CoopReflect: Towards Natural Language Communication for Cooperative Autonomous Driving via Multi-Agent Learning

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ABSTRACT

Past work has demonstrated that autonomous vehicles can drive more safely if they communicate with each other. However, this communication is usually not 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. To explore the potential use of natural language for V2V communication, we develop LLM-based driving agents and study their interactions in a new simulation environment, TalkingVehiclesGym, which features traffic scenarios where communication can potentially help avoid imminent collisions and/or support efficient traffic flow. While LLM agents relying solely on chain-of-thought reasoning struggle to coordinate effectively, we introduce CoopReflect, a multi-agent learning framework that equips agents with knowledge for both natural language message generation and high-level decision-making through trial and error and multi-agent debriefing. Experiments show that CoopReflect produces more meaningful and human-understandable messages than existing baselines, enabling stronger cooperation. Finally, we distill scenario-specific knowledge into a unified language model policy, achieving cross-scenario generalization and substantially reducing decision-making latency. Our code and demo videos are available at https://talking-vehicles.github.io/

KEYWORDS

V2V Communication; Learning LLM Agents; Autonomous Driving

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1 INTRODUCTION

Driving is inherently a multi-agent problem [11, 28], in which 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 feasible and can offer significant benefits even when implemented in a limited capacity. Past research has demonstrated the advantages of cooperation among autonomous cars for perception [34, 40], prediction [35], and planning [8]. 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.

As vision-language models become increasingly prevalent for language-conditioned reasoning and high-level planning in complex traffic environments, the use of natural language as a complementary, general-purpose communication interface offers significant potential for both vehicle–human and vehicle–vehicle coordination. Prior work has made progress toward this vision by training driving agents to generate and explain driving decisions in natural language [18, 36] or to coordinate with human drivers within a single vehicle [9], often leveraging large-scale datasets [16, 17, 24, 31]. However, **inter-vehicle** communication using natural language is relatively underexplored, particularly with respect to its feasibility and design considerations in cooperative driving scenarios, despite a few contemporaneous efforts [13, 14]. These efforts demonstrate a growing interest in the problem but remain preliminary in scope

and evaluation. Complementing and extending this contemporaneous work, we introduce **TalkingVehiclesGym**, a multi-agent simulation framework that models vehicle-to-vehicle communication and enables closed-loop evaluations of natural language interactions across a suite of accident-prone traffic scenarios.

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 study how LLM agents can interact using natural language and optimize communication strategies through trial-and-error multi-agent interactions. Our initial experiments show that LLM agents relying only on chain-of-thought reasoning struggle to perform well, and single-agent reflection methods provide only modest improvements in coordination. Hence, we introduce **CoopReflect**, a multi-agent learning method enabling LLM agents to engage in centralized reflection to refine their cooperation strategies. The resulting reflections are later incorporated as memories into decentralized agent execution. Our experimental results in simulation indicate that, when LLM agents initially fail to collaborate effectively, our proposed learning method helps them both learn what to communicate and how to respond to messages through interactions. Finally, we distill the learned behaviors of large models in each scenario into a compact language model, achieving scenario and role generalization, as well as near-real-time inference with decision latency under 500 ms, compared to the 10 s required by large models in wall-clock time.

In summary, our contributions are threefold:

(1) We introduce TalkingVehiclesGym, a multi-agent simulation environment that enables closed-loop evaluation of natural language communication in cooperative driving scenarios;
(2) We propose CoopReflect, a multi-agent learning framework that enables LLM agents to refine cooperation strategies through centralized reflection over multi-agent interactions;
(3) We demonstrate that the cooperative strategies learned by CoopReflect can be distilled into a single compact language model, achieving efficient inference and generalization.

While this exploratory work does not attempt to address the challenges required to make it fully human-usable — 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 and providing a testbed that allows closed-loop improvements.

2 PROBLEM DEFINITION

In this paper, we focus on the subset of agents that actively participate 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* ($\mathcal{F}$) [1] — 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

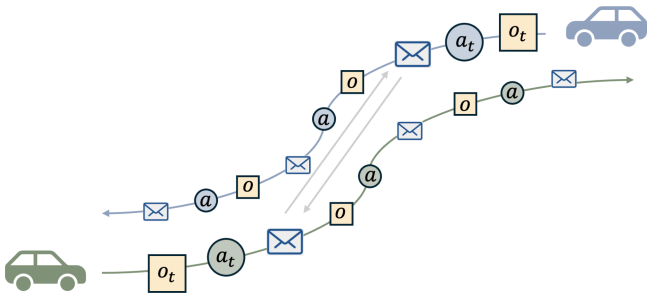


Figure 1: Overview of the In-Episode Communication Mechanism. At each time step, every agent simultaneously generates control actions and messages (a_t) conditioned on its observation (o_t). The exchanged messages are then passed among agents, and the resulting dialogue is incorporated into decision-making at the next time step.

observations and messages received from other agents. In this problem, each agent's action space comprises two main components: **(1) message generation** and **(2) vehicle control**. In this work, the message generation space is *open-vocabulary* over natural language (English), instead of being restricted to predefined templates.

We define a POSG with a deterministic observation function and undiscounted rewards as the tuple

$$\langle \mathcal{I}, \mathcal{S}, \{\mathcal{O}_i\}, \{\mathcal{A}_i\}, \mathcal{P}, \{\mathcal{R}_i\} \rangle,$$

where $\mathcal{I} = \{1, 2, ..., N\}$ 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 $\mathcal{S} \times \mathcal{A}_1 \times \mathcal{A}_2 \times ... \times \mathcal{A}_N \to \mathcal{S}$; $\mathcal{R}_i$ 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 $\mathcal{I}$. Here, an agent refers to an entity in the POSG (*e.g.*, a vehicle), controlled by a policy π_i that specifies how agent i selects actions based on its available information. The goal of each agent $i \in \mathcal{F}$ is to learn a policy π_i to maximize the expected cumulative task returns of all agents in $\mathcal{F}$, given background agent policies outside the focal group: $\max_{\{\pi_i\}_{i\in\mathcal{F}}} \mathbb{E}\left[\sum_{i\in\mathcal{F}} \sum_{t=0}^{t=T} R_i(s_t, \mathbf{a}_t) \middle| \{\pi_j\}_{j\notin\mathcal{F}, j\in\mathcal{I}} \right]$, where s_t is the state at time t, and $\mathbf{a_t} = (a_1^t, a_2^t, ..., a_N^t)$ is the joint action of all agents at time t.

The agent's policy is structured to output both control and communication commands. Specifically, $\pi_i(O_i, \{M_j\}_{j\in\mathcal{F}}) \to \mathcal{A}_i$ maps the observation of agent i and the received messages $\{M_j\}_{j\in\mathcal{F}}$ to its action space $\mathcal{A}_i = \langle \mathcal{M}_i, C_i \rangle$, where $\mathcal{M}_i$ represents the message generation space, which is constrained to natural language, and 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 connected agents within a certain communication radius at the next time step $t+1$ (Figure 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 [5, 33] 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 realistic simulated communication protocol based on MQTT, a lightweight publish–subscribe protocol widely used in distributed systems. The simulation dynamics are implemented in CARLA [12], which provides realistic vehicle physics and complex urban traffic layouts.

3.1 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 3. Scenarios labeled with `Cooperative Perception` are cases where agents can benefit from receiving information about regions beyond their own line of sight, and scenarios labeled with `Negotiation` are cases where agents must communicate to resolve conflicts in their intended plans. Each scenario features a focal group ($\mathcal{F}$) of agents operating 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 to achieve their tasks.

3.2 Observation Space (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 observations.

3.3 Action Space ($\mathcal{A}$)

The action space for each agent encompasses both vehicle control and message generation. The vehicle control space C is three-dimensional, consisting of throttle, brake, and steering. To reduce the decision-making frequency, agents execute high-level vehicle motion commands represented as temporal sequences of low-level vehicle controls $(C_t, C_{t+1}, ..., C_{t+k})$, 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`. They are composed through a combination of a global route planner and a local PID controller. The message generation space $\mathcal{M}$ is open-vocabulary, restricted to natural language tokens in this work, but the communication system 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).

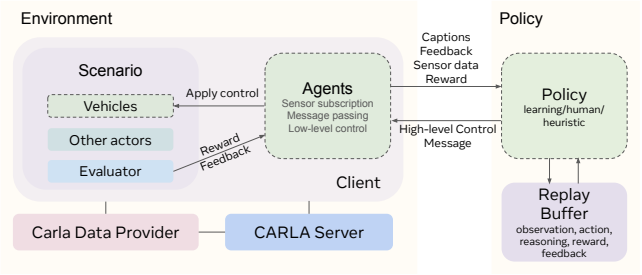


Figure 2: *TalkingVehiclesGym* Simulation framework. An agent is defined within the scenario and has a specific sensor registration and action space. A policy takes observations from an agent, computes actions, and learns from the experience replay buffer.

4 METHOD

The core technical challenge of the *talking vehicles* problem is to enable embodied agents to *communicate in natural language for cooperative purposes and to adjust their actions dynamically according to the conversation.* While prior works relied on extensive imitation learning data from human play to train agent policies that can speak or make decisions in natural language contexts [3], we instead explore leveraging pre-trained large language models to endow agents with such communication and reasoning capabilities. To establish an initial solution, we adopt an **LLM agent framework** (Figure 4) that employs LLMs as a foundational prior for autonomous agents to engage in human-like communication, structuring messages within natural language space, and allowing agents to interpret messages to make informed driving decisions. However, LLMs are typically not trained for cooperative driving tasks. To address this limitation, we introduce **CoopReflect**, a **novel multi-agent learning method for LLM agents** built upon feedback loops that allow LLM agents to iteratively refine their communication and 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.

4.1 Agent Policy

Each agent i follows a 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 agent i's comprehensive observation encompassing task and goal descriptions, environment details, and common traffic rules, expressed as a text or token sequence $\{t_i^o\}$. A received message $M_j = \{t_j^m\}$ from agent j 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 control 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 ";"

Figure 3: ***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.**

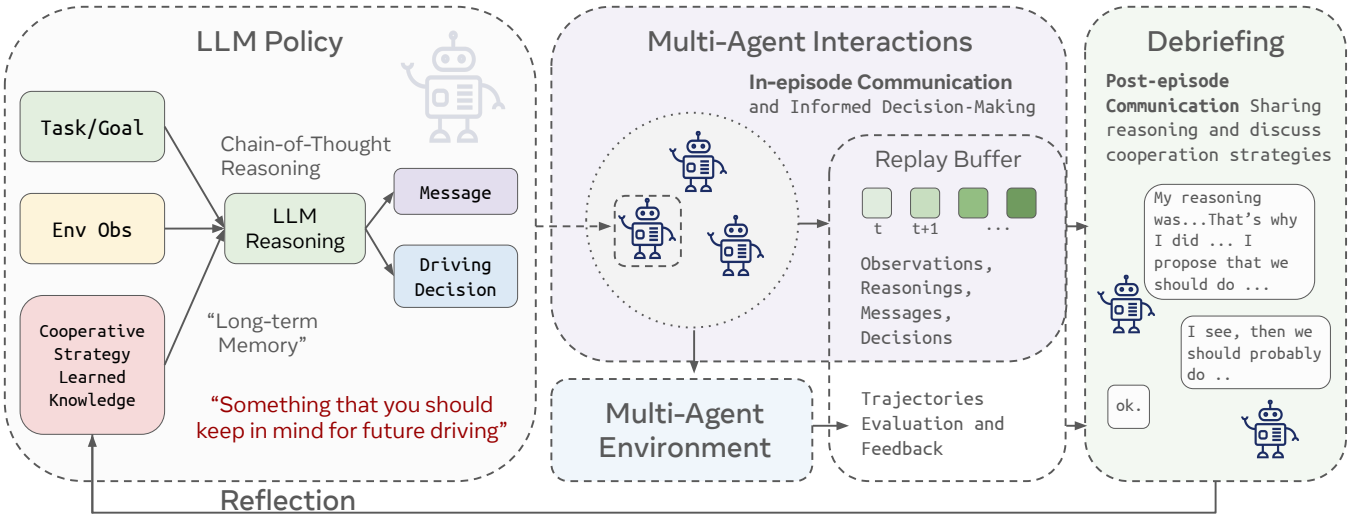


Figure 4: ***CoopReflect Agent Framework and Agent Learning Pipeline.***

indicates text concatenation and a large language model serves as the oracle to determine the probabilities.

In-Context Knowledge. Rather than fine-tuning LLM weights through gradient-based updates, CoopReflect adapts agent policies by modifying the *context*, leveraging the auto-regressive nature of LLMs. 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. LLM agents often generate better decisions by producing intermediate reasoning traces that structure their understanding of the situation [37]. 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 intermediate text sequence, denoted as $R_i = \{t_i^r\}$. The LLM agent then sample action token sequences $\{t_i^m\}$ and $\{t_i^c\}$ according to the probability distribution:

$$P_i(\{t_i^m\}; \{t_i^c\} | \{t_i^k\}; \{t_i^s\}; \{t_i^o\}; \{\{t_j^m\}\}_{j \in \mathcal{F}}; \{t_i^r\}).$$

The resulting output is formatted in JSON with two keys: `"command"` and `"message"`.

4.2 Agent Learning: Post-Episode Debriefing

The learning process is depicted in Figure 4. Initially, the LLM agents interact with each other in the scenarios and accumulate 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 summarized 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. Each agent i stores their trajectories locally. Each trajectory is a temporal sequence of transition data $T_i = \langle o_{i,t}, a_{i,t}, o_{i,t+1} \rangle$, which includes current and next local 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 reflects on its individual experience from their perspective first. While analyzing the entire trajectory would provide a comprehensive understanding of failure cases, computational and context window constraints necessitate sampling a subset (**batch**) of key frames from its replay buffer. To prioritize relevant data, the sampling process heuristically assigns higher probabilities following Equation 1[1] 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. When an episode ends due to the fault of a single agent, only that agent performs individual reflection. A debriefing (cooperative reflection) session is initiated when an episode ends in failure (either due to a collision or stagnation) arising from poor cooperation among agents. The debriefing session proceeds in a **turn-based** manner over N rounds, with the aim of improving cooperative behavior 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 ($S_1, S_2, ...S_{i\in\mathcal{F}}$) for everyone participating in the debriefing (the focal group). This agent begins by reasoning through its local transition data batch, analyzing the consequences of its actions, their influence on others and vice versa, 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 will later 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 [4], a widely used approach in multi-agent learning.

[1]In this work, each transition data is sampled according to the heuristic weight:

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

where $\mathbb{1}$ represents the indicator function that takes the value 1 when the event happens, and 0 otherwise.

5 EXPERIMENTS

This section presents an empirical evaluation of CoopReflect and baseline approaches across different cooperative driving scenarios. We investigate the following research questions:

(1) Can LLM agents establish collaboration through chain-of-thought reasoning without prior interactions? (The evaluated LLMs in this work can not.)
(2) Does decentralized reflection enable LLM agents to improve their collaborative ability as they gain more interaction experiences? (Yes.)
(3) Does centralized discussion among LLM agents provide additional improvements in collaboration and communication compared to decentralized reflection? (Yes.)
(4) Can natural language communication enhance the performance and coordination of LLM agents compared to those without communication? (Only if well trained.)

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[2], 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 with equal percentages. 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 [3] to either report the *"solved"* result, or otherwise, the last run for each

[2]Except for CoopReflect, which is only tested under the *Comm* setting since it is particularly designed for improving multi-agent communication.
[3]Knowledge reset is done by clearing the learned knowledge before reaching a *solved state indicator*, defined by 20 consecutive successful training episodes in this work.

seed. 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) **Zero-shot**: a base LLM agent using Chain-of-Thought (CoT) reasoning only,
(2) **Reflection**: an LLM agent with CoT reasoning contextualized with knowledge from self-reflection,
(3) **Correction+RAG (Silent)**: 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 adapts DiLU [38], a non-communicating single-agent LLM-based approach that drives via reflection, to our environment.
(4) **Correction+RAG (Comm)**: an LLM agent that resembles AgentsCoDriver [14], the multi-agent communication extension of DiLU, 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 **Coopernaut** [8], a LiDAR-based cooperative driving method, as an aspirational reference point for cooperative perception. Note that Coopernaut is not directly comparable because it processes sensory data and communicates intermediate neural representations rather than natural languages. We do not compare with other multi-agent communication baselines for the same reasons.

5.1 Quantitative and Qualitative Results

Table 1 presents 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. Based on these results, we provide responses to the research questions posed at the start of the section.

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. At the time of writing, preliminary experiments with other LLMs such as `Llama 3` and `gpt-4o` follow a similar pattern. Future work could systematically examine whether large reasoning models like `gpt-o4` can mitigate these limitations.

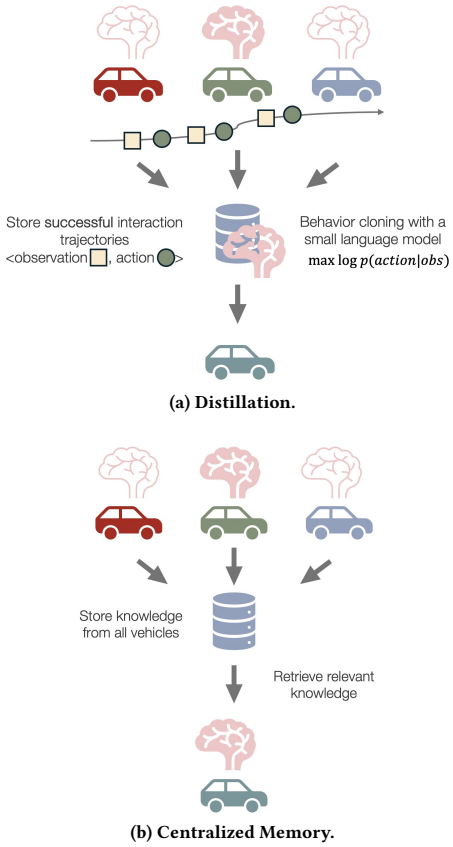
R2: Decentralized learning can enable LLM agents to improve their collaborative ability as they gain more interaction experiences. The decentralized learning methods, Reflection and Correction+RAG, show significant improvement in reducing collision rates from Zero-Shot across tasks. Reflection allows agents to individually analyze their experience to generate knowledge, but the knowledge is often more reactive than proactive. The Correction+RAG method records successful episodes to preserve successful coordination patterns and correct commands and messages at key frames selected through a heuristic batch sampling. However, although the method improves the control response strategy, we find that it qualitatively does not always produce messages that are consistent with the actions, likely due to its open-loop message revision process. 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. Qualitatively, the resulting conversations are human-interpretable, paving the way for future human–AI communication in cooperative driving scenarios. Please refer to our supplementary videos for examples of the generated dialogues. The primary performance boost of CoopReflect stems from the formalized coordination strategy, which explicitly defines how each agent should communicate and respond within a dialogue across different scenarios. Interestingly, CoopReflect reveals that LLMs can struggle to understand complex AI-generated messages that resemble natural language, so agents eventually develop concise communication protocols (like "hold" and "go") to ensure that their intentions are easily interpretable among themselves. However, open challenges still remain. For example, although the learned strategies are easy to verify, the debriefing process used to identify them can sometimes fail, where no agents can find issues with the cooperation strategies in harder and longer-horizon tasks, such as `negotiation-highway-exit`.

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 can add complexity and 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.

Table 1: Experimental results for per-scenario learning. Each method is trained and evaluated independently in each scenario, using three random seeds and 30 evaluation episodes per seed. Results are reported as `mean ± standard deviation`. *Zero-shot (Silent)* and *Zero-shot (Comm)* denote LLM agents using chain-of-thought reasoning without or with communication, respectively. *+Reflection* and *+Correction+RAG* indicate single-agent learning through reflection or correction with retrieval-augmented generation. *+Debrief* is our proposed multi-agent learning method CoopReflect. *Coopernaut* is a non-LLM communication baseline for cooperative perception only.

Method \ Scenario	Cooperative Perception Scenarios						Negotiation Scenarios					
	Overtake (Perception)		Red Light		Left Turn		Overtake (Negotiation)		Highway Merge		Highway Exit	
	CR (%) ↓	SR (%) ↑	CR (%) ↓	SR (%) ↑	CR (%) ↓	SR (%) ↑	CR (%) ↓	SR (%) ↑	CR (%) ↓	SR (%) ↑	CR (%) ↓	SR (%) ↑
Zero-shot (Silent)	93.3 ± 3.4	0.0 ± 0.0	93.3 ± 6.7	6.7 ± 6.7	93.3 ± 5.8	6.7 ± 5.8	89.9 ± 2.8	7.2 ± 3.8	100.0 ± 0.0	0.0 ± 0.0	33.3 ± 9.3	66.1 ± 9.2
+Reflection	87.8 ± 3.4	0.0 ± 0.0	94.4 ± 6.9	5.6 ± 6.9	76.7 ± 20.8	23.3 ± 20.8	32.8 ± 29.4	36.7 ± 52.1	15.0 ± 23.1	84.4 ± 22.6	32.8 ± 13.4	67.2 ± 13.4
+Correction+RAG	62.0 ± 31.9	4.4 ± 7.7	93.3 ± 3.3	6.7 ± 3.3	64.4 ± 15.0	35.6 ± 15.0	46.7 ± 21.9	33.3 ± 28.0	35.6 ± 29.4	64.4 ± 29.4	33.9 ± 28.4	51.1 ± 14.2
Zero-shot (Comm)	91.1 ± 5.1	4.4 ± 5.1	60.0 ± 11.5	38.9 ± 10.7	85.6 ± 8.4	14.4 ± 8.4	87.8 ± 5.9	11.7 ± 6.7	67.2 ± 27.1	32.8 ± 27.1	53.3 ± 11.5	46.7 ± 11.5
+Reflection	63.3 ± 14.5	34.4 ± 10.7	37.8 ± 18.4	47.8 ± 18.4	51.1 ± 37.2	47.8 ± 36.0	55.6 ± 38.9	43.3 ± 37.1	20.0 ± 1.7	80.0 ± 1.7	53.9 ± 24.1	45.6 ± 23.6
+Correction+RAG	4.4 ± 1.9	90.0 ± 6.7	13.3 ± 12.0	66.7 ± 27.3	43.3 ± 38.4	38.9 ± 22.7	38.3 ± 6.0	61.1 ± 5.4	40.0 ± 18.0	60.0 ± 18.0	49.4 ± 49.2	43.3 ± 39.8
+Debrief (ours)	**1.1 ± 1.9**	**94.4 ± 6.9**	**0.0 ± 0.0**	**93.3 ± 5.8**	**6.7 ± 3.3**	**92.2 ± 3.8**	**3.3 ± 3.3**	**95.6 ± 3.8**	**6.7 ± 11.5**	**93.3 ± 11.5**	**18.3 ± 21.7**	**81.1 ± 21.2**
Coopernaut (Comm)	4.5 ± 3.1	90.5 ± 1.2	17.7 ± 7.8	80.7 ± 7.6	18.1 ± 6.2	80.7 ± 5.2	N/A	N/A	N/A	N/A	N/A	N/A



(a) Distillation.

(b) Centralized Memory.

Figure 5: Generalization Methods. (a) Distillation performs full-parameter fine-tuning by matching the probability distribution of expert decisions from successful trajectories, producing a compact model that acts directly on observations without explicit reasoning. (b) Centralized Memory aggregates learned knowledge and cooperative strategies from all vehicles across all scenarios into a shared memory. Each vehicle accesses this memory to retrieve the most relevant knowledge based on its observation and dialogue, followed by Chain-of-Thought reasoning and decision-making.

5.2 Towards Real-Time Cross-Scenario Cross-Role Generalization

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*** (Figure 5). ***Centralized Memory*** aggregates all agents' *most effective* knowledge—identified by the highest estimated success rate across learning trials—into a unified vector memory. Agents then search in the memory according to the observation and dialogue for the most relevant knowledge. ***Distillation*** performs full-parameter fine-tuning of a small language model, DistilGPT2 [25, 27], to directly **imitate** the behavior of the CoopReflect agent with the most effective knowledge. 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.

As shown in Table 3, 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 and asynchrony have not been fully considered. Evaluation results of the two methods in accident-prone scenarios are listed in Table 2. Remarkably, the distilled model generalizes well across scenarios and even surpasses the performance of its teacher model (CoopReflect) in some cases. However, we observe that it tends to behave overly conservatively in safe `perception-overtake` scenarios, suggesting room for further improvement, potentially through expert-guided correction methods such as DAgger [26].

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 [39] due to their reasoning

Table 2: Cross-scenario generalization results. Policies are trained once and evaluated over 3 seeds (30 episodes per seed). We report the mean ± standard error across seeds. *Debrief (per-scenario)* is an oracle baseline trained separately for each scenario, used to benchmark the generalization of *Centralized Memory* and *Distillation*.

Method \ Scenario	Cooperative Perception Scenarios						Negotiation Scenarios					
	Overtake (Perception)		Red Light		Left Turn		Overtake (Negotiation)		Highway Merge		Highway Exit	
	CR (%) ↓	SR (%) ↑	CR (%) ↓	SR (%) ↑	CR (%) ↓	SR (%) ↑	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	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	2.2 ± 1.1	93.3 ± 1.9	0.0 ± 0.0	**100.0 ± 0.0**	4.4 ± 2.9	93.3 ± 3.3	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	**0.0 ± 0.0**	83.3 ± 1.9	0.0 ± 0.0	91.1 ± 4.4	**0.0 ± 0.0**	**96.7 ± 0.0**	**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 3: Decision Latency, Message Size using `Distilled` LLM Policy

Latencies \ Scenario	Overtake (Perception)	Left Turn	Red Light	Overtake (Negotiation)	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

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 [14, 38]. 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 [22] and convert them to textual descriptions [7, 15, 21, 29]. Some other studies tackled this challenge by introducing Visual Language Models (VLMs), which are adapted to driving domains through in-context instruction tuning [18] or fine-tuning [10, 36, 41, 42]. To enhance LLM agents' reasoning ability, prior works have investigated incorporating handcrafted guidance and examples in the prompts [7, 15, 29], structuring the reasoning procedure [22, 31], 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 [10, 18, 41] or augment large-scale multimodal driving datasets [6, 20, 32] with language labels [23, 24, 30, 31]. 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 [15, 29, 30], we conduct closed-loop evaluation of the proposed method and baseline methods in CARLA [12].

Natural Language Communication for Driving. There is a scarcity of prior research on optimizing LLM agents in multi-agent settings with natural language vehicle-to-vehicle communication, with only a few concurrent but distinct efforts such as [13, 14]. AgentsCoDriver [14] leverages a vector memory that stores and corrects vehicle control actions associated with specific situations, but it only optimizes the control actions through self-reflection while leaving message generation to the emergent capability of LLMs. Other studies on multi-agent collaboration for autonomous robots do not employ trial-and-error optimization; instead, they rely on human-engineered structures or prompting schemes to guide coordination. For example, LangCoop [13] designs a structured in-context knowledge format to facilitate intent inference among interactive agents, CoMAL [43] adds a collaboration module prompting agents to determine their respective roles, and GameChat [19] constructs a multi-round communication process to ensure agents reach consensus in constrained navigation tasks. In summary, TalkingVehiclesGym serves as a comprehensive testbed for studying multi-agent natural language communication among autonomous vehicles, and CoopReflect represents the first CTDE-style multi-agent reinforcement learning approach for multi-LLM-agent systems that jointly optimizes both communication and control in a closed-loop manner.

7 CONCLUSION AND FUTURE WORK

This work explores how autonomous vehicles can communicate and coordinate through natural language, offering a path toward future human–AI collaboration in cooperative driving. We introduce TalkingVehiclesGym, a multi-agent simulation environment for closed-loop evaluation of collaboration through vehicle-to-vehicle dialogue, and propose CoopReflect, a multi-agent learning framework that enables LLM-based driving agents to refine communication and control through iterative reflection and debriefing. Experiments show that while zero-shot LLM agents fail to collaborate effectively, reflective and centralized learning yields stable, human-interpretable cooperation across both perception and negotiation tasks. By distilling the learned behaviors into a compact model, we further achieve near-real-time, cross-scenario generalization. Overall, this study establishes natural language as a promising medium for cooperative autonomy and highlights future works for grounding communication in more realistic perception and communication mechanisms, improving multi-agent learning stability, and evaluating the agents in real human–AI collaborative driving.

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