LLMs as NPCs: Toward Human-Like and Interpretable Multi-Agent Driving Simulation

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Abstract: High-fidelity simulation platforms for evaluating and refining autonomous driving algorithms are crucial. Current simulators often lack realistic human-like driving non-player characters (NPCs) for multi-agent interactions. To address this, we introduce SimLLM, a novel simulator that employs large language models (LLMs) as NPCs to enhance realism and adaptability. Its closed-loop architecture enables customizable decision-making algorithms, optimizing both efficiency and transparency in decision-making and planning modules. Empirical validation confirms SimLLM's effectiveness in handling rare but vital driving situations, achieving high fidelity in simulating human-like driving decisions. This not only improves the interpretability of simulations but also marks an advancement in human-like driving.

Keywords: Simulation, Autonomous Driving, Large Language Models

1 Introduction

Autonomous driving simulators, empowered by advancements in machine learning, sensor technology, and high-performance computing, play a pivotal role in the refinement of autonomous driving technologies. These platforms provide an essential environment for conducting safe experiments, allowing for the detailed analysis of vehicle dynamics, algorithm validation, and the optimization of decision-making processes. Their capacity to render ultra-realistic environmental simulations and to dissect multi-agent dynamics in a user-friendly manner significantly enhances the ability to mimic complex driving scenarios and to advance the capabilities of autonomous driving systems.

However, the endeavor to accurately emulate human-like driving behaviors presents substantial challenges within current simulation frameworks. Many simulators rely on simplistic non-player character (NPC) models, which fail to adequately represent the intricate blend of technical skills, social interactions, and cultural nuances inherent to human driving. Additionally, a notable issue with existing autonomous driving simulators is their lack of transparency and interpretability. The "black box" nature of these simulators' backend systems severely limits the ability to understand, modify, and customize the core decision-making algorithms, thus impeding progress in algorithm refinement and the adaptation of simulators to meet specific research or engineering requirements. This lack of flexibility and customizability in decision-making and planning modules represents a significant obstacle for researchers and engineers alike.

In response to these identified limitations, our research introduces SimLLM, a novel multi-agent simulator designed to replicate human-like behaviors while maintaining interpretability. What distinguishes SimLLM is its incorporation of large language models (LLMs) as non-player characters (NPCs). This innovative integration endows the simulator with exceptional adaptability, granularity, and situational awareness. LLMs within the SimLLM framework take into account an array of factors, ranging from psychological attributes and adherence to social norms to dynamic variables like sudden incidents. We argue that this LLM-powered platform strikes an ideal balance between

Table 1: Comparisons on NPC Construction Between Our Simulator (SimLLM) And Existing Simulation Platforms.

Simulation	Method	Data Agnostic	Intervention Free	Training Free	Human-like Driving	Language Configurable
Model-Based	Tree Search	✓	✗	✓	✗	✗
	Expert System	✓	✗	✓	✗	✗
	Game Theory	✓	✓	✓	✗	✗
Data-Driven	Straight Forward	✗	✓	✓	✓	✗
	Deep Learning	✗	✓	✗	✓	✗
	Reinforcement Learning	✗	✓	✗	✓	✗
SimLLM	Large Language Model	✓	✓	✓	✓	✓

transparency and efficiency in decision-making and planning modules. Consequently, SimLLM improves the fidelity and analytical rigor of autonomous driving simulations, pushing the boundaries of our ability to replicate real-world driving scenarios.

SimLLM transcends mere mechanical evaluations, providing a multifaceted analytical platform that encompasses the social and psychological aspects of driving behavior. This covers cultural practices of yielding at intersections and the intricate mechanics of lane-merging in high-congestion scenarios—areas commonly neglected in current simulation models. Employing a closed-loop architecture, SimLLM enables the research of multi-agent interactions with high fidelity. SimLLM leverages LLM to simulate human-like driving behaviors, specifically designed to explore rare yet critical driving scenarios that are often omitted in existing frameworks. Our SimLLM is validated through empirical assessments of both single and multiple agents, confirming its effectiveness in replicating human driving in conditions that closely resemble real-world scenarios. In summary, we are actively developing a new benchmark for high-fidelity, planning-centric driving simulations, serving as a testbed for the next wave of autonomous driving methods.

2 Related Work

2.1 NPCs in Autonomous Driving Simulation

Constructing non-player characters (NPCs) within high-fidelity autonomous driving (AD) simulators [1, 2, 3, 4, 5, 6] offers a compelling avenue for research but is fraught with complexities. Existing methodologies for NPC design in such environments can be broadly categorized into two paradigms [7, 8]: 1) Model-Based, predicated upon a set of manually crafted rules, heuristics, or algorithms; and 2) Data-Driven, guided by trajectory data to emulate realistic traffic conditions. Each paradigm has its merits and limitations, thus necessitating a nuanced approach for human-like and interpretable NPC behavior modeling.

2.1.1 Model-Based Simulation

Heuristic-driven, rigidly scripted simulations depend on manually defined behavioral models. Related simulations [9, 10, 11, 12] emphasize real-world multi-agent interactions via diverse expert models, while optimization-based methods [13, 14, 15, 16] model game-theoretic vehicle interactions effectively. Furthermore, search-based techniques [17, 18, 19] address interactions using tree structures, such as Monte Carlo Tree Search (MCTS), improving algorithmic efficiency through action space sampling. Nonetheless, these strategies encounter scalability and adaptability issues due to dependence on labor-intensive, hand-crafted heuristics.

2.1.2 Data-Driven Simulation

Learning-based, data-driven simulation extracts driving policies from extensive driving trajectories [20, 21, 22, 23, 24, 25, 26, 27]. Straight-forward simulation reproduces real-world driving scenarios through the playback of recorded data. Established platforms such as MetaDrive [28] and TrafficSim [29] employ real-world data to simulate human-like driving conduct, generating scenarios and NPC behaviors that closely approximate real-world conditions. Moreover, the learning-based simulation [30, 31, 32] produces NPCs through model training and prediction from the driving dataset. Deep learning methods [8, 33, 34, 35] utilize real-world data to discern interaction patterns. In parallel, reinforcement learning algorithms [36, 37, 38, 39] facilitate dynamic and sequential decision-making with high adaptability. However, these techniques often lack variability, flexibility, multi-agent decision-level interactions, and explicit representation of driving intentions, rely heavily on data, and are restricted to specific environments [40].

Our proposed algorithm, SimLLM, advances beyond existing techniques by using large language models (LLMs) to dynamically simulate driving decision-making. This eliminates the need for manual oversight and extensive data collection, simplifying training. SimLLM autonomously generates a variety of NPC agents, enhancing the simulation's capability, diversity, flexibility, and interpretability. A detailed comparison with existing solutions is shown in Table 1.

2.2 Large Language Models as Autonomous Agents

The landscape of large language models (LLMs) has undergone significant transformation in recent epochs, notably catalyzed by the introduction of ChatGPT [41] from OpenAI. These models excel in mimicking human cognitive faculties such as reasoning, interpretation, and autonomous decision-making [42, 40]. Noteworthy instances include GPT-4 [43], PaLM-2 [44], LLaMA-2 [45], ChatGLM [46], and Baichuan-2 [47]. As a testament to their versatility, LLMs have become a cornerstone in the development of autonomous agents, outperforming in various tasks through self-guided planning and decision-making [48, 49, 40]. For instance, Fu *et al*. [50] delved into the capacity of LLMs to comprehend and reason within automotive environments, scrutinizing their capabilities in interpretation and memory retention. However, a conspicuous gap remains in the literature: the deployment of LLMs as NPCs in high-fidelity and planning-intensive AD simulations remains largely unexplored, particularly where multi-agent interactions and interpretable driving policies are concerned. To the best of our knowledge, our work introduces the first multi-agent interactive simulator that incorporates LLMs as NPCs. This integration confers unprecedented levels of adaptability, interpretability, and contextual awareness to the domain.

3 LLMs as NPCs

In this section, we present SimLLM, a comprehensive framework enhancing NPC decision-making in autonomous driving simulations by integrating SUMO [1], CARLA [2], and LimSim [11] for realistic traffic and visual modeling. As illustrated in Figure 1, SimLLM incorporates a conversation interface with large language models (LLMs) to boost user engagement and real-time decision-making, supporting adaptability in both human-like and multi-agent systems through event-driven strategies. From a technical standpoint, the decision-making and planning module for each NPC is tasked with generating viable driving trajectories that exhibit a broad range of behaviors.

3.1 Describe Driving State in Natural Language

To achieve our objective of contextualizing the driving environment for LLMs, we aim to articulate the driving context in a manner that allows LLMs to understand the current state. Natural language serves as a sophisticated medium for conveying intricate information, essential for decision-making under dynamic driving conditions.

Table 2 presents a comprehensive enumeration of situational parameters, encompassing speed limit, current velocity, proximity to intersections, and presence of nearby vehicles. LLMs leverage these parameters to select the most appropriate action from a predefined repertoire, elaborated in Table 3. Actions are organized into six distinct categories, primarily emphasizing speed modulation and lane-changing maneuvers. Additionally, LLMs generate accompanying explanations to elucidate their

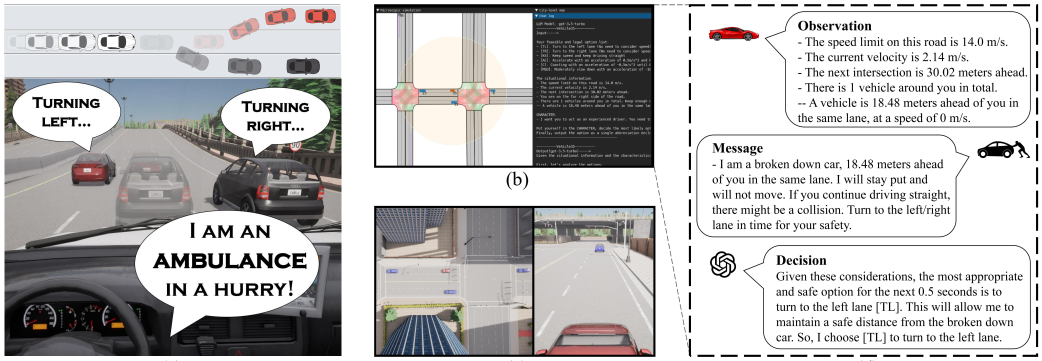

Figure 1: **Our SimLLM presents a novel multi-agent simulation featuring photorealistic visuals, modular decision-making algorithms, and LLM-powered dialogue interfaces.** (a) SimLLM leverages V2V communication to enhance multi-agent interactions, setting a new standard for simulating rare emergency scenarios with human-like behavior. (b) The interface offers a bird's eye view of the operational field, supported by an LLM-driven decision-making subsystem. (c) Additionally, SimLLM integrates seamlessly with photorealistic platforms like CARLA, enabling smooth transitions between ego-centric and aerial perspectives. (d) The system uses LLMs to enrich the simulation with driving state analysis, inter-vehicle communication, and context-aware prompts.

Table 2: Situational Information for Prompting LLMs.

Info	Example
Road Constraint	The speed limit on this road is 14.0 m/s.
Current Velocity	The current velocity is 12.12 m/s.
Next Intersection	The next intersection is 326.75 meters ahead.
Nearby Vehicle	There are 1 vehicles around you in total. A vehicle is 25.0 meters behind you in the same lane, at a speed of 12.56 m/s.

Table 3: Predefined Available Actions and Descriptions.

Action	Description
TL	Turn to the left lane
TR	Turn to the right lane
KS	Keep speed and keep driving straight
AC	Accelerate with an acceleration of 1m/s^2
DC	Coasting with an acceleration of -1m/s^2
SD	Slow down with an acceleration of -10m/s^2

decision-making rationale, significantly enhancing the interpretability of otherwise opaque decision-making processes.

We construct three scenarios to illustrate the convenience of SimLLM in manually building specific scenes (see Section 4.3). We let the human-like agents in SimLLM drive in those scenarios, enabling simulated non-player characters (NPCs) to broadcast timely situational updates and hazard warnings to nearby vehicles. For instance, a scenario where an emergency vehicle requires a clear path is elaborated further in Section 4.3. In this context, the following message would be disseminated to proximate NPCs:

> I am an ambulance located 42.95 meters behind you in the same lane, moving at a speed of 8.92 m/s. I am carrying a patient in critical condition requiring immediate medical intervention. Please clear your current lane by merging either left or right to facilitate my unimpeded transit.

Choosing natural language as the primary communication medium offers several advantages. Most significantly, it amplifies interpretability for human overseers by eliminating the need for specialized jargon or coded syntax. This attribute becomes especially pertinent in hybrid multi-agent systems comprising both human-driven and autonomous vehicles, thus fostering transparent and explicit human-robot interactions.

3.2 Drive by Prompting Large Language Models

Once the situational information is encoded in natural language, the next step specifies the driving style to diversify driving behaviors. We also formulate the task definition to guide LLMs in performing the desired driving maneuvers. Unlike traditional heuristic or data-driven methods where

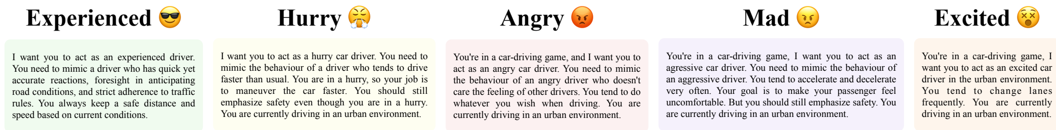

Figure 2: **Our SimLLM accommodates a wide spectrum of driving personas, including but not limited to *Experienced*, *Hurry*, *Angry*, *Mad*, and *Excited*.** These personas represent distinct driving behaviors, strategies, and responses, meticulously modeled within a simulated environment. Customizing these personas is both feasible and straightforward, allowing adaptation to specific research or application needs. Additionally, our framework supports diverse character profiles, enhancing the simulation's realism and applicability.

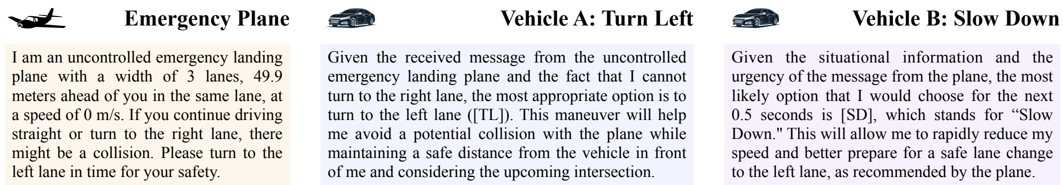

Figure 3: **Our SimLLM facilitates the creation of customizable scenarios using human-like NPCs.** The diagram illustrates an emergency aircraft making an unscheduled highway landing. We develop a multi-agent communication framework for Vehicle-to-Vehicle (V2V) interactions with LLMs, demonstrating the adaptability of SimLLM's NPCs. The aircraft updates nearby vehicles on its status, which they integrate with environmental data to execute appropriate maneuvers, such as veering left or decelerating, ensuring an intelligent, coordinated response.

NPCs rely on pre-defined scripts or state machines for environmental interactions, LLMs in SimLLM dynamically adjust their behaviors according to the current context, enhancing policy-centric simulation realism. Figure 2 provides a comprehensive list of driver personas, which are detailed prompts that offer behavior-level specifications. These personas guide LLMs to drive in various ways via prompts.

Driving behavior diversity stems from not only personas but also pre-training regimens. LLMs trained with different datasets can yield different behaviors. Models like Baichuan-2 [47], ChatGLM [46] and LLaMA-2 [45] well exemplify this disparity, which we evaluate in Section 4.2.

The final step entails defining the task in natural language to direct the LLMs in executing specific maneuvers. Utilizing the capabilities of LLMs, we can dynamically adapt driving behaviors based on real-time context, making simulations more immersive. Specifically, the task description used in all experiments is as follows:

> Assume the driver persona, consider the situational information and incoming messages, determine the most appropriate action (select only one) to last for 0.5 seconds, and document your reasoning. Finally, output the selected action as a single abbreviation enclosed in square brackets.

In this manner, LLMs obtain all the necessary information for decision-making. Figure 3 illustrates a representative interaction in V2V conversation during an urgent landing of a small aircraft on a freeway. By integrating both situational information and incoming messages, the LLM selects the optimal action tailored to the specific driver persona. It also elucidates the reasoning process behind its decisions, thereby demystifying the black-box model.

3.3 Translate Decision into Drivable Trajectory

Following the utilization of an LLM-powered agent for decision-making, the next phase involves converting these decisions into executable paths through a planning algorithm with a parallel architecture. SimLLM initially predicts the terminal state from current conditions and LLM decisions, and then it forges a smooth, continuous trajectory while adhering to kinematic constraints like turning radius and speed/acceleration limits. Should the vehicle be unable to follow this trajectory, the planner adjusts the target state space to find an alternative, possibly modifying maneuvers like lane changes or initiating emergency stops.

Contrasting with prior approaches [12, 11] that consider a broad spectrum of paths, SimLLM selectively focuses on a constrained set of trajectories, enhancing decision-making speed and ensuring planning aligns closely with LLM decisions. The algorithm's operation in a continuous action space broadens the behavioral options for LLM-powered agents, enabling precise, context-specific actions.

4 Experimental Results

We assess SimLLM's functionality in diverse scenarios, from urban traffic to rare events like emergency vehicle interactions and unusual airplane landings. The method mimics human-like driving and performs well in both realism and adaptability. We outline our experiment design (Section 4.1), evaluate SimLLM's human-like driving ability in urban settings (Section 4.2), and highlight key interstate scenarios showcasing multi-agent simulation (Section 4.3).

4.1 Experimental Setup

Our simulation framework leverages the capabilities of LimSim [11], an advanced platform that seamlessly integrates SUMO's robust traffic flow modeling [1] with CARLA's photorealistic rendering [2]. For decision-making, we employ various large language models (LLMs) like ChatGPT [41], LLaMA-2 [45], ChatGLM [46], and Baichuan-2 [47] as non-player characters (NPCs) with distinct driving personas. This enhances realism and diversity, serving as a valuable research tool (Figure 2).

We assess SimLLM's human-like driving ability in busy urban settings using key behavioral metrics:

- **Completion Rate**: The ratio of trips without deviations or collisions.
- **Red-Light Violation**: The frequency of red-light offenses increases with each infraction.
- **Collision Rate**: Measures the collision instances across all tests.
- **Runtime**: Time taken for a vehicle to reach its target in seconds.
- **Discomfort Index**: Average discomfort during tests, calculated as $\left(\frac{da}{dt}\right)^2$, with a as acceleration. Capture effects of sudden speed changes on passengers.
- **Lane Change Frequency**: an alterations counts over the course of each test run.
- **Energy Expenditure**: Calculated as $(a \times v)^2 + v^3$, demonstrating energy use.

Normalized discomfort and fuel consumption values are used to weaken the effects of outliers in acceleration. The normalization function $\text{metric}_x = \min(4, \alpha_x \cdot x)$ is employed, with $\alpha_{\text{discomfort}} = \frac{2}{9}$ and $\alpha_{\text{consumption}} = \frac{1}{1000}$. This limits the metrics to the [0,4] range for more consistent analyses.

4.2 Human-Like Driving Ability

LLMs as Competent Drivers To evaluate SimLLM's effectiveness in human-like driving ability, we orchestrate three intricate urban driving scenarios within the confinements of CARLA's Town05 [2] and scrutinize metrics such as lane changes, car-following, and traffic signal obedience. Route A spans a distance of 130.99 meters and incorporates a singular intersection, serving as a rudimentary test case. Route B, slightly more complicated, extends over 249.66 meters and features dual intersections. Lastly, Route C covers a distance of 178.12 meters while also hosting one intersection. As a key performance metric, the minimum requisite maneuvers, specified in terms of turns, are zero for Route A, one for Route B, and two for Route C. Each test is replicated five times for statistical rigor. Our results affirm the value of LLMs in real-world vehicular scenarios.

Table 4: Performance of Varied Personas in Navigating Route A.

Persona	Runtime	Discomfort	Energy Expenditure	Lane Change
Experienced	40.0 ± 5.61	1.8 ± 0.12	1.0 ± 0.0042	0.0
Hurry	19.0 ± 5.43	2.1 ± 0.31	1.4 ± 0.23	0.0
Angry	18.4 ± 4.50	2.0 ± 0.14	1.4 ± 0.21	2.0
Mad	24.4 ± 8.68	2.5 ± 0.17	1.3 ± 0.24	0.0
Excited	27.6 ± 4.04	2.0 ± 0.42	1.1 ± 0.035	3.0

Table 5: Performance of Diverse LLMs in Navigating Route A.

LLMs	Completion	Runtime	Discomfort	Energy Expenditure	Lane Change
ChatGPT [41]	100%	36.9 ± 4.94	1.6 ± 0.08	1.0 ± 0.06	0.0
LLaMA-2 [51]	100%	15.9 ± 0.32	1.4 ± 0.05	1.2 ± 0.07	0.0
ChatGLM [46]	40%	34.5 ± 2.52	2.1 ± 0.16	1.0 ± 0.03	2.5
Baichuan-2 [52]	30%	24.7 ± 4.73	1.3 ± 0.18	1.0 ± 0.00	8.0

Figure 4 shows that an *Experienced* LLM persona achieves nearly an 80% route completion rate and complies fully with traffic laws. Its low collision rate further underscores LLMs' adaptability and safety in various driving conditions. It is the foundation of SimLLM's human-like driving.

Customizable Driving Styles We test different driving personas on three urban routes. Figure 4 shows the *Experienced* driver performs best, with a high Completion Rate and low Red-Light and Collision Rates. Conversely, the *Hurry* and *Angry* drivers exhibit more accidents and infractions. Other personas like the *Mad* and *Excited* show erratic movements and frequent lane changes. We then narrow our focus to Route A, as described in Table 4, because *Angry* and *Mad* drivers struggle on Routes B and C. Metrics are mainly presented as mean values with standard deviations, except for Lane Change Frequency, conveyed via median. The *Experienced* driver excels in route completion, passenger comfort, and energy efficiency. In contrast, the *Mad* driver causes passenger discomfort due to sudden throttle and brake, and both *Angry* and *Excited* drivers have larger Lane Change Frequency. Our findings establish a strong correlation between persona and driving behavior, highlighting SimLLM's capability to simulate diverse human-like actions.

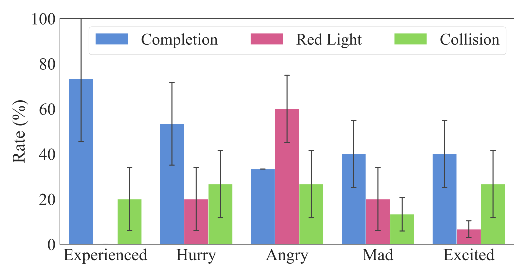

Figure 4: **Performance variations are evident across distinct personas on three urban routes: Route A, Route B, and Route C.** The persona labeled *Experienced* excels in driving proficiency, achieving the highest route completion rates while adhering to traffic signals. Conversely, the *Angry* persona manifests a predictably elevated rate of red-light infringements.

LLMs Comparative Analysis Our analysis extends beyond ChatGPT to include ChatGLM, Baichuan-2, and LLaMA-2. As illustrated in Table 5, when tested under identical Route A conditions, ChatGLM and Baichuan-2 achieve 40% and 30% completion rates due to flawed decision-making. In contrast, LLaMA-2 and ChatGPT both achieve 100% completion but differ in traffic light compliance and passenger comfort. Specifically, LLaMA-2 consistently ignores traffic signals, resulting in red-light violations, whereas ChatGLM and Baichuan-2 exhibit dynamic lane-changing at the cost of passenger comfort.

Table 6: Average Travel Time of Multi-Agent Collaboration.

Simulation Platform	Emergency Vehicle	Sudden Breakdown	Aircraft Landing
LimSim [11]	✗	25.5	✗
SimLLM w/o comm.	✗	21.5	✗
SimLLM	50.9	20.0	43.0

4.3 Multi-Agent Simulation

In high-density traffic environments with multiple autonomous agents, we evaluate dynamic adaptability through vehicle-to-vehicle (V2V) communication protocols. The empirical evidence presented in Table 6 substantiates that strategic inter-vehicle messaging significantly diminishes average transit durations while enhancing overall traffic throughput, thereby validating efficient multi-agent coordination mechanisms. The resilience of our approach is rigorously validated across three distinct scenarios.

To demonstrate the versatile functionalities of SimLLM, we have established three multi-agent simulation scenarios. These scenarios are designed to help users understand the customizable features of SimLLM's LLM-based NPCs and on their own facilitate the creation of additional simulations. The scenarios include:

- **Path Clearance for Emergency Vehicles:** This case focuses on the real-time allocation of an unobstructed route for emergency vehicles. Emergency information are transmitted to vehicles ahead in the path, which simulates a common scene of emergency incident.
- **Mitigation of Sudden Breakdown Impacts:** This scenario tackles the challenge of an abrupt vehicle failure within a high-speed traffic corridor. Once the vehicle breaks down, it will warn others through V2V channels. Every vehicle will encounter this scenario countless times.
- **Emergency Aircraft Landing:** This simulation models an urgent situation where an aircraft requires an immediate landing on a bustling highway. It's a rare and long-tail case of autonomous driving, which can be built easily utilizing SimLLM.

The scenarios above are only a demonstration of the functionality of SimLLM. We welcome more users to join the community and construct various scenarios utilizing SimLLM's customizable NPCs with diverse human-like driving styles. Challenges and competitions can also be launched on SimLLM, aiming to rich the data of long-tail cases.

In this paper, we also experiment on the three scenarios above to showcase the flexible adaptability of SimLLM's human-like drivers. In contrast to agents relying on LimSim [11]'s rudimentary planner, which suffers performance degradation due to constrained lane-changing and overtaking capabilities, those controlled by independent LLMs display only incremental gains in speed during traffic breakdown scenarios but falter in other operational conditions. To address these shortcomings, our SimLLM's human-like drivers seamlessly integrates collaborative LLMs with V2V communication protocols within the simulation environment. We posit that the incorporation of V2V natural language communication not only enriches the diversity of agent behaviors but also opens new avenues for future research in multi-agent interaction dynamics.

5 Conclusion

In conclusion, SimLLM introduces a customizable platform featuring human-like NPCs, significantly advancing autonomous driving simulations. Our platform excels in creating realistic scenarios by leveraging these NPCs, facilitating the construction of environments that closely mimic real-world conditions. It stands out for its ability to easily configure a wide range of scenarios, from simple to complex. This capability not only sets a new standard in driving simulations but also invites broader utilization for diverse scenario building, competitions, and challenges.

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