

Towards Natural Language Communication for Cooperative Autonomous Driving via Self-Play

Jiaxun Cui¹, Chen Tang¹, Jarrett Holtz², Janice Nguyen³,
Alessandro G. Allievi², Hang Qiu³, Peter Stone^{1,4}

¹The University of Texas at Austin ²Robert Bosch LLC

³University of California, Riverside ⁴Sony AI

Abstract: Past work has demonstrated that autonomous vehicles can drive more safely if they communicate with one another than if they do not. However, their communication has often not been human-understandable. Using natural language as a vehicle-to-vehicle (V2V) communication protocol offers the potential for autonomous vehicles to drive cooperatively not only with each other but also with human drivers. In this work, we propose a suite of traffic tasks in autonomous driving where vehicles in a traffic scenario need to communicate in natural language to facilitate coordination in order to avoid an imminent collision and/or support efficient traffic flow. To this end, this paper introduces a novel method, LLM+DEBRIEF, to learn a message generation and high-level decision-making policy for autonomous vehicles through multi-agent discussion. To evaluate LLM agents for driving, we developed a gym-like simulation environment that contains a range of driving scenarios. Our experimental results demonstrate that LLM+DEBRIEF is more effective at generating meaningful and human-understandable natural language messages to facilitate cooperation and coordination than a zero-shot LLM agent. Our code and demo videos are available at <https://github.com/cuijiaxun/talking-vehicles>.

Keywords: multi-agent communication, LLM agent, autonomous driving

1 Introduction

Driving is inherently a multi-agent problem [1]: each driver makes independent decisions based on their own perceptions while interacting with others on the road. As we transition towards (semi-)autonomous vehicles, centralized control [2] of all cars may appear efficient, but it is impractical and unlikely to gain widespread adoption. On the other hand, cooperative driving through communication channels is more practical and can still offer significant benefits even when implemented in a limited capacity. Past research has demonstrated the advantages of cooperative perception among autonomous cars [3, 4, 5]. However, these benefits are limited to vehicles that use the same learned environmental representation and communication language, limiting broader participation from those with different representations or language and leaving human drivers reliant solely on their local perceptions without being privy to the collaboration efforts.

With the rise of visual-language models that are capable of language-conditioned high-level reasoning and planning in complex traffic situations, using natural language as a universal communication channel for both vehicle-human and vehicle-vehicle coordination holds significant promise. To this end, we have developed a cooperative driving system that leverages natural language for communication and coordination, thus freeing each participant to reason in its own representation. Prior work has explored training driving agents to make and explain driving decisions in natural language [6, 7] or to coordinate with human drivers within a vehicle [8], leveraging extensive datasets [9, 10, 11, 12]. However, there is a lack of datasets and prior work featuring **inter-vehicle** communication in natural language alongside corresponding driving actions to facilitate cooperation.

Recent advances in Large Language Models (LLMs) present new opportunities for agents to learn to speak and understand natural language messages in cooperative driving scenarios. In this work, we explore the potential of LLM agents to collaborate using natural language and optimize communication and collaboration strategies over **self-play** interactions, avoiding the need to collect real-world data. For this purpose, we develop TalkingVehiclesGym, a multi-agent simulation framework that realistically models vehicle-to-vehicle communication in a set of accident-prone scenarios. Building on an LLM agent framework, this paper introduces a multi-agent learning method for LLM agents, LLM+DEBRIEF, which enables LLM agents to engage in centralized discussions post-interaction to refine their cooperation strategies, which are later incorporated into decentralized agent execution. Our experimental results in simulation demonstrate that when LLM agents struggle to collaborate effectively, our proposed learning method helps them learn what to communicate and how to respond to messages through interactions. Finally, we distill the learned behaviors of large models into a compact language model for near-real-time inference.

While this work has not gotten to the point of fully human-usable communication — e.g., by enforcing short, real-time messaging — this paper takes a crucial step in that direction by restricting all messages to be in natural language. We demonstrate that natural language enables LLM-powered autonomous vehicles to engage in cooperative perception and negotiation, allowing effective coordination that improves traffic efficiency and safety even without human involvement.

2 Problem Definition

In this paper, we focus on the subset of agents that are actively participating in the cooperation. We assume that these cooperative vehicles implicitly aim to help each other, treating all other (referred to as "background") vehicles as uncontrollable elements of the environment. Therefore, we frame the problem of *Talking Vehicles* as a partially observable stochastic game (POSG), focusing on optimizing the social welfare of a *focal population* (\mathcal{F}) [13] — defined as the joint reward of all participating agents — as the primary objective. The reward functions associated with each agent's individual tasks may or may not fully align, necessitating coordination among agents to achieve high joint rewards. Each agent's observation space is limited to a partial view of the full state, and agents make decisions in a decentralized manner based on their own partial observations and messages received from other agents. In this problem, each agent's action space comprises two main components: **(1) generating messages** and **(2) controlling the vehicle**. In this work, the message generation space is defined over natural language (English).

A POSG is defined by the tuple $\langle \mathcal{I}, \mathcal{S}, \{\mathcal{O}_i\}, \{\mathcal{A}_i\}, \mathcal{P}, \{\mathcal{R}_i\} \rangle$, where $\mathcal{I} = \{1, 2, \dots, N\}$ refers to the identities of all agents in a scenario; \mathcal{S} is the state space comprehensively describing the environment; \mathcal{O}_i is the observation space describing agent i 's view of the state; \mathcal{A}_i is the action space of agent i ; \mathcal{P} is the state transition function $\mathcal{S} \times \mathcal{A}_1 \times \mathcal{A}_2 \times \dots \times \mathcal{A}_N \rightarrow \mathcal{S}$; \mathcal{R}_i is the reward function of agent i . The focal group of agents is denoted by $\mathcal{F} \subseteq \mathcal{I}$, representing a subset of all agents \mathcal{I} . The goal for each agent $i \in \mathcal{F}$ is to optimize a policy π_i to maximize the expected cumulative task returns of all the agents in \mathcal{F} , given background agent policies outside the focal group: $\max_{\{\pi_i\}_{i \in \mathcal{F}}} \mathbb{E} \left[\sum_{i \in \mathcal{F}} \sum_{t=0}^{t=\infty} R_i(s_t, \mathbf{a}_t) \mid \{\pi_j\}_{j \notin \mathcal{F}, j \in \mathcal{I}} \right]$, where s_t is the state at time t , and $\mathbf{a}_t = (a_1^t, a_2^t, \dots, a_N^t)$ is the joint action of all agents at time t .

The agent's policy is structured to output both control and communication commands. Specifically, $\pi_i(\mathcal{O}_i, \{M_j\}_{j \in \mathcal{F}}) \rightarrow \mathcal{A}_i$ maps the observation of agent i and the received messages $\{M_j\}_{j \in \mathcal{F}}$ to its action space $\mathcal{A}_i = \langle \mathcal{M}_i, \mathcal{C}_i \rangle$, where \mathcal{M}_i represents the message generation space, which is constrained to natural language, and \mathcal{C}_i denotes the vehicle control space with dimensions for throttle, brake, and steering inputs. At time step t , the message M_i generated by agent i is broadcast to all the connected agents within a certain communication radius, at the next time step $t + 1$.

This problem presents the following technical challenges: (1) How can agents understand the situation and **generate** meaningful messages to collaboratively perceive the environment or negotiate in natural language; (2) How can agents **comprehend** incoming natural language messages and **incorporate** them into driving decision-making?

3 Environment

To provide concrete and typical driving scenarios that expose the *talking vehicles* challenge, we have developed a simulation environment, **TalkingVehiclesGym**, which is a multi-agent gymnasium environment for the closed-loop evaluation of urban driving policies. TalkingVehiclesGym supports a flexible configuration of multi-agent scenarios, incorporating heterogeneous agents such as language agents, sensory agents, human agents, heuristic behavior agents, etc. It also enables **in-episode** communication between agents using a realistically simulated communication protocol **MQTT**. The simulation dynamics are built on CARLA [14], a high-fidelity urban driving simulator.



Figure 1: Overview of Scenarios and Agent Roles. **Green circles:** Focal agents, agents aim at establishing coordination through communication; **Red circles:** Potential colliders; **Blue circles:** Background agents.

Scenarios (\mathcal{P}) and Rewards (\mathcal{R}). TalkingVehiclesGym has been set up with several accident-prone scenarios where multi-agent communication could be beneficial, as shown in Figure 1. Scenarios labeled with **Cooperative Perception** are cases where agents can benefit from receiving information about regions beyond their own line of sight and scenarios tagged with **Negotiation** are cases where it is necessary for the agents to discuss and resolve in their plans. In each scenario, a focal group (\mathcal{F}) of agents is defined. They operate alongside background agents with pre-scripted behaviors. Each focal agent is assigned a task described in natural language, with success defined as reaching its target location within a time limit without collisions. Agents without motion targets, such as a stationary truck in cooperative perception tasks, do not earn rewards directly for themselves. However, the optimization objective encourages these agents to send messages that assist others in achieving their tasks. More scenario descriptions and reward setups are detailed in Appendix C.

Observation Space (\mathcal{O}). Our environment integrates a diverse range of sensor and simulator inputs inherited from CARLA. To focus on reasoning and multi-agent learning, we simplify environmental perception for **text-based agents** by introducing a rule-based, **partially observable captioner**. This module abstracts away the perception task, which would otherwise require object detection or vision-language models, by directly converting scenario information—such as the states of the ego vehicle and others, lane details, and road conditions—into natural language descriptions that convey **factual** information while maintaining the partial observability imposed by the agent’s line-of-sight sensors. For agents equipped with a transmitter/receiver device (**transceiver**), real-time communication is enabled during episodes, and the message dialog is included as part of their observation. An example of a text-based observation is provided in Appendix D.

Action Space (\mathcal{A}). The action space for each agent encompasses both vehicle control and communication. The control space \mathcal{C} is three-dimensional, consisting of throttle, brake, and steering. To reduce decision-making frequency, agents execute high-level vehicle motion commands represented as temporal sequences of low-level vehicle controls ($C_t, C_{t+1}, \dots, C_{t+k}$), where each command spans k time steps. These high-level commands are atomic actions such as go (adapt to a target speed), stop, slow down, speed up, and change to the left lane. The message generation space \mathcal{M} is restricted to natural language tokens in this work, but is flexible enough to support other communication modes. In this work, messages are generated alongside the high-level control commands every 0.5 seconds ($k = 10$ simulation steps).

4 Method

The core technical challenge of the *talking vehicles* problem is to enable agents to communicate in natural language in order to facilitate cooperation and act correspondingly. To establish an initial solution, we adopt an **LLM agent framework** (Figure 2) that prompts LLMs as a foundational prior for autonomous agents to engage in human-like communication, structuring the message within natural language space, allowing agents to interpret messages and make informed driving decisions. A key challenge of using LLMs lies in that they are not specifically trained for driving tasks. To overcome this limitation, we introduce **LLM+DEBRIEF** (Algorithm 1), a **novel multi-agent learning methods for LLM agents** built upon feedback loops that allow LLM agents to iteratively refine their communication and motion control policies through trial-and-error interactions with confederate agents. Inspired by how humans reflect and debrief after a cooperative game such as Hanabi, we enable agents to discuss cooperative strategies after each interaction episode.

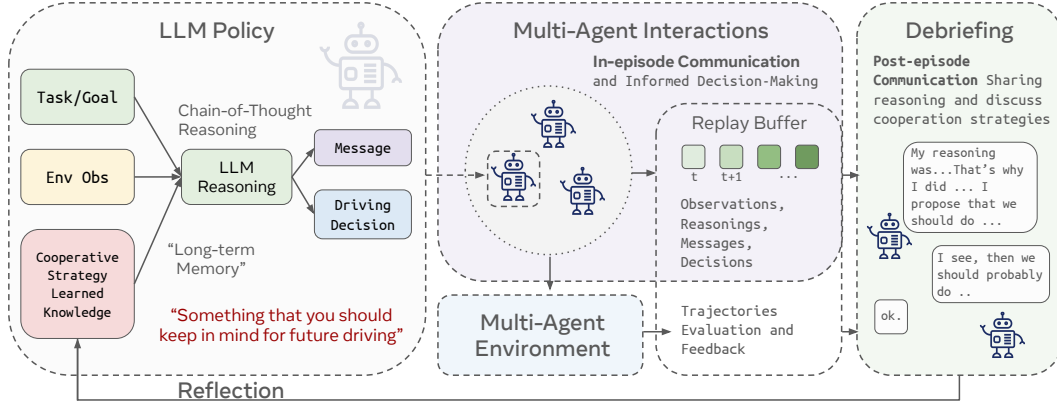


Figure 2: LLM+DEBRIEF Agent Framework and Agent Learning Pipeline.

4.1 Agent Policy

An agent acts according to an LLM policy $\pi_i(O_i, \{M_j\}_{j \in \mathcal{F}}) \rightarrow \langle \mathcal{M}_i, C_i \rangle$, where the distribution over actions follows the LLM used by the agent. Here, O_i represents a comprehensive text observation encompassing task and goal descriptions, environment details, and common traffic rules, expressed as a text sequence (**prompt**) $\{t_i^o\}$. A received message $M_j = \{t_j^m\}$ and a message to send $M_i = \{t_i^m\}$ are also text sequences generated by language agents. $C_i = \{t_i^c\}$ represents a text sequence for high-level commands. The joint probability of selecting a command and generating a message is expressed as $P_i(\{t_i^m\}; \{t_i^c\} | \{t_i^o\}; \{\{t_j^m\}\}_{j \in \mathcal{F}})$ where ";" indicates text concatenation and the language model serves as the oracle to determine the probabilities.

In-Context Knowledge. Instead of fine-tuning the weights of LLMs via gradient-based methods, we adapt the policy by modifying contexts. Define $K_i = \{t_i^k\}$ as agent i 's accumulated knowledge and $S_i = \{t_i^s\}$ as its cooperative strategy. The joint probability of generating commands and messages is then influenced by these additional prompt tokens: $P_i(\{t_i^m\}; \{t_i^c\} | \{t_i^k\}; \{t_i^s\}; \{t_i^o\}; \{\{t_j^m\}\}_{j \in \mathcal{F}})$.

Chain-of-Thought (CoT) Reasoning. Research has shown that LLMs make decisions better when provided with sufficient context [15]. To leverage this observation, we prompt LLMs to reason step-by-step about the environment, incorporating observations, received messages, and in-context knowledge. The reasoning process generates an output text sequence $R_i = \{t_i^r\}$. Following this reasoning, the LLM agent generates structured action tokens by combining the reasoning with the inputs: $P_i(\{t_i^m\}; \{t_i^c\} | \{t_i^k\}; \{t_i^s\}; \{t_i^o\}; \{\{t_j^m\}\}_{j \in \mathcal{F}}; \{t_i^r\})$. The final output is in a JSON format with keys: "command" and "message".

4.2 Agent Learning: Post-Episode Debriefing

The learning process is depicted in Figure 2. Initially, the LLM agents interact with each other in the scenarios, accumulating experience, which is stored in a replay buffer. Following the interaction

phase, the agents engage in a debriefing session where they utilize past experiences as context to collaboratively refine a cooperative strategy. The outcomes of these discussions are distilled into two critical components: knowledge ($K_i = \{t_i^k\}$) and cooperative strategies ($S_i = \{t_i^s\}$). These components are subsequently integrated as in-context knowledge for future interactions, playing a pivotal role in shaping and improving the policy.

Replay Buffer. We store transition data $T_i = \langle o_{i,t}, a_{i,t}, o_{i,t+1} \rangle$, which includes current and next observations, commands, messages, and reasoning in a **replay buffer**, serving as a repository for further learning and iterative refinement. When an episode concludes, the environment evaluates each agent’s performance and provides scalar rewards along with **verbal feedback**, such as “Vehicle 109 collided with Vehicle 110 after 2 seconds.” or “Vehicle 111 stagnated for too long to complete its task.” Each transition in the replay buffer is subsequently **retrospectively labeled** with enriched metadata, including responses from other agents, collision details (e.g., time to collision), stagnation specifics, and final rewards and outcomes.

Batch Context Sampling. Before engaging in the post-episode discussion (debriefing), each learning agent analyzes its past experience first. While analyzing the entire trajectory would provide a comprehensive understanding of failure cases, computational constraints necessitate sampling a subset (**batch**) of keyframes from its replay buffer. To prioritize relevant data, the sampling process heuristically assigns (following Equation 1) higher probabilities to transitions that occur immediately before collisions, involve actions contributing to collisions, or lead to stagnation due to agents slowing down. Additionally, transitions that feature more intensive multi-agent interactions are given more weight. These selected samples serve as the context for subsequent analysis and strategy formulation, allowing the agent to focus on critical timesteps for improving performance.

Debriefing. A debriefing session begins when an episode concludes in failure (collision or stagnation) and is conducted in a **turn-based** manner over N rounds, with a focus on improving cooperation in future interactions. The speaking order is deterministic in this work for each session, and agents take turns speaking in a round-robin format. The agent chosen to speak first is responsible for proposing a **joint** cooperative strategy ($S_1, S_2, \dots, S_{i \in \mathcal{F}}$) for everyone participating in the debriefing (the focal group). This agent begins by reasoning through its transition data batch, analyzing the consequences and influence on other agents of its actions, and formulating a proposed strategy. Subsequently, the other agents take turns sharing their perspectives, providing feedback, or offering alternative insights based on their analysis of their own experience batch. After the discussion, each agent summarizes the discussion to develop **individual** cooperative strategies (S_i) and knowledge (K_i). These outcomes serve as in-context guidelines for future driving tasks. This joint discussion for future individual decision-making structure mirrors the principles of the Centralized Training Decentralized Execution (CTDE) framework [16], a widely used approach in multi-agent learning. Our implementation details are available in Appendix A.1.

5 Experiments

This section presents an empirical evaluation of LLM+DEBRIEF and baseline approaches across different cooperative driving scenarios. We investigate the following research questions: **Q1:** Can LLM agents establish collaboration through chain-of-thought reasoning without prior interactions? **Q2:** Does decentralized reflection enable LLM agents to improve their collaborative ability as they gain more interaction experiences? **Q3:** Does centralized discussion among LLM agents provide additional improvements in collaboration and communication compared to decentralized reflection? **Q4:** Can natural language communication enhance the performance and coordination of LLM agents compared to those without communication?

Metrics. Evaluation metrics are established based on the outcomes of agents who can incur reward (reward-eligible) for their tasks in the focal group, which is scenario-specific. For a scenario with N reward-eligible agents in the focal group, evaluated over M episodes, we utilize two key metrics: 1. the **average collision rate (CR)**, normalized by the group size, is $\frac{1}{N} \cdot \frac{1}{M} \sum_{m=1}^M \sum_{i \in \mathcal{F}} \mathbb{1}(\text{agent } i \text{ involved in a collision})$, where collisions may involve both focal and

background agents; 2. the **average success rate (SR)**, also normalized by the group size, is $\frac{1}{N} \cdot \frac{1}{M} \sum_{m=1}^M \sum_{i \in \mathcal{F}} \mathbb{1}(\text{agent } i \text{ succeeded})$. Here, $\mathbb{1}$ is the indicator function, equal to 1 if the event occurs and 0 otherwise. The remaining failure cases, where agents exceed the time limit, heuristically determined to represent the upper bound for efficient task completion, without success or collision, are captured by the **average time out rate**, which can be derived as $TR = 1 - SR - CR$.

Experimental Setup. For each baseline, We consider two settings labeled as "Silent" and "Comm". In the "**Silent**" setting, LLM agents focus solely on controlling the vehicle based on their individual perception and reasoning without communication. The "**Comm**" setting allows a method to generate either only messages or both messages and driving commands. For each LLM-based learning method, we allow agents to interact for up to 60 episodes per scenario, which is a random sequence alternating between safe (or randomized agent positions for highway negotiation settings) and accident-prone configurations. We define a "solved" criterion for learning success in a scenario as 20 consecutive successful episodes. Due to the uncontrollable randomness in the OpenAI models, we give each learning method 3 knowledge reset opportunities to either report the "solved" result, otherwise the last run for each seed (details in Appendix A.1). After learning, each method is evaluated for 30 episodes per scenario configuration per seed. We report experimental results aggregated with 3 seeds.

Baselines. We established several baselines and scenarios to answer the research questions: 1. an LLM agent using Chain-of-Thought (CoT) reasoning only (**Zero-shot**), 2. an LLM agent with CoT reasoning contextualized with knowledge from decentralized reflection (**Reflection**), 3. an LLM agent that corrects past actions via self-reflection, storing these corrections in a vector-based, retrievable memory and uses few-shot retrieved example augmented generation (**Correction+RAG**). The retrieval augmented method without communication (**Correction+RAG (Silent)**) adapts DiLU [17], a non-communicating single-agent LLM-based approach that drives via reflection, to our environment. The multi-agent communication extension of DiLU, AgentsCoDriver [18], resembles the **Correction+RAG (Comm)** method, but they do not actively optimize the messages. For a fair comparison across baseline LLM agents, we do not initialize the knowledge with human data, nor is there human involvement during the learning process. Moreover, we apply the same batch context sampling method for reflection or correction for all LLM agent baselines as our method. Additionally, we include **Cooperonaut** [4], a LiDAR-based cooperative driving method, as an aspirational reference point for cooperative perception. Note that Cooperonaut is not directly comparable because it processes sensory data and communicates intermediate neural representations rather than natural languages.

5.1 Quantitative and Qualitative Results

Tables 1 and 2 present the quantitative evaluation of all methods across tasks. Notably, in this proof of concept, none of the LLM methods compared operate in real-time, requiring approximately 10 real-world seconds per decision step (0.5 seconds equivalent in simulation) using gpt-4o-mini. The inference latency primarily depends on reasoning, but we demonstrate an approach towards real-time inference in Section 5.2. On average, the natural language message bandwidth remains below 300 bytes per decision step, requiring less than 0.01 Mbps communication bandwidth. Table 3 in Appendix A provides detailed latency measurements and message size statistics. Based on these results, we provide responses to the research questions posed at the start of the section.

Table 1: Cooperative Perception Scenarios. mean \pm std over 3 trials, each using 30 evaluation episodes.

Scenario			Overtake (Perception)		Red Light		Left Turn	
Method	LLM	Comm	CR (%) \downarrow	SR (%) \uparrow	CR (%) \downarrow	SR (%) \uparrow	CR (%) \downarrow	SR (%) \uparrow
Zero-shot	Yes	No	93.3 \pm 3.4	0.0 \pm 0.0	93.3 \pm 6.7	6.7 \pm 6.7	93.3 \pm 5.8	6.7 \pm 5.8
+Reflection	Yes	No	87.8 \pm 3.4	0.0 \pm 0.0	94.4 \pm 6.9	5.6 \pm 6.9	76.7 \pm 20.8	23.3 \pm 20.8
+Correction+RAG	Yes	No	62.0 \pm 31.9	4.4 \pm 7.7	93.3 \pm 3.3	6.7 \pm 3.3	64.4 \pm 15.0	35.6 \pm 15.0
Zero-shot	Yes	Yes	91.1 \pm 5.1	4.4 \pm 5.1	60.0 \pm 11.5	38.9 \pm 10.7	85.6 \pm 8.4	14.4 \pm 8.4
+Reflection	Yes	Yes	63.3 \pm 14.5	34.4 \pm 10.7	37.8 \pm 18.4	47.8 \pm 18.4	51.1 \pm 37.2	47.8 \pm 36.0
+Correction+RAG	Yes	Yes	4.4 \pm 1.9	90.0 \pm 6.7	13.3 \pm 12.0	66.7 \pm 27.3	43.3 \pm 38.4	38.9 \pm 22.7
+Debrief	Yes	Yes	1.1 \pm 1.9	94.4 \pm 6.9	0.0 \pm 0.0	93.3 \pm 5.8	6.7 \pm 3.3	92.2 \pm 3.8
Cooperonaut	No	Yes	4.5 \pm 3.1	90.5 \pm 1.2	17.7 \pm 7.8	80.7 \pm 7.6	18.1 \pm 6.2	80.7 \pm 5.2

Table 2: Negotiation Scenarios. mean \pm std over 3 trials, each using 30 evaluation episodes.

Scenario			Overtake (Negotiation)		Highway Merge		Highway Exit	
Method	LLM	Comm	CR (%) \downarrow	SR (%) \uparrow	CR (%) \downarrow	SR (%) \uparrow	CR (%) \downarrow	SR (%) \uparrow
Zero-shot	Yes	No	89.9 \pm 2.8	7.2 \pm 3.8	100.0 \pm 0.0	0.0 \pm 0.0	33.3 \pm 9.3	66.1 \pm 9.2
+Reflection	Yes	No	32.8 \pm 29.4	36.7 \pm 52.1	15.0 \pm 23.1	84.4 \pm 22.6	32.8 \pm 13.4	67.2 \pm 13.4
+Correction+RAG	Yes	No	46.7 \pm 21.9	33.3 \pm 28.0	35.6 \pm 29.4	64.4 \pm 29.4	33.9 \pm 28.4	51.1 \pm 14.2
Zero-shot	Yes	Yes	87.8 \pm 5.9	11.7 \pm 6.7	67.2 \pm 27.1	32.8 \pm 27.1	53.3 \pm 11.5	46.7 \pm 11.5
+Reflection	Yes	Yes	55.6 \pm 38.9	43.3 \pm 37.1	20.0 \pm 1.7	80.0 \pm 1.7	53.9 \pm 24.1	45.6 \pm 23.6
+Correction+RAG	Yes	Yes	38.3 \pm 6.0	61.1 \pm 5.4	40.0 \pm 18.0	60.0 \pm 18.0	49.4 \pm 49.2	43.3 \pm 39.8
+Debrief	Yes	Yes	3.3 \pm 3.3	95.6 \pm 3.8	6.7 \pm 11.5	93.3 \pm 11.5	18.3 \pm 21.7	81.1 \pm 21.2

R1: LLM agents with CoT examined in this paper do not establish collaboration through communication in zero-shot interactions. Our experiments show that Zero-Shot agents (gpt-4o-mini), even with communication enabled, fail to coordinate effectively. The failure modes are (1) agents do not communicate effectively to understand each other’s needs in perception or achieve agreement in negotiation; or (2) even when the messages make sense to humans, agents do not respond with appropriate driving commands. This result suggests that without prior training or explicit strategies, chain-of-thought reasoning alone is insufficient to foster effective coordination. Future work will examine whether reasoning models like gpt-o4 can overcome these failures.

R2: Decentralized learning can enable LLM agents to improve their collaborative ability as they gain more interaction experiences. The decentralized learning methods, Reflection and Correction+RAG, show significant improvement in reducing collision rates from Zero-Shot across tasks. Reflection allows agents to individually analyze their experience to generate knowledge, but the knowledge is often more reactive than proactive (see Appendix E.7 for example). The Correction+RAG method records successful episodes to preserve successful coordination patterns and correct commands and messages at key frames selected through heuristic batch sampling. However, although the method improves the control response strategy, we find that it qualitatively does not always generate messages that are consistent with the actions, possibly due to the open-loop revisions. Both methods show promise but have room for improvement.

R3: Centralized debriefing enhances coordination more than decentralized reflection. The debriefing method, which focuses on generating explicit cooperation strategies, enables LLM agents to achieve more stable collaboration compared to decentralized reflection or zero-shot approaches, evidenced by higher success rates than baselines across tasks. The main performance boost comes from the formalized coordination strategy, which both defines how to communicate and how to respond given a dialogue. Interestingly, this method reveals that LLMs sometimes fail to understand complex natural language messages, so the agents eventually develop concise communication protocols (like "hold" and "go" in Section E.8) to ensure their intentions are easily interpretable among themselves. However, open challenges still remain. For example, the debriefing process can go awry where no agents can find issues with the cooperation strategies in harder and longer-horizon tasks like negotiation-highway-exit. We further provide detailed qualitative analysis in Section B.

R4: Natural language communication in cooperative driving can be effective, but may pose safety risks without good communication strategies. Our method, which operates with natural language communication, provides a proof of concept for natural-language-based multi-agent coordination across scenarios. However, learning to communicate effectively remains challenging. In cooperative perception tasks, communication-enabled methods consistently outperform silent ones, highlighting the critical role of information sharing. In contrast, in negotiation scenarios such as highway-merge and highway-exit, agents generally perform better in silent mode. This result suggests that communication adds complexity and can hinder coordination when not well-optimized. We speculate that the root cause lies in the suboptimal communication strategies learned under decentralized training, where messages may introduce noise rather than useful signals.

5.2 Cross-Scenario Generalization and Distillation towards Real-Time Inference

Up to this point, a separate policy was trained to handle each of the TalkingVehiclesGym scenarios. However, for practical deployment, it is desirable to develop a single policy that can handle a broad

range of challenging driving scenarios. We explore two independent approaches for achieving cross-scenario generalization: **Centralized Memory** and **Distillation**. While **Centralized Memory** aggregates all agents’ *most effective* knowledge—identified by the highest estimated success rate across learning trials—into a unified vector memory, **Distillation** performs full-parameter fine-tuning of a small language model, DistilGPT2 [19, 20], to directly **imitate** the behavior of the large memory-augmented LLM+DEBRIEF agent. The imitation dataset is aggregated from all *successful* evaluation episodes across scenarios, and the distillation model is trained to minimize the token-level cross-entropy loss against the large model’s outputs. During inference, decisions are generated via random sampling with a temperature of 0.2. Evaluation results of the two methods are listed in Table 4.

The Distillation model achieves decision generation times between **100 ms** and **470 ms** on an NVIDIA A40 GPU, depending on message generation length (**50 bytes** to **300 bytes**), getting close to the 500 ms decision-making frequency though time delays have not been fully considered. Remarkably, the distilled model generalizes well across scenarios and even surpasses the performance of its teacher model in some cases. We observe that it tends to behave overly conservatively in perception-overtake scenarios, suggesting room for further improvement, potentially through expert-guided correction methods such as DAgger [21]. More details about this section appear in Appendix A.3.

6 Related Work

LLM Agents for Autonomous Driving. have shown potential to address various autonomous driving tasks. In particular, they are promising in tackling corner cases [22] due to their reasoning ability and the common-sense knowledge embedded, yielding a more generalizable autonomous driving stack. Recent studies have explored various approaches to tailor state-of-the-art LLMs for driving [17, 18]. However, a foundational challenge lies in grounding LLM agents in the real world—they need to perceive and understand the traffic scenarios. A straightforward approach is to obtain the observations from oracle perception models [23] and convert them to textual descriptions [24, 25, 26, 27]. Some other studies tackled this challenge by introducing Visual Language Models (VLMs), which are adapted to driving domains through in-context instruction tuning [7] or fine-tuning [6, 28, 29, 30]. To enhance LLM agents’ reasoning ability, prior works have investigated incorporating handcrafted guidance and examples in the prompts [25, 26, 27], structuring the reasoning procedure [23, 12], and fine-tuning the models on driving datasets. Notably, fine-tuning LLMs and VLMs requires an extensive amount of driving data with language labels. Several works have attempted to adapt existing language-driving datasets for LLM fine-tuning [29, 28, 7] or augment large-scale multimodal driving datasets [31, 32, 33] with language labels [11, 34, 12, 35]. In contrast, our work generates scalable driving data through agent self-play. Note that existing models were predominantly evaluated in an *open-loop* fashion. In contrast, similar to some prior works [34, 25, 26], we conduct closed-loop evaluation of the proposed method and baseline methods in CARLA [14]. More importantly, none of the existing works have explored optimizing LLM agents in a multi-agent setting with natural language vehicle-to-vehicle communication, with [18, 36] representing concurrent but distinct efforts.

7 Conclusion

This work introduces the Talking Vehicles problem, a novel setting for multi-agent autonomous driving in which vehicles communicate and coordinate using natural language. We contribute a multi-agent simulation environment, TalkingVehiclesGym, and present LLM+DEBRIEF, a self-play learning framework that equips LLM agents with the ability to generate, interpret, and act upon natural language messages through reflective and collaborative debriefing. Our experiments demonstrate that, while zero-shot LLMs fail to establish effective coordination, iterative learning via decentralized reflection and centralized debriefing substantially improves cooperative performance across both perception and negotiation scenarios. Furthermore, we show that these learned behaviors can be distilled into efficient models capable of generalizing across diverse driving tasks under real-time constraints. This study represents an important step toward integrating natural language as a universal protocol for V2V communication, bridging the gap between human-understandable coordination and autonomous decision-making.

8 Limitations and Future Work

While our work provides promising initial evidence of the potential of LLM agents and LLM+DEBRIEF’s in addressing the *talking vehicles* problem, it comes with several limitations and opens up rich directions for future research:

Agent Perception. In this work, the LLM agents rely on text observations, assuming an idealized perception system. This choice stems from the strong performance of current LLMs and the early-stage development of multi-modal models. However, TalkingVehiclesGym environment supports multi-modal sensory input. Future work should develop agents that integrate multi-sensor perception and reasoning to fully leverage the rich context in realistic observations.

Communication Challenges. We assume that agents intend to communicate truthfully, reliably conveying their intentions and following through on their stated decisions. However, real-world vehicle-to-vehicle communication faces numerous challenges, including time delays that result in outdated information and the risk of adversarial or deceptive messages. Future research should develop methods to handle these challenges, ensuring timely and secure exchanges of information. Techniques such as real-time data verification and robust communication protocols will be critical for enhancing the reliability and safety of vehicle-to-vehicle communication systems.

Training Scalability and Ad Hoc Teamwork. While this paper reports on a successful proof-of-concept, the scalability of LLM+DEBRIEF to learn in diverse traffic scenarios and different environmental conditions has not been exhaustively tested. A limitation of our method is that, although it is sample-efficient, requiring only a few interaction episodes, the analysis must occur immediately after an episode concludes, which hinders scaling up learning. Future work could potentially scale up the training using multi-agent reinforcement learning to finetune the agents while using strong Kullback–Leibler regularization with a foundation model to ensure the agents speak human language during self-play. Additionally, future work should address ad hoc teamwork, where agents adapt to collaborators following different conventions.

Human Interface and Human Evaluation. To extend these methods to human-autonomous cooperation, intuitive and user-friendly interfaces (e.g., speech) are essential. Although our research opens up the potential for autonomous cars to cooperate with human drivers, the complexity of effective communication interfaces for humans is substantial. Comprehensive human-centered evaluations using human-friendly interfaces are deferred to future studies.

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A Method

The Algorithm 1 implements LLM+DEBRIEF, a centralized multi-agent learning framework that leverages communication and reflection using large language models (LLMs) to enhance coordination between agents in a simulated environment.

A.1 Implementation Details

We utilize gpt-4o-mini with a temperature of 0.2 for the agent policy, making decisions and collecting experiences every 0.5 seconds (10 simulation frames). Received message dialogs are maintained within a 2-second window based on message age during each episode. The debriefing process is conducted after each episode for a total of 60 episodes, comprising $N = 1$ round of discussion among agents followed by a final round of individual reflection to summarize and consolidate the discussion outcomes. To enable stronger reasoning and summarization capabilities, gpt-4o is employed for the debriefing sessions and reflection. The transition data are sampled from the trajectory with a batch size of 4.

The **Batch Context Sampling** follows the following heuristic to assign probability mass on each transition data point and sample according to the normalized probability mass:

$$\begin{aligned} \text{Weight}_i = & 1 + 2 \times \mathbb{1}\{\text{exists other agents}\} \\ & + 5 \times \max(2 - \text{time to collision}, 0) \\ & + 10 \times \mathbb{1}\{\text{actions contribute to collision}\} \\ & + 0.1 \times \mathbb{1}\{\text{stagnation}\} \times \{\text{timestep}\} \\ & + 2 \times \mathbb{1}\{\text{actions contribute to stagnation}\} \end{aligned} \quad (1)$$

Note on Knowledge Reset: Due to the uncontrollable randomness in OpenAI models, the learned knowledge can be unpredictably corrupted during training. Therefore, we allow each LLM agent method up to three resets (clearing the knowledge) before reaching a solved state (defined as 20 consecutive successful episodes) or using the final attempt after the last reset.

A.2 Inference Latencies

Table 3 summarizes the average latencies and message sizes for each scenario under the communication setting, evaluated using gpt-4o-mini on Nvidia A100 GPUs and Intel Gen 10 CPUs. The metrics include partial observable captioner latency (in seconds), reasoning latency (in seconds), decision latency (in seconds, excluding reasoning latency), and message size (in Mb). Data is aggregated over 10 episodes at each LLM decision step. Scenarios without communication exhibit slightly lower reasoning and decision latencies compared to those with communication within the same order of magnitude.

Table 3: Captioning, Reasoning, Decision Latency, Message Size using gpt-4o-mini LLM Policy

Scenario	Overtake	Left Turn	Red Light	Overtake	Highway Merge	Highway Exit
Latencies						
Captioner Latency (s)	0.022	0.023	0.025	0.022	0.017	0.016
Reasoning Latency (s)	10.32	10.89	9.93	9.57	12.10	10.55
Decision Latency (s)	1.06	1.25	1.37	0.86	1.05	1.27
Message Size (Mb)	0.0016	0.0013	0.0014	0.0014	0.0005	0.0005

A.3 Generalization and Acceleration

In the **Centralized Memory** approach, we select the most effective knowledge—identified by the highest estimated success rate across learning trials—and store the corresponding experience in a vector-based memory. This memory enables unified policy execution across multiple tasks by retrieving relevant knowledge based on the agent’s current observation.

Algorithm 1 Multi-Agent Centralized Debrief Reflection with Communication

Input: Multi-agent Simulation Environment env , LLM agents $\{\pi_{i \in \mathcal{I}}\}$, Debriefing round R .
Initialize: Knowledge $\{K_{i \in \mathcal{I}}\}$, Replay Buffer ReplayBuffer
for $j=1, 2, 3 \dots$ // Training epoch **do**
 $\{\text{obs}_i\} = \text{env.reset}()$
 while $t < T$ // Time step **do**
 for $i = 1, \dots, N$ //Per agent, but execute in parallel **do**
 // Get CoT reasoning for each agent based on observation and knowledge
 $\text{reasoning}_i \leftarrow \text{agents.reason}(\text{obs}_i, K_i)$
 // Get decisions for each agent based on observation and knowledge
 $\text{message}_i, \text{control}_i \leftarrow \text{agents.act}(\text{obs}, K_i, \text{reasoning}_i)$
 end for
 // Step the environment with actions
 $\{\text{next_obs}_i\} \leftarrow \text{env.step}(\{\text{message}_i, \text{control}_i\})$
 // Store experience to the replay buffer
 $\text{ReplayBuffer.add}(\text{obs}, \text{next_obs}, \text{reasonings}, \text{messages})$
 // Message Dialog becomes part of the observation
 $\{\text{obs}_i\} \leftarrow \{\text{next_obs}_i\} \cup \{\text{message}_i\}$
 end while
 // Get episode feedback from the environment
 $\text{feedback} \leftarrow \text{env.evaluate}()$
 // Label all the transition data in hindsight
 $\text{data_post_processing}(\text{ReplayBuffer})$
 // Debriefing and learning from feedback, update knowledge
 // Randomly decide debrief order
 for $r = 1, \dots, R$ **do**
 if $\text{strategy} = \text{None}$ **then**
 $\text{cooperation_strategy} = \text{agent}_r.\text{propose}()$
 else
 $\text{cooperation_strategy} = \text{agent}_r.\text{revise}()$
 end if
 end for
 // Summarize the dialogue and use it for future learning
 $\{K_i\} \leftarrow \text{agent.reflect}(\{K_i\})$
end for
last $\{\pi_{i,j}\}$ during the last iteration of self-play

In the **Distillation** approach, we perform full-parameter fine-tuning of a small language model, DistilGPT2 [19, 20], to directly imitate the behavior of the large memory-augmented LLM+DEBRIEF agent. The imitation dataset is aggregated from all *successful* evaluation episodes across scenarios, and the distillation model is trained to minimize the token-level cross-entropy loss against the large model’s outputs. During inference, decisions are generated via random sampling with a temperature of 0.2.

We evaluate the performance of each unified policy independently across different scenarios using three random seeds, reporting the mean performance and the standard error of the mean in Table 4. For reference, we also report the performance statistics of the individually selected knowledge (Debrief (per-scenario)).

The Centralized Memory policy maintains strong performance across tasks. However, we observe a performance drop in overtaking scenarios (perception-overtake and negotiation-overtake). We hypothesize that this drop is due to structural and objective similarities across tasks, leading the memory to occasionally retrieve mismatched strategies. Moreover, negotiation-based tasks require proactive communication initiation by the agent, whereas perception-focused tasks do not, further exacerbating mismatches in coordination strategies. These findings raise important challenges for future research on ad hoc teamwork and generalizable communication protocols.

As shown in Table 5, the Distillation model achieves decision generation times between 100ms and 470ms on an NVIDIA A40 GPU, depending on message generation length (50bytes to 300bytes), satisfying the 500ms real-time decision-making constraint while maintaining low communication bandwidth. Remarkably, the distilled model generalizes well across scenarios and even surpasses the performance of its teacher model in some cases. We observe that it tends to behave overly conservatively in perception-overtake scenarios, suggesting room for further improvement, potentially through expert-guided correction methods such as DAgger [21].

Table 4: Experimental results for **Generalization** across scenarios. Each policy is evaluated using three random seeds, with 30 episodes per seed. We report the mean performance over the 30 episodes, along with one standard error of the mean across seeds. *Debrief* (per-scenario) represents policies learned individually for each scenario and serves as an oracle baseline for comparison with the generalization performance of Centralized Memory and Distillation.

Method \ Scenario	Overtake (Perception)		Red Light		Left Turn	
	CR (%) ↓	SR (%) ↑	CR (%) ↓	SR (%) ↑	CR (%) ↓	SR (%) ↑
Debrief (per-scenario)	1.1 ± 1.1	98.9 ± 1.1	0.0 ± 0.0	96.7 ± 0.0	4.4 ± 2.9	94.4 ± 2.2
Centralized Memory	2.2 ± 1.1	93.3 ± 1.9	0.0 ± 0.0	100.0 ± 0.0	4.4 ± 2.9	93.3 ± 3.3
Distillation	0.0 ± 0.0	83.3 ± 1.9	0.0 ± 0.0	91.1 ± 4.4	0.0 ± 0.0	96.7 ± 0.0

Method \ Scenario	Overtake (Negotiation)		Highway Merge		Highway Exit	
	CR (%) ↓	SR (%) ↑	CR (%) ↓	SR (%) ↑	CR (%) ↓	SR (%) ↑
Debrief (per-scenario)	10.0 ± 3.8	87.2 ± 3.9	2.2 ± 2.2	97.8 ± 2.2	13.3 ± 6.0	86.7 ± 6.0
Centralized Memory	12.2 ± 2.9	86.7 ± 1.9	1.1 ± 1.1	98.9 ± 1.1	16.1 ± 4.8	82.8 ± 5.3
Distillation	10.0 ± 3.3	88.9 ± 4.4	0.0 ± 0.0	100.0 ± 0.0	3.3 ± 0.0	96.7 ± 0.0

Table 5: Decision Latency, Message Size using Distilled LLM Policy

Latencies \ Scenario	Overtake	Left Turn	Red Light	Overtake	Highway Merge	Highway Exit
Decision Latency (s)	0.45	0.44	0.38	0.14	0.19	0.20
Message Size (bytes)	223.3	297.9	223.0	28.0	59.0	59.0

B Qualitative Analysis

This section uses the negotiation-highway-merge scenario as an example scenario to analyze policy behaviors and qualitatively examines the learned knowledge and cooperation strategies. For detailed insights into the learned knowledge, see Appendix E, and refer to the supplementary videos for comprehensive demonstrations of policy behaviors.

First, we present a recorded communication exchange between agents in a demonstration video:

Vehicle 121 (on the highway): Vehicle 120, I am slowing down to create a gap for your merge. Please proceed safely.

Vehicle 120 (merging) replied: Thank you, Vehicle 121, I will speed up to merge into the gap you create. Please maintain your speed to facilitate my merge.

This form of communication is human-interpretable, paving the way for future human participation in multi-agent collaboration. In contrast, the $(x, y, z, feature)$ latent representation generated by Coopernaut lacks interpretability for humans and requires all vehicles in the system to share the same encoder, limiting its flexibility in mixed-autonomy settings. While in this work we do not enforce that the communication be suitable for humans to participate in the collaboration directly, the results suggest that it may be possible to move in that direction in the future by enforcing short, real-time messages.

Second, the in-context knowledge developed through the debriefing process demonstrates a **clear and coherent cooperation strategy**, defining each agent’s role and their coordination mechanisms

(Appendix E.5), in contrast to the purely reactive policies formed through self-reflection without explicit discussion of cooperation strategies (Appendix E.7).

Third, **agents behave according to their learned knowledge and cooperation strategy**. In the negotiation-highway-merge scenario, the debriefing-based policy’s behavior follows the developed structured cooperation strategy: when the merging vehicle requests to enter the highway, highway vehicles explicitly slow down to create a gap, enabling a smooth and coordinated merge. In contrast, under the Correction+RAG (Silent) mode, the lack of clear cooperation strategy leads to uncertainty. Both the merging and highway vehicles struggle to determine the right of way, often resulting in either a collision or a prolonged indecisive interaction at the junction. We encourage readers to watch the supplementary videos accompanying this paper for a deeper understanding of the qualitative differences between policies.

C Environment

The environment follows gymnasium and PettingZoo API, assuming a parallel-acting environment because we leverage this feature to parallel language model inference. We made significant changes to support multi-agent communication and heterogeneous agent configuration in CARLA. TalkingVehiclesGym wraps around the CARLA server and the client to set up agents as a bridge between the simulator and learning agent policies that are able to learn from replay buffers. Language Communication Agents can the MQTT-based transceiver we implemented, and the communication is among Agents instead of going through server.

Talking Vehicles Gym

A multi-agent, gymnasium (PettingZoo), high-fidelity, communication-supporting, scenario-based environment

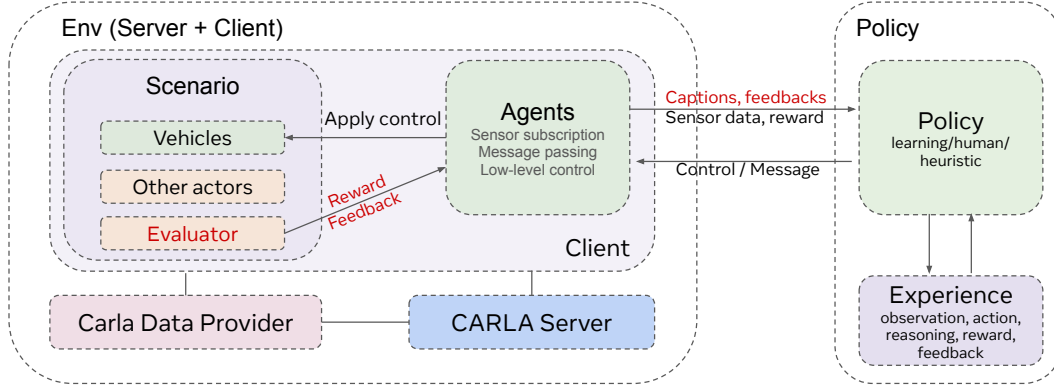


Figure 3: *TalkingVehiclesGym* Simulation framework. An agent is defined within the scenario and has a specific sensor registration and action space. A policy takes observations from an agent, computes actions, and learn from the experience replay buffer.

Rewards. An agent who successfully completes the task earns a reward of $+1$, while any agent involved in a collision incurs a penalty of -1 . Remaining stagnant at any point until timeout results in a reward of 0 , because conservative policies are safe though not ideal.

D Example Agent Prompting Flow

This figure serves as a demonstration of the prompts; the prompts that we use are more complex as they are structured in the code.

Table 6: Example Scenarios. Here we describe the fundamental composition of each accident-prone scenario, where the background agents can be configured in terms of density, controlling policies, and communication capabilities.

Interaction Type	Scenario Name	Description
Cooperative Perception	Overtake	A vehicle plans to overtake a broken and stopped truck by moving into the opposite lane. The truck can still communicate but the opposite-going car can not.
	Left Turn	A vehicle tries to turn left on a left-turn yield light when a truck is blocking the view of the opposite lane. The truck is able to communicate.
	Red Light Violation	A vehicle is crossing the intersection when there is another vehicle running the red light. Lidar fails to sense the other vehicle because of the lined-up vehicles waiting for a left turn, one of those cars being able to communicate.
Negotiation	Overtake	A vehicle is going to borrow the opposite lane to overtake a stopped truck. The truck is not able to connect, but an opposite-going car is able to communicate.
	Highway Merge	A vehicle is going to merge onto the highway but the target lane has continuous traffic flows. A vehicle on that lane is able to communicate and alter plans.
	Highway Exit	A vehicle is going to exit the highway but it needs to cross lanes where there is a traffic flow. A vehicle in the flow is able to communicate and alter plans.

E Example Learned Knowledge and Cooperative Strategies

The following knowledge is fully generated by LLMs without human modification.

E.1 Overtake (Perception)

Car1 (Overtaking Car)

knowledge: To efficiently and safely overtake a stationary vehicle in lane 1 by moving into lane -1, I will integrate active sensor use with continuous communication. The stationary vehicle will monitor lane -1 and provide real-time alerts on traffic status. Simultaneously, I will use my sensors to independently verify lane status. If both sources confirm lane -1 is clear, I will promptly proceed with the overtaking maneuver to avoid stagnation. If the stationary vehicle detects traffic, it will immediately advise me to hold my position. I will remain ready to accelerate smoothly once the lane is confirmed clear. This dual-verification approach, with proactive sensor use and real-time communication, will prevent collisions and ensure a timely and safe overtaking maneuver.

cooperative strategy: In our refined cooperative strategy, the stationary vehicle in lane 1 will continuously monitor lane -1 for any approaching traffic and provide real-time alerts. Meanwhile, the overtaking vehicle will actively use its sensors to independently verify the status of lane -1. If both the stationary vehicle’s observations and the overtaking vehicle’s sensors confirm that lane -1 is clear, the overtaking vehicle will promptly proceed with the maneuver to avoid stagnation. If the stationary vehicle detects any traffic in lane -1, it will immediately communicate this, advising the overtaking vehicle to hold its position. The overtaking vehicle will remain ready to accelerate smoothly once the lane is confirmed clear. This dual-verification approach, combining sensor data and real-time communication, ensures a timely and safe overtaking maneuver, preventing collisions and minimizing stagnation.

Truck (Stopped Truck in Lane 1)

knowledge: As the stationary truck in lane 1, my role is to continuously monitor lane -1 for any visible traffic and provide immediate alerts if I detect any vehicles, advising the overtaking vehicle to

System

You are driving a car, and your goal is pass the intersection if the traffic lights are green safely and timely, do not stagnate if everything is safe.
You can coordinate with any other vehicles to avoid collisions and or reduce wait time. I will give you description of the driving situation from your LiDAR perception, but note that it may be partially observable.
The observations are formatted as:
Observation: <observation>
Possible actions are: 1. Stop 2. go (follow the planned route) 3. speed up 4. slow down

1. Sign of the Lane ID indicate the direction of the lane.
2. Your received messages are from other vehicles. Be sure to analyze the messages and how that message will affect you.
3. You decide an action every 10 frames (0.5 seconds).
4. Do not switch your action unless it is necessary.

User

Observation: You are driving Vehicle 241, a vehicle.lincoln.mkz_2020. Your current speed is 0.00 m/s, and the speed limit is 10.00 m/s. Your current speed is lower than the speed limit. The traffic light for you is currently green. You are at a 4-way intersection with traffic lights.

Around you, there are other vehicles:

(1) Vehicle 249 is a vehicle.carlamotors.carlacola. Vehicle 249 is stationary. It is in lane -1, a single-lane road on the left-turning point of road 4 at the intersection. Vehicle 249 is side-by-side and 1.29 meters on your left...

Start of Message Dialog: (Received Message from Vehicle 249, 2.0 seconds ago: Attention all vehicles: Vehicle 242 (Audi) is approaching the intersection at 8.55 m/s against a red light, located 3.54 meters in front of me and 10.56 meters to my left. Vehicle 241, please remain stationary until I confirm the threat has stopped. Vehicle 248, you are safe to remain stationary as well. I will provide updates shortly.) ... **End of Message**
It is your turn to send a message to other vehicles now

Agent

Based on the current observations and the received messages, here is the assessment of the situation: 1. **Traffic Light Status**: The traffic light for Vehicle 241 (me) is green, which typically allows me to proceed through the intersection. 2. **Surrounding Vehicles**:
- **Vehicle 249**: Stationary, providing updates about the situation.
- **Vehicle 248**: Stationary, following the instructions from Vehicle 249.
- **Vehicle 247**: Stationary, also following the instructions from Vehicle 249.
- **Vehicle 242**: Approaching the intersection at 7.62 m/s against a red light, currently 6.84 meters in front of me. This vehicle poses a significant threat as it is not complying with the traffic signal. 3. **Received Messages**:
- Vehicle 249 has consistently warned all vehicles to remain stationary due to the approaching Vehicle 242, which is running a red light. The updates indicate that Vehicle 242 is getting closer and remains a threat. 4. **Potential Outcomes**:
- If I proceed (go): I risk a collision with Vehicle 242, which is approaching the intersection against a red light. This is unsafe and could lead to an accident. ...

User

You MUST respond with an action, formatted as a JSON object with the following structure:
command: <command>
where you replace <command> with your actual command, choosing from: go, stop
Do nothing else but return the action.

Agent

```
{'command': 'stop', 'message': 'Vehicle 241: Acknowledging the updates from Vehicle 249. I will remain stationary until further notice. Please keep me updated on the status of Vehicle 242. Safety first.'}
```

Figure 4: Example Agent Prompting Flow.

hold its position. The overtaking vehicle should actively use its sensors to independently verify lane status. If both my observations and the overtaking vehicle's sensors confirm that lane -1 is clear, the overtaking vehicle should promptly proceed with the overtaking maneuver to avoid stagnation. This dual-verification approach ensures a safe and efficient overtaking maneuver, preventing collisions and minimizing stagnation.

cooperative strategy: In our refined cooperative strategy, as the stationary truck in lane 1, I will continuously monitor lane -1 for any approaching traffic and provide immediate alerts if I detect any vehicles, advising the overtaking vehicle to hold its position. Meanwhile, the overtaking vehicle will actively use its sensors to independently verify the status of lane -1. If both my observations and the overtaking vehicle's sensors confirm that lane -1 is clear, the overtaking vehicle should promptly proceed with the overtaking maneuver to avoid stagnation. This dual-verification approach, combining sensor data and real-time alerts, ensures a timely and safe overtaking maneuver, preventing collisions and minimizing stagnation.

E.2 Red Light (Perception)

Car1 (Proceeding Forward with Green Lights)

knowledge: As a vehicle with a green light at an intersection, my primary task is to pass through safely and timely. I should communicate my intention to proceed to nearby cooperative vehicles and request confirmation that the intersection is clear. I must remain vigilant for warnings from vehicles with a clear view of the intersection about potential threats, such as vehicles approaching against a red light. If a warning is received, I should remain stationary until the monitoring vehicle confirms the intersection is clear. Continuous communication and responsiveness to updates are key to preventing collisions and avoiding unnecessary delays, allowing me to proceed promptly when it is safe.

cooperative strategy: In our cooperative strategy, the vehicle with the best view of the intersection, typically positioned to turn left, will lead in monitoring and communicating updates about potential threats. This vehicle will provide real-time information about any approaching vehicles against a red light, including their distance and speed, and confirm when they have stopped or are no longer a threat. If a threat is detected, the vehicle with the green light, ready to proceed straight through the intersection, should remain stationary until the intersection is confirmed clear. The monitoring vehicle will send updates every few seconds to keep all vehicles informed. Once the threat is resolved, the monitoring vehicle will confirm the intersection is clear, allowing the vehicle with the green light to proceed promptly and safely. This plan ensures safety by preventing collisions and minimizes unnecessary delays by enabling vehicles to pass through the intersection efficiently when it is safe to do so.

Truck (Stopped at Intersection)

knowledge: As the stationary truck with a clear view of the intersection, my primary role is to monitor traffic and provide real-time updates to ensure the safe and efficient passage of vehicles. If I detect any vehicle approaching the intersection against a red light, I must immediately alert all nearby vehicles, providing specific information about the threat's distance and speed. The vehicle with the green light should remain stationary until I confirm that the threat has stopped or is no longer present. I will send updates every few seconds to keep all vehicles informed. Once the intersection is clear, I will confirm this, allowing the vehicle with the green light to proceed promptly and safely. This proactive communication ensures that all vehicles are aware of potential threats and can take appropriate actions to prevent collisions, while minimizing unnecessary delays by enabling vehicles to pass through the intersection efficiently when it is safe. My task is to facilitate this communication and coordination to maintain a balance between safety and efficiency at the intersection.

cooperative strategy: In our cooperative strategy, the vehicle with the best view of the intersection, which is the stationary truck (myself), will lead in monitoring and communicating updates about potential threats. If a vehicle is detected approaching against a red light, I will immediately alert all vehicles, providing specific information about the threat's distance and speed. The vehicle with the

green light, positioned to proceed straight through the intersection, should remain stationary until I confirm that the threat has stopped or is no longer present. I will send updates every few seconds to keep all vehicles informed. Once the intersection is clear, I will confirm this, allowing the vehicle with the green light to proceed promptly and safely. This plan ensures safety by preventing collisions and minimizes unnecessary delays by enabling vehicles to pass through the intersection efficiently when it is safe to do so.

E.3 Left Turn (Perception)

Car1 (Left-Turning)

knowledge: To execute a northbound left turn at the intersection while yielding to oncoming southbound traffic from lane -2, I should first slow down to assess the speed and distance of any oncoming vehicles. I will rely on the stationary vehicle at the intersection to continuously monitor traffic and provide real-time updates. This vehicle will send messages advising me when it is safe to proceed and instruct the oncoming vehicle to yield. I should only proceed with the turn once I receive confirmation that the oncoming vehicle has acknowledged the yield instruction. If the oncoming vehicle does not acknowledge or adjust its speed, I should stop and wait until it is safe to proceed. This approach ensures a safe and efficient left turn without causing collisions or unnecessary stagnation.

cooperative knowledge: In our revised cooperative strategy, the stationary vehicle at the intersection will continuously monitor the traffic flow and provide real-time updates to both the left-turning vehicle (myself) and the oncoming vehicle. The stationary vehicle will send a message advising me to slow down and assess the situation, ensuring I only proceed with the left turn when I receive confirmation that the oncoming vehicle has acknowledged the yield instruction. Simultaneously, the stationary vehicle will instruct the oncoming vehicle to yield and adjust its speed to allow me to pass safely. If the oncoming vehicle does not acknowledge or adjust its speed, the stationary vehicle will alert me to stop and wait until it is safe to proceed. This plan ensures that all vehicles are aware of each other's intentions, allowing me to make the left turn safely and efficiently without causing collisions or unnecessary stagnation.

Truck (Stopped at Intersection)

knowledge: As a stationary vehicle with a clear view of the intersection, my primary task is to facilitate the safe and quick passage of the northbound left-turning vehicle by sharing critical traffic information. I must continuously monitor the intersection and assess the speed and distance of any oncoming vehicles. If an oncoming vehicle is approaching at a speed that could lead to a collision, I will send timely messages advising the left-turning vehicle to slow down and assess the situation, ensuring it only proceeds when the oncoming vehicle has acknowledged the yield instruction. I will also instruct the oncoming vehicle to yield and adjust its speed. If the oncoming vehicle does not acknowledge or adjust its speed, I will alert the left-turning vehicle to stop and wait until it is safe to proceed. This ensures clear communication and proactive monitoring, preventing collisions and avoiding unnecessary stagnation.

cooperative knowledge: In our revised cooperative strategy, as the stationary vehicle with a clear view of the intersection, I will continuously monitor the traffic flow and provide real-time updates to both the northbound left-turning vehicle and the oncoming vehicle. I will send a message to the left-turning vehicle advising it to slow down and assess the situation, ensuring it only proceeds when it receives confirmation that the oncoming vehicle has acknowledged the yield instruction. Simultaneously, I will send a message to the oncoming vehicle instructing it to yield and adjust its speed to allow the left-turning vehicle to pass safely. If the oncoming vehicle does not acknowledge or adjust its speed, I will alert the left-turning vehicle to stop and wait until it is safe to proceed. This plan ensures that all vehicles are aware of each other's intentions, allowing the left-turning vehicle to pass the intersection safely and quickly without causing collisions or unnecessary stagnation.

E.4 Overtake (Negotiation)

Car1 (Overtaking Car)

knowledge: To successfully overtake the stopped broken truck in lane 1 by using lane -1, prioritize clear communication and adaptive speed management. Before attempting the maneuver, send a message to any oncoming vehicle in lane -1, indicating your intention to overtake and requesting a slight temporary speed reduction to create a safe gap. Wait for acknowledgment and ensure the gap is sufficient before proceeding. During the overtaking, minimize your time in lane -1 to reduce collision risk. Once safely back in lane 1, send a confirmation message to allow the oncoming vehicle to resume its speed. This approach ensures a coordinated and safe overtaking maneuver without causing unnecessary delays or collisions.

cooperative strategy: In our cooperative strategy, when I, as the vehicle intending to overtake a stationary truck in my lane, need to move into the opposite lane, I will first send a message to the oncoming vehicle in the opposite lane, indicating my intention to overtake and requesting a temporary speed reduction to create a safe gap. The oncoming vehicle should acknowledge this request and, if feasible, slightly slow down to create a safe gap, but avoid coming to a complete stop to prevent stagnation. Once the gap is sufficient, I will proceed with the overtaking maneuver and return to my original lane as quickly and safely as possible. After completing the maneuver, I will send a confirmation message, allowing the oncoming vehicle to resume its target speed. This plan ensures that I minimize my time in the opposite lane while the other vehicle maintains its urgency, thus preventing collisions and avoiding stagnation. Effective communication and adaptive speed adjustments are key to ensuring both vehicles can complete their tasks safely and efficiently.

Car2 (Opposite Car)

knowledge: To effectively execute the task of going forward and keeping lane in lane -1 while in a hurry, prioritize maintaining speed and lane. If a vehicle in the opposite lane intends to overtake a stationary vehicle and needs to temporarily move into my lane, anticipate receiving a message indicating this intention. Upon receiving such a message, acknowledge it and, if feasible, slightly slow down to create a safe gap for the overtaking maneuver, but avoid coming to a complete stop to prevent stagnation. Ensure the gap is sufficient for safe passage. Once the overtaking vehicle has safely returned to its original lane, resume the target speed. This approach maintains urgency while facilitating safe and efficient traffic flow, preventing collisions and avoiding stagnation. Prioritize effective communication and adaptive speed adjustments.

cooperative strategy: In our cooperative strategy, when a vehicle in the opposite lane intends to overtake a stationary vehicle and temporarily move into my lane, it should first send a message indicating its intention and request a temporary speed adjustment. As the vehicle tasked with going forward and keeping lane, I should acknowledge this request and, if feasible, slightly slow down to create a safe gap, but avoid coming to a complete stop to prevent stagnation. The overtaking vehicle should proceed with the maneuver as quickly and safely as possible, minimizing its time in my lane. Once the overtaking vehicle has safely returned to its original lane, it should send a confirmation message, allowing me to resume my target speed. This plan ensures that the overtaking vehicle minimizes its time in the opposite lane while I maintain my urgency, thus preventing collisions and avoiding stagnation. Effective communication and adaptive speed adjustments are key to ensuring both vehicles can complete their tasks safely and efficiently.

E.5 Highway Merge (Negotiation)

Car1 (Merging Vehicle)

knowledge: To effectively merge onto the highway when in a hurry, I should initiate communication by indicating my intention to merge and request the vehicle directly on the highway lane to my left to create a gap by slightly slowing down or temporarily changing lanes if feasible. I must observe the responses from vehicles already on the highway, particularly the one closest to the merge point, and adjust my speed to align with the newly created gap. I should not accelerate until the highway vehicle

has stabilized its speed and distance. Continuous communication is crucial to ensure all vehicles are aware of each other's actions, allowing for coordinated speed and lane adjustments. If the gap is insufficient, I should be prepared to slow down significantly or stop to reassess the situation, ensuring a safe and efficient merge without causing collisions or stagnation.

cooperative strategy: In the cooperative strategy, as the merging vehicle, I will initiate communication by indicating my intention to merge onto the highway and requesting the vehicle directly to my left on the highway to create a gap by slightly slowing down or, if feasible, temporarily changing lanes. The highway vehicle should acknowledge this request and adjust its position accordingly, ensuring it maintains a safe distance. Meanwhile, I will adjust my speed to align with the newly created gap, ensuring I do not accelerate until the highway vehicle has stabilized its speed and distance. The vehicle behind the highway vehicle should maintain its speed or slightly slow down to prevent closing the gap prematurely. Continuous communication will be maintained, with updates on speed adjustments and intentions, to ensure all vehicles are aware of each other's actions. This approach will prevent collisions by ensuring a clear and sufficient gap for merging while avoiding stagnation by coordinating speed and lane adjustments effectively.

Car2 (Highway Vehicle)

knowledge: To execute the task of keeping on the original highway lane and going forward while in a hurry, prioritize maintaining a safe and efficient flow of traffic. When approaching a merge junction, be vigilant for merging vehicles and anticipate their need to enter the highway. If a merging vehicle communicates its intention, acknowledge the request and slightly reduce speed to create a sufficient gap, facilitating a safe merge. Ensure clear communication of actions to allow the merging vehicle to adjust its speed accordingly. Maintain your lane and continue moving forward, gradually accelerating to the desired speed once the merging vehicle has safely merged. Ensure the vehicle behind maintains its speed to prevent closing the gap prematurely. Continuous communication and dynamic speed adjustments are key to preventing collisions and avoiding stagnation, allowing the task to be fulfilled efficiently.

cooperative strategy: In the cooperative strategy, the merging vehicle should initiate communication by indicating its intention to merge onto the highway and requesting the highway vehicle directly to its left to create a gap by slightly slowing down. The highway vehicle, which is myself, should acknowledge this request and slightly reduce speed to create a safe merging space, while maintaining my lane and preparing to accelerate once the merge is complete. The merging vehicle should adjust its speed to align with the gap, ensuring it does not accelerate until I have stabilized my speed and distance. The vehicle behind me on the highway should maintain its speed or slightly slow down to prevent closing the gap prematurely. Continuous communication should be maintained, with updates on speed adjustments and intentions, to ensure all vehicles are aware of each other's actions. This approach will prevent collisions by ensuring a clear and sufficient gap for merging while avoiding stagnation by coordinating speed adjustments effectively.

E.6 Highway Exit (Negotiation)

Car1 (Exiting Highway)

knowledge: To exit the highway via the leftmost lane, initiate communication with the vehicle in the leftmost lane at least 100 meters before the exit junction, clearly indicating your intention to merge. Maintain a reasonable speed in the high-speed lane while seeking a safe gap to merge ahead of the traffic flow. If the vehicle in the leftmost lane is slightly ahead or side-by-side, it should decelerate slightly to create a gap. Adjust your speed dynamically to align with the gap being created, ensuring a smooth and safe transition into the left lane. Physically verify that the gap is sufficient for a safe merge before attempting the lane change. If the vehicle in the leftmost lane is stationary or unable to create a gap, communicate to confirm this status and seek alternative gaps or adjust your route if necessary. Prioritize visual confirmation over communication alone, and be prepared to adapt your strategy to the current traffic conditions to prevent collisions and avoid traffic stagnation.

cooperative knowledge: In our cooperative strategy, as the vehicle in the high-speed lane intending to exit, I will initiate communication with the vehicle in the leftmost lane at least 100 meters before the exit junction, clearly indicating my intention to merge. If the vehicle in the leftmost lane is slightly ahead or side-by-side, it should decelerate slightly to create a gap ahead, allowing me to merge smoothly without causing stagnation. I will maintain a speed that allows me to observe the gap being created and will only proceed with the lane change once I have a clear visual confirmation of a safe gap. If the vehicle in the leftmost lane is stationary or unable to create a gap due to traffic conditions, it should communicate this status immediately. In such cases, I will adjust my speed to maintain a safe distance and seek an alternative gap or prepare to slow down significantly if necessary. Both vehicles should actively communicate their speed adjustments and confirm when a safe gap is established, ensuring that the lane change is executed without collision or stagnation.

Car2 (Leader of the Left Flow Staying on the Highway)

knowledge: To effectively execute the task of staying in the leftmost lane and proceeding forward on the highway while prioritizing safety in a hurry, I should keep the following updated knowledge in mind: 1. **Proactive Communication:** Monitor for messages from adjacent vehicles intending to merge into my lane, ensuring communication is initiated at least 100 meters before exit junctions, and respond promptly to facilitate coordination. 2. **Adaptive Speed Management:** Decelerate slightly to create a sufficient gap when a merging vehicle is slightly ahead or side-by-side, allowing it to merge smoothly without causing stagnation. 3. **Enhanced Situational Awareness:** Continuously assess the speed and position of vehicles in adjacent lanes to anticipate merging actions and adjust my speed accordingly, ensuring a safe and efficient merge. 4. **Coordinated Communication:** Actively communicate and confirm speed adjustments with the merging vehicle to establish a safe gap, preventing collisions and maintaining traffic flow. 5. **Task Focus:** Maintain my position in the leftmost lane and proceed efficiently, ensuring cooperative actions support safety and fluid traffic flow, especially near exit junctions.

cooperative knowledge: In our cooperative strategy, when a vehicle in the adjacent lane intends to merge into the leftmost lane for a highway exit, it should initiate communication at least 100 meters before the exit junction, clearly indicating its intention to merge. As the vehicle currently in the leftmost lane, my responsibility is to promptly acknowledge this message and assess the traffic situation. If I am slightly ahead or side-by-side with the merging vehicle, I will decelerate slightly to create a gap ahead, allowing the merging vehicle to merge smoothly without causing stagnation. The merging vehicle should maintain a speed that allows it to observe the gap being created and only proceed with the lane change once it has a clear visual confirmation of a safe gap. If I am stationary or unable to create a gap due to traffic conditions, I will communicate this status immediately. In such cases, the merging vehicle should adjust its speed to maintain a safe distance and seek an alternative gap or prepare to slow down significantly if necessary. Both vehicles should actively communicate their speed adjustments and confirm when a safe gap is established, ensuring that the lane change is executed without collision or stagnation."

E.7 Highway Merge (Negotiation) Silent Reflection

Car1 (Merging Vehicle) knowledge: Updated Knowledge for Merging onto the Highway: 1. **Continuous Monitoring:** Always be aware of vehicles behind, directly in front, or to the side, as they pose immediate collision risks. 2. **Early Gap Identification:** Identify potential merging gaps early and adjust speed in advance to align with these gaps, considering both vehicles ahead and behind. 3. **Dynamic Speed Adjustment:** Accelerate only when a clear and safe gap is confirmed. Be ready to slow down if a vehicle behind is approaching quickly or if a vehicle ahead is close. 4. **Maintain Safe Distance:** Prioritize keeping a safe distance from vehicles directly ahead and behind. If a vehicle is too close, adjust speed to increase the gap before merging. 5. **Safety Over Speed:** Prioritize safe merging over speed. Avoid aggressive maneuvers that could lead to collisions, even if it means a slight delay. 6. **Flexible Strategy:** Adapt strategies based on real-time traffic conditions. Reassess and choose a safer alternative if a planned action seems unsafe. 7. **Immediate Threat Focus:** Pay special attention to vehicles approaching from behind in your intended merging path. Adjust your

strategy to create a safe gap with these vehicles before merging.8. **Proximity Awareness:** If a vehicle is within a critical distance behind, prioritize adjusting speed to ensure a safe merging gap.9. **Cautious Acceleration:** When a vehicle is directly in front and moving slower, maintain speed or slow down to allow it to move further away before attempting to merge.By applying these strategies, you can merge onto the highway more effectively and safely, even when in a hurry.

Car2 (Highway Vehicle) knowledge: Updated Knowledge for Navigating Highway Merge Junctions

- Early Detection and Assessment:** Identify merging vehicles early, focusing on their speed and proximity. If they are close, prepare to adjust your speed promptly to facilitate safe merging.
- Prioritize Safety Over Speed:** Always prioritize avoiding collisions over maintaining speed. Adjust your speed to ensure safe distances from merging vehicles, even if it causes a slight delay.
- Dynamic Speed Adjustment:** Be ready to slow down significantly if a merging vehicle is very close. Avoid abrupt speed increases that could reduce merging space and lead to collisions.
- Continuous Monitoring:** Maintain awareness of the speed and position of nearby vehicles, especially those merging. Be vigilant of vehicles approaching from behind and to the side.
- Proactive Space Creation:** Act promptly to create space for merging vehicles. Adjust your speed early to prevent conflicts and maintain a smooth flow.
- Anticipate Merging Intentions:** If a vehicle is close and in a merging lane, anticipate its intention to merge and adjust your speed or position accordingly to prevent collisions.
- Balance Urgency with Caution:** While in a hurry, balance the need for speed with safety. Ensure that any speed adjustments do not compromise the safety of merging vehicles.
- Immediate Response to Close Proximity:** When a merging vehicle is extremely close, prioritize immediate action to slow down or create space, even if it means temporarily reducing speed significantly.
- Evaluate Lane Change Options:** If safe and necessary, consider a temporary lane change to allow merging vehicles to enter your lane smoothly, while maintaining your original route.
- Avoid Stagnation:** Ensure that actions do not cause stagnation or impede traffic flow. Adjust speed dynamically to maintain progress while ensuring safety.

E.8 Overtake (Perception) Communication Protocol by LLM+DEBRIEF, seed 12, checkpoint-28

Car1 (Overtaking Car)

knowledge: To successfully overtake the stopped broken truck using lane -1, I will maintain a flexible speed and use my sensors to independently assess the speed and distance of oncoming traffic in lane -1. The stationary truck will continuously monitor lane -1 and provide real-time updates, sending a **"hold"** message if the gap is not safe. I will only proceed with the overtaking maneuver when both the stationary truck's updates and my sensor data confirm a safe gap, at which point the stationary truck will send a **"go"** message. This ensures alignment and minimizes the risk of collision. If no safe gap is available, I will maintain my position and communicate my readiness to adapt speed as necessary, ensuring a coordinated and safe overtaking process.

cooperative strategy: In the revised cooperative strategy, the stationary truck in lane 1 will continuously monitor the traffic in lane -1 and provide real-time updates on the speed and distance of oncoming vehicles. If the gap is not safe for overtaking, the stationary truck will send a **"hold"** message to prevent premature maneuvers. As the overtaking vehicle, I will use my sensors to independently verify the traffic conditions in lane -1 and maintain a flexible speed, ready to adapt dynamically. I will only proceed with the overtaking maneuver when both the stationary truck's updates and my sensor data confirm a safe gap, at which point the stationary truck will send a **"go"** message. This dual verification approach ensures alignment in our actions, minimizing the risk of collision and avoiding stagnation by allowing me to adjust my speed based on real-time conditions. If no safe gap is available, I will maintain my position and communicate my readiness to adapt speed as necessary, ensuring a coordinated and safe overtaking process.

Truck (Stopped Truck in Lane 1)

knowledge: As the stationary truck in lane 1, my role is to assist the overtaking vehicle by continuously monitoring traffic in the opposite lane (-1) and providing real-time updates on the speed and

distance of oncoming vehicles. If the gap is not safe for overtaking, I will send a **"hold"** message to prevent premature maneuvers. The overtaking vehicle should independently verify the traffic conditions using its sensors and maintain a flexible speed, ready to adapt dynamically. If both my updates and the overtaking vehicle's sensor data confirm a safe gap, I will send a **"go"** message, allowing the overtaking vehicle to proceed. This dual verification approach ensures alignment in decision-making, minimizes collision risk, and avoids stagnation by allowing the overtaking vehicle to adjust its speed based on real-time conditions.

cooperative strategy: In our revised cooperative strategy, as the stationary truck in lane 1, my role is to continuously monitor the traffic in the opposite lane (lane -1) and provide real-time updates on the speed and distance of oncoming vehicles. If the gap is not safe for overtaking, I will send a **"hold"** message to the bypassing vehicle to prevent premature maneuvers. The bypassing vehicle, meanwhile, should use its sensors to independently verify the traffic conditions in lane -1 and maintain a flexible speed, ready to adapt dynamically. If both my updates and the bypassing vehicle's sensor data confirm a safe gap, I will send a **"go"** message, and the bypassing vehicle should proceed with the overtaking maneuver. This dual verification approach ensures that both vehicles are aligned in their actions, minimizing the risk of collision by confirming safety from two perspectives and avoiding stagnation by allowing the bypassing vehicle to adjust its speed based on real-time conditions. If no safe gap is available, the bypassing vehicle should maintain its position and communicate readiness to adapt speed as necessary, ensuring a coordinated and safe overtaking process.