position Right Before TL:

AV TL:green

- - - - -

H

Simulation ended.

Our Approach: Test Scenarios

Stop Sign on Partial Road

```
-----  
-----  
Initial Position:  
AV      S  
-----  
-----  
Position Right Before STOP sign:  
      AV S  
-----
```

Traffic Light Recognition

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

Sudden Pedestrian Crossing

```
AV  
-----  
-----  
Position Right Before H:  
  
      AV  H  
-----
```

- Using these scenarios, we will test the LLM's capabilities in **logical reasoning**, **rule compliance**, and **dynamic decision-making** for autonomous systems.

Our Approach: Response from Top Commercial LLM

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

R' 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?
just answer STOP or FORWARD

Based on the scenario you've described, the

FORWARD

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

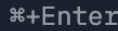
Initial Position:
AV TL:green

H

Position Right Before TL:
AV TL:green

H

what the AV car on the above would do? please just

Compute 

STOP

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

 FORWARD 

 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

FORWARD 

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

 Falcon3 7B Instruct
FORWARD

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.

  < 5/5 >

R

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.


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.

Compute 

STOP

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

FORWARD

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

H

Position Right Before TL:
 AV TL:green

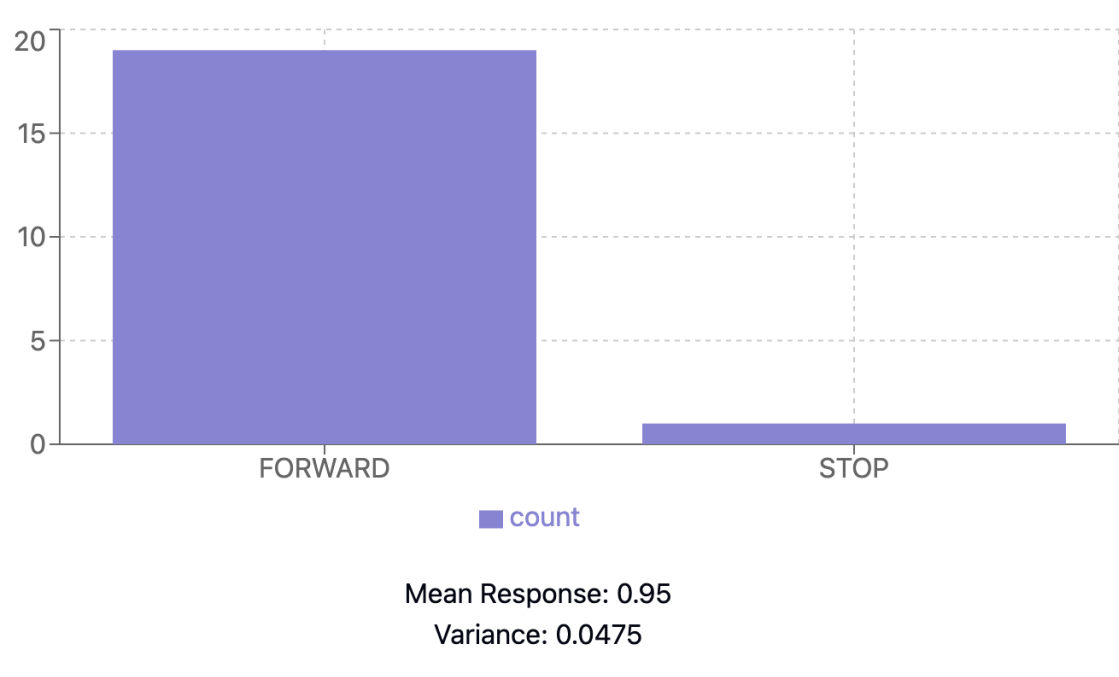
 H

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

< 3 / 3 >

 FORWARD

Our Approach: Consistency Test



- **Sub Research Question**, "Does repeated querying of LLMs on the same scenario lead to variations in decision-making outcomes?"
- To test this, We executed the prompt at least 20 times using the OpenHermes-2.5-Mistral, and the consistency results are shown in Figure.
- Mean closer to 1 indicates greater consistency with expected response
- But the variation in responses across multiple runs are **unacceptable** for autonomous vehicles

Why Multiagent Approach:

- This paper [Ayache 2017] presents an autonomous vehicular 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 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

Our Approach: Communication Agent Framework

```
1 import json
2 from dataclasses import dataclass, asdict
3 from typing import Dict, List, Any
4 import random
5 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
```

- Multi-Agent Framework: Communication and Decision Agents
 - 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.**

Our Approach: Extended Test Assumption



- 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 their information)

Our Approach: Extended Scenario with V2V Communication

In this extended scenario,

- AV2(an autonomous car) follows AV1 (an autonomous truck), with a stop sign ahead
- AV2 cannot see stop sign due to AV1 blocking line of sight

AV2 = Autonomous Car,
AV1 = Autonomous Truck,
S = Stop Sign

AV1 S

Initial Position:

AV2 AV1 S

Position Right Before STOP:

 AV2 AV1 S

Simulation ended.

Our Approach: LLMs response without V2V Communication

- **Prompt:** *"What would the AV on the above do? Just answer STOP or FORWARD."*
- **Model (GPT-4 Turbo) Response:**
FORWARD
- **Concern:** Could cause **accident** due to missed stop sign.

AV2 = Autonomous Car- cant see the stop sign
AV1 = Autonomous Truck,
S = Stop Sign

AV1 S

Initial Position:

AV2 AV1 S

Position Right Before STOP:

AV2 AV1 S

Simulation ended.

What the AV2 on the above would do? Please just answer STOP or FORWARD.

FORWARD



Our Approach: LLMs response with V2V Communication

- **Prompt:** *"What would the AV on the above do? Just answer STOP or FORWARD."*
- **Model (GPT-4 Turbo) Response:**
STOP
- Safe decision based on shared contextual information

Information from communication agent:
AV2 Communication Agent: Sending Own Status ---
Vehicle 2 Status Details:
Vehicle ID: 2
Obstacle Presence: True
Obstacle Proximity: 14 meters
Traffic Density: light
Intended Action: Forward

AV2 Communication Agent: Receiving Status from AV1 ---
Received Status Details:
Vehicle ID: 001
Obstacle Presence: True
Obstacle Proximity: 5 meters
Traffic Density: light
Intended Action: stop

What the AV2 on the above would do? Please just answer STOP or FORWARD.

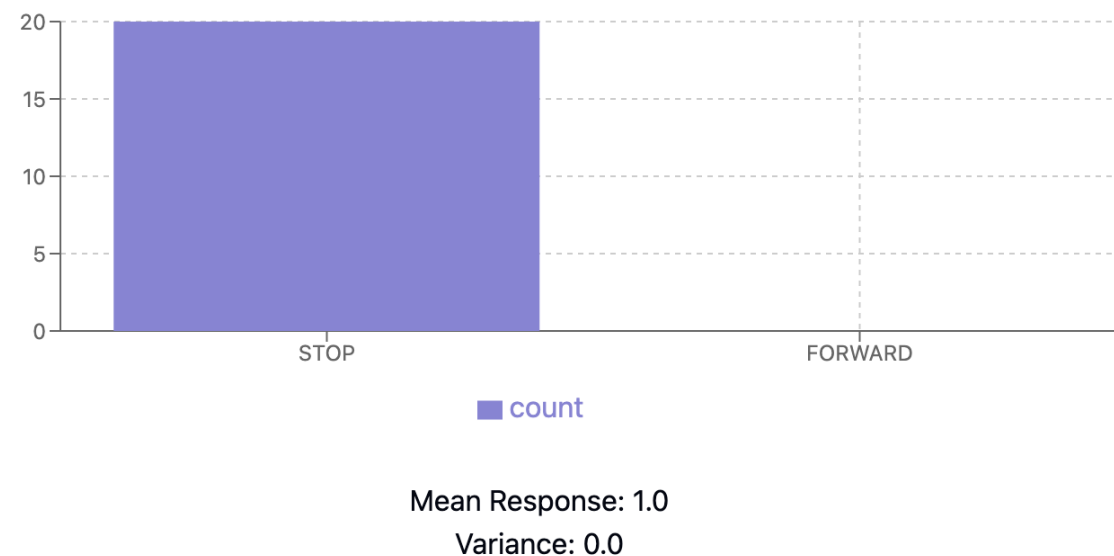


STOP

Our Approach: Consistency Test with V2V Communication

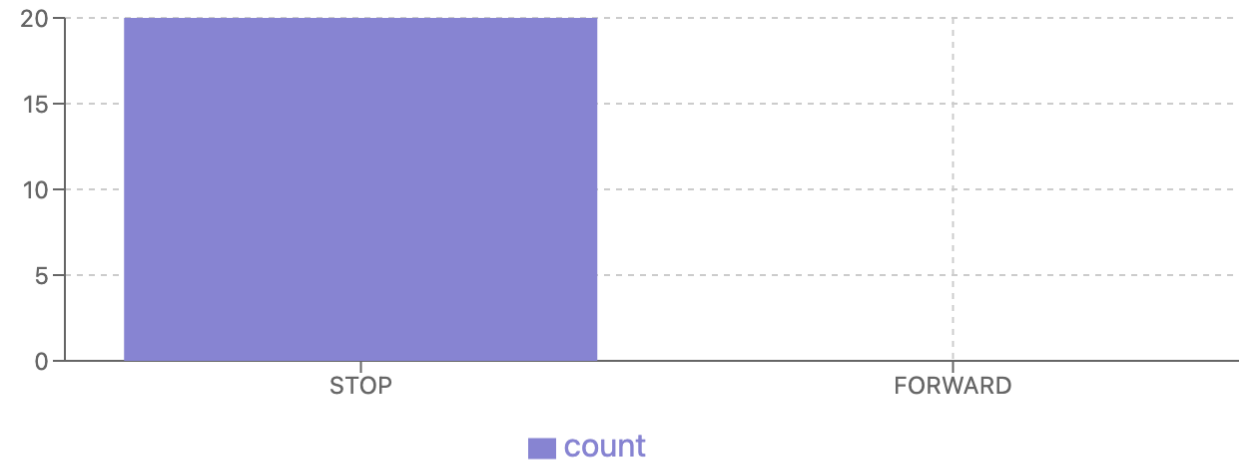
The prompt was tested **20 times** using **GPT-4**,

- **All 20 responses were “STOP”**, which is the expected correct behavior in this context.
- A **mean consistency score of 1.0** was calculated by mapping:
 - FORWARD = 1
 - STOP = 0
- This demonstrates that **V2V data helps the LLM make reliable and safe decisions** even in unknown unsafe traffic scenarios.



Our Approach: Consistency Test with V2V Communication

- The prompt was tested **20 times** using **GPT-4**,
- **All 20 responses were “STOP”**, which is the expected correct behavior in this context.
- A **mean consistency score of 1.0** was calculated by mapping:
 - FORWARD = 1
 - STOP = 0
- This demonstrates that **V2V data helps the LLM make reliable and safe decisions** even in unknown unsafe traffic scenarios.



Mean Response: 1.0

Variance: 0.0

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 will addition prompt engineering affect the decision?

Key Findings & Contributions

Research Question Answers:

- 1.LLMs can make decisions without specific learning processes** for new situations when provided with proper context
- 2.Multi-agent approach shows significant advantages** over single-agent systems, especially with V2V communication
- 3.Consistency Challenge Identified:** Repeated querying of LLMs leads to variations in decision-making outcomes, which is critical for safety

Quantitative Results:

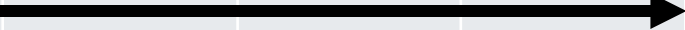

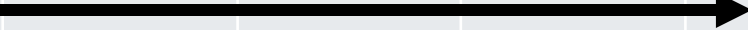



- Consistency varies** significantly across different LLM models and individual runs
- V2V communication improves decision accuracy** from inconsistent to perfect consistency (GPT-4 Turbo: mean = 1.0)
- Structured data sharing** enhances contextual understanding and decision stability

Future Work & Next Steps

Immediate Development:

- Expanded Scenarios:** More complex traffic situations and edge cases
- Real-world Integration:** Testing with actual vehicle systems
- Model Optimization:** Improving consistency and reliability across all models

Research Timeline

Step / Timeline	2025					
	MAR	APR	MAY	JUN	JUL	AUG
Developing our approach						
Conference Preparation (IIAI AAI 2025)						
Implementation						
Results Analysis						
Thesis writing						
Conference publication						

Thank you

Our Approach: Research Assumptions

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.

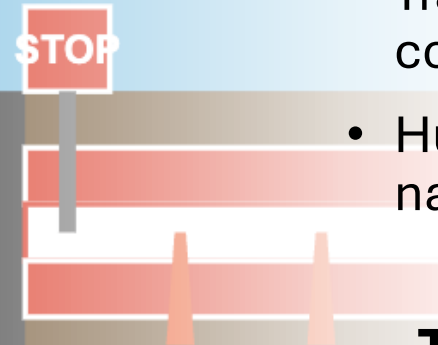
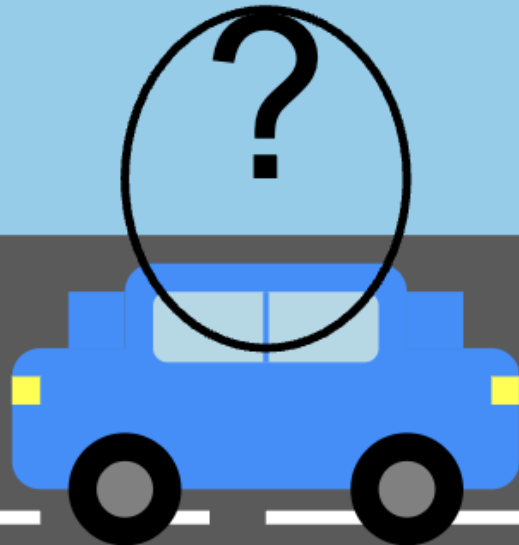
Traditional AVs Limitations

- 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.



Our Approach: Test Scenarios

- Stop Sign on Partial Road
- Traffic Light Recognition
- Sudden Pedestrian Crossing

Using these scenarios, we will test the LLM's capabilities in **logical reasoning**, **rule compliance**, and **dynamic decision-making** for autonomous systems.

```
H = Human,  
AV = Autonomous Vechiels,
```

```
Initial Position:
```

```
AV  
-----
```

```
-----  
Position Right Before H:
```

```
      AV      H  
-----  
-----
```

```
Simulation ended.
```

```
H = Human Car,  
AV = Autonomous Vechiels,  
TL = traffic light.
```

```
Initial Position:  
AV      TL:green  
-----  
H
```

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

```
-----  
Simulation ended.
```

```
AV = Autonomous Vechiels,  
S = Stop Sign of a partial road,  
Other lane is open.
```

```
AV      S  
-----
```

```
-----  
Initial Position:  
AV      S  
-----
```

```
-----  
Position Right Before STOP sign:  
      AV S  
-----
```

```
-----  
Simulation ended.
```

Our Approach: Test Scenarios

- **Stop sign on Partial road:** Testing common-sense reasoning **Traffic Light:** Testing basic rule following **Human suddenly crossing road:** Testing emergency response 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.

H = Human,
AV = Autonomous Vechiels,

Initial Position:

AV

Position Right Before H:

AV H

Simulation ended.

H = Human Car,
AV = Autonomous Vechiels,
TL = traffic light.

Initial Position:

AV TL:green

H

Position Right Before TL:

AV TL:green

H

Simulation ended.

AV = Autonomous Vechiels,
S = Stop Sign of a partial road,
Other lane is open.

AV S

Initial Position:

AV S

Position Right Before STOP sign:

AV S

Simulation ended.

Our Approach: Environment Setup

- To test these selected models, we have prepared a set of simple text-based simulation of real-life traffic scenarios.
- We ran this prompt “*What would the AV do in this situation? Please, just answer STOP or FORWARD*”.

```
H = Human,  
AV = Autonomous Vechiels,
```

```
Initial Position:
```

```
AV
```

```
- - - - -
```

```
-----
```

```
Position Right Before H:
```

```
      AV      H
```

```
- - - - -
```

```
-----
```

```
Simulation ended.
```

Our Approach: Model Selection

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)

AV2 = Autonomous Car- cant see the stop sign

AV1 = Autonomous Truck,

S = Stop Sign

AV1 S

Initial Position:

AV2 AV1 S

Position Right Before STOP:

AV2 AV1 S

Simulation ended.

What the AV2 on the above would do? Please just answer STOP or FORWARD.

FORWARD



\caption{LLM Model response with Communication agent's
information (GPT-4 Turbo)}

Information from communication agent:

AV2 Communication Agent: Sending Own Status ---

Vehicle 2 Status Details:

Vehicle ID: 2

Obstacle Presence: True

Obstacle Proximity: 14 meters

Traffic Density: light

Intended Action: Forward

AV2 Communication Agent: Receiving Status from AV1 ---

Received Status Details:

Vehicle ID: 001

Obstacle Presence: True

Obstacle Proximity: 5 meters

Traffic Density: light

Intended Action: stop

What the AV2 on the above would do? Please just answer STOP or FORWARD.



STOP

{LLM Model response without Communication agent's information (GPT-4 Turbo)}

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.

AV2 = Autonomous Car- cant see the stop sign
AV1 = Autonomous Truck,
S = Stop Sign

AV1 S

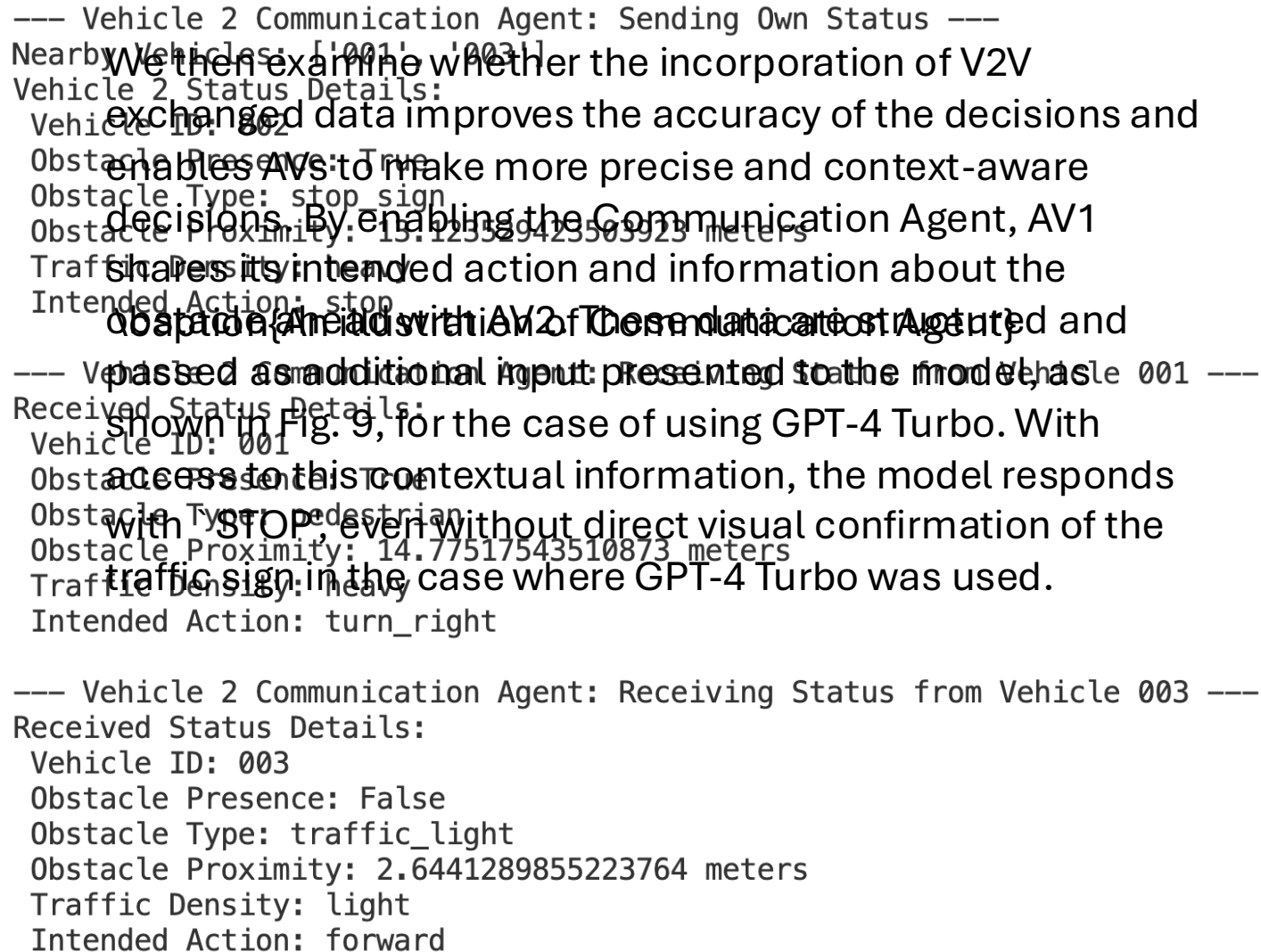
Initial Position:
AV2 AV1 S

Position Right Before STOP:
AV2 AV1 S

Simulation ended.
What the AV2 on the above would do? Please just answer STOP or FORWARD.



PROBLEMS OUTPUT PORTS TERMINAL

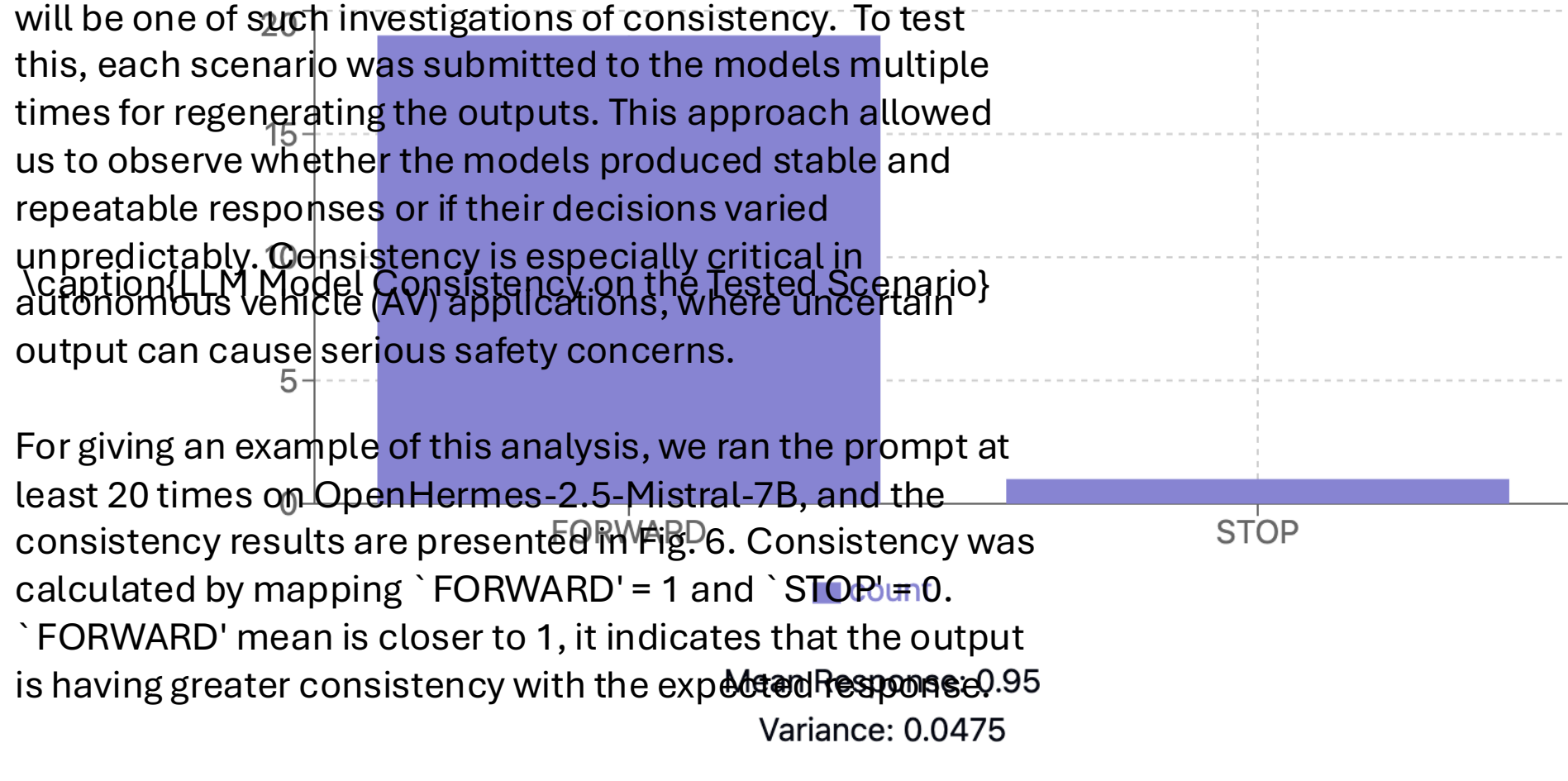


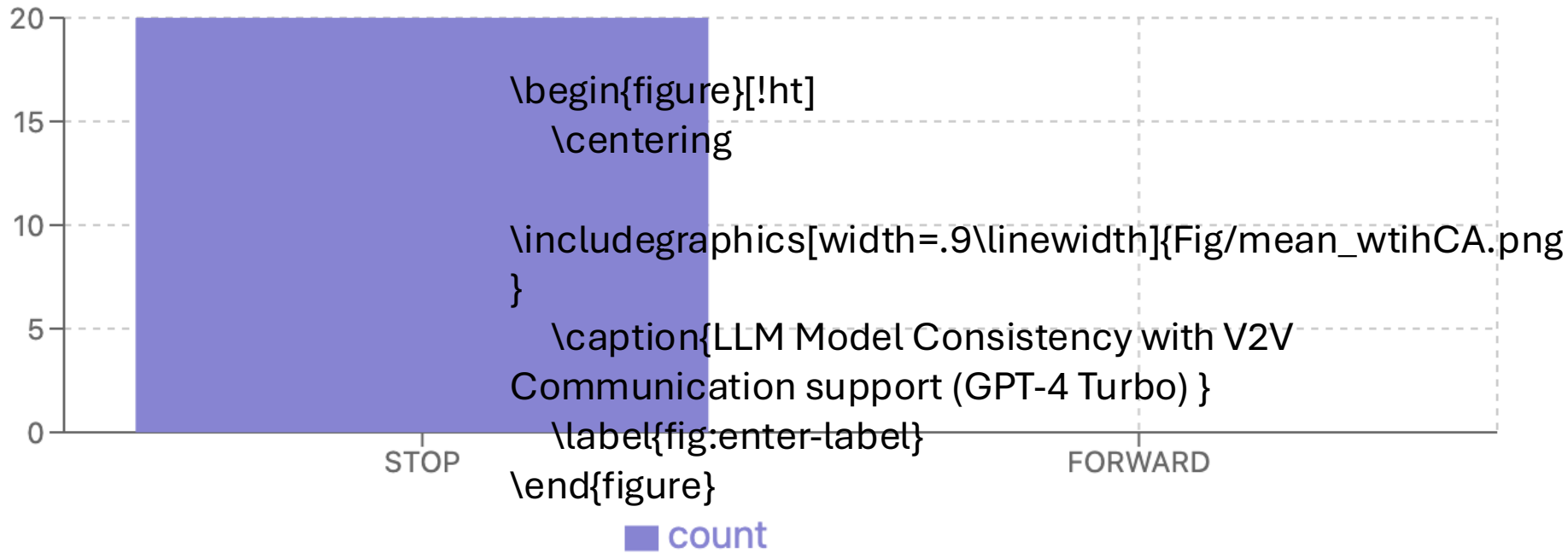
A major consideration was consistency. The subresearch question, 'Does repeated querying of LLMs on the same scenario lead to variations in decision-making outcomes?' will be one of such investigations of consistency. To test this, each scenario was submitted to the models multiple times for regenerating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

Mean Response: 0.95

Variance: 0.0475





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.