# Drive Like a Human: Rethinking Autonomous Driving with Large Language Models

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AuE6930 Milestone #2

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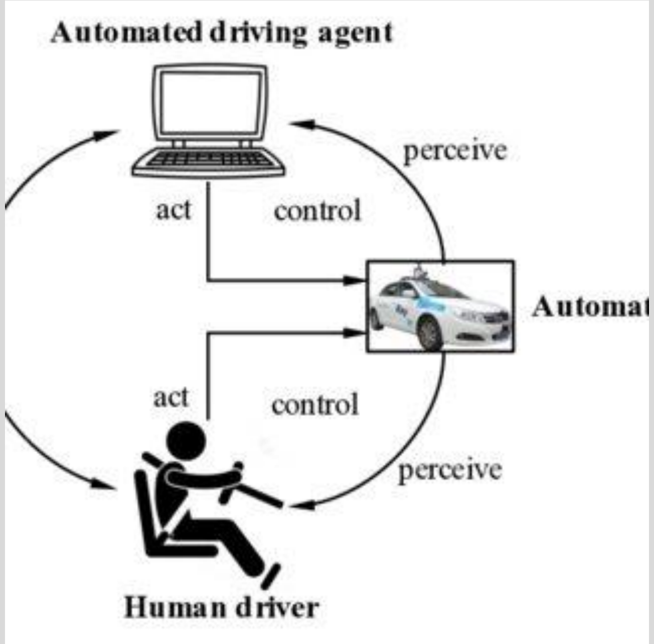
# Introduction

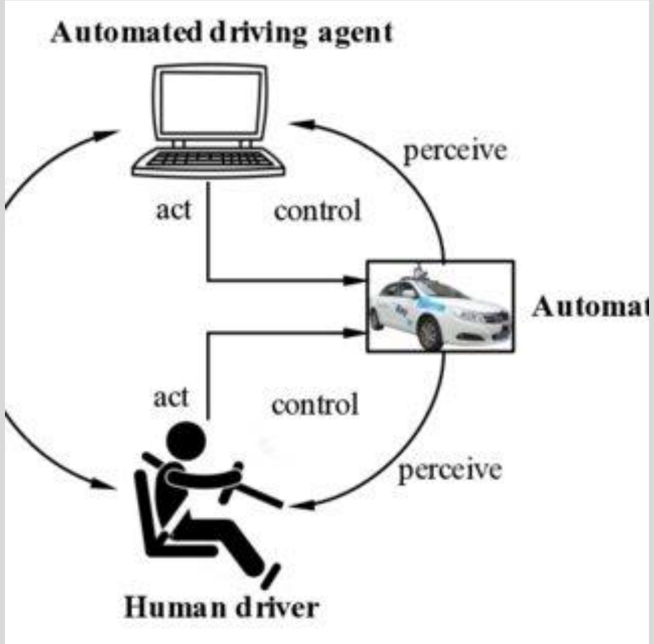
# Introduction

- **Autonomous driving today**: Modern autonomous driving (AD) systems excel in **frequent, well-covered scenarios** but often fail in rare or unusual "long-tail" cases such as erratic drivers, unusual merges, or partially occluded vehicles.
- **Data and generalization gap**: Classical end-to-end policies need **massive labeled datasets** and still struggle to robustly generalize to corner cases not seen during training.
- **Human drivers as inspiration**: In contrast, human drivers leverage **common sense, prior experiences, and causal reasoning** to quickly adapt to new situations without seeing millions of exact replicas.
- **Research question**: We ask whether **large language models**, with their strong reasoning and abstraction capabilities, can be integrated into a driving stack to make the system **behave more like an experienced human driver** rather than a brittle pattern recognizer.



# Motivation, Why Drive like a human?

- **Long-tail challenges**: Rare events—unusual merges, sudden cut-ins, stalled cars at odd locations—are exactly where current AD stacks are **least reliable**, yet they matter the most for safety.
- **Common sense vs pattern matching**: Traditional policies mostly rely on **pattern recognition**; they are strong when data is abundant but fragile when confronted with novel configurations of vehicles and rules.
- **Human-like reasoning**: Humans constantly **reason about intent** ("that car is probably going to cut in"), **anticipate future risks**, and **adapt** using high-level knowledge of physics and road rules.
- **LLM opportunity**: Large language models encode rich semantic and commonsense knowledge; our motivation is to see whether that knowledge can be turned into a **high-level decision policy** that complements numerical planners.
- **Ultimate goal**: Move from "drives like a deterministic rule engine" to **"drives like a cautious, experienced human"**, especially in ambiguous or under-specified situations.



# Challenges

- **Poor generalization to corner cases:** Baseline policies often overfit to training distributions and make **unsafe or irrational choices** when scenes deviate from typical patterns.
- **Lack of interpretability:** Many AD policies operate as **black boxes**, making it difficult to understand *why* a particular action was taken or to debug failures.
- **No mechanism for learning from mistakes:** Conventional pipelines rarely have a **dedicated mechanism** that takes crashes or near-misses, explains them, and converts them into reusable lessons.
- **Safety without guarantees:** Prompting an LLM to “be safe” is not enough—there is **no numeric notion of risk**, headway, or time-to-collision, so obviously dangerous maneuvers may still be issued

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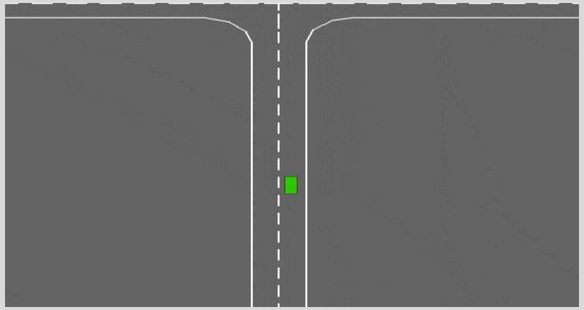
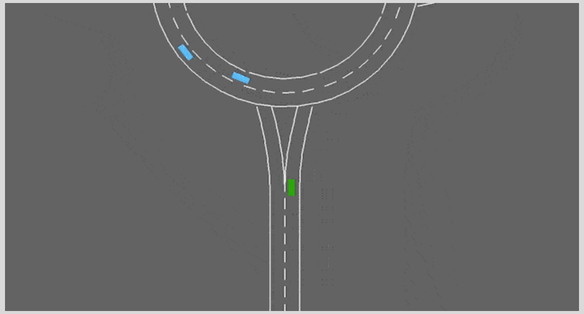
# Problem Statement/ Goals(objectives)

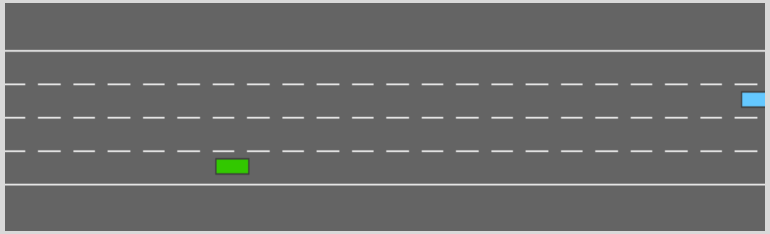
- **Limitations we target:**
  - Poor generalization to corner cases
  - Inability to explain decisions
  - No mechanism to incorporate past mistakes
  - Rigid rule-based planners
- **Our objective:** Build an **LLM-driven high level policy** that can:
  - Understand scenario semantics
  - Reason about intent, safety and traffic rules
  - Improve iteratively via a *failure memory bank*
  - Operate inside a real-time HighwayEnv loop across 4 in-built scenarios; **Highway, Merge, Roundabout, and Intersection**



**Video 1. Intersection Scenario** – Ego vehicle navigating a multi-lane intersection in HighwayEnv, interpreting right-of-way and cross traffic while choosing a safe path through the junction.



**Video 2. Roundabout Scenario** – Ego vehicle approaching and driving through a roundabout in HighwayEnv, selecting safe entry gaps, maintaining lane position, and exiting at the correct branch.



**Video 3. Highway Scenario** – Ego vehicle driving on a multi-lane highway in HighwayEnv, interacting with surrounding traffic while maintaining lane position and safe headway during lane-change

**Video 4. Merge Scenario** – Ego vehicle approaching an on-ramp merge in HighwayEnv, reasoning about gaps, adjusting speed, and selecting a safe lane to integrate smoothly into flowing traffic.

# Methods and Details:

# System Setup

- **Configuration:**

| Category | Specification |
|---|---|
| Simulator | **HighwayEnv** wrapped by the **DriveLikeAHuman** pipeline. |
| Environment/ Scenarios | highway-v0, merge-v0, roundabout-v0 and intersection-v1 |
| Episode | Each episode lasts up to **20 s.** If it doesn't stop with collision. |
| Observation space | HighwayEnv **Kinematics observation**: for ego + surrounding vehicles, the simulator provides positions, velocities, lane indices, and heading in each timestep. |
| Action space | HighwayEnv **DiscreteMetaAction** control: high-level maneuvers {LANE_LEFT, LANE_RIGHT, FASTER, SLOWER, IDLE}. |
| Collision reward | -1 |
| speed-based reward | Encouraging 20–30 m/s cruising speed while avoiding collisions. |
| API provider | OpenAI |
| Max tokens per response | **1024 tokens** maximum per call. |
| Request timeout | 60 s |

# Methods & Details: System Architecture Overview

- **Layered design**: Our system is organized into four main layers: **HighwayEnv (Environment)**, **Scenario Engine**, **LLMDriver (Cognitive)**, and **Safety Wrapper (Execution)**.
  - **Environment layer – HighwayEnv**: Provides the **kinematic state** (position, speed, lane index) of the ego vehicle and surrounding traffic at each timestep.
  - **Scenario Engine**: Converts raw numerical observations into a **structured JSON representation**, logs frames into **SQLite**, and maintains relationships such as "front vehicle," "left neighbor," and "right neighbor."
  - **LLMDriver**: Acts as the **reasoning core**, applying traffic rules, tool calls, memory retrieval, and multi-step predictions to output high-level actions.
  - **Safety Wrapper**: Filters the LLM's action through **numerical safety checks** (gaps, time-to-collision, lane-change viability) before sending commands back to HighwayEnv, creating a robust **perception → reasoning → action → logging** loop.

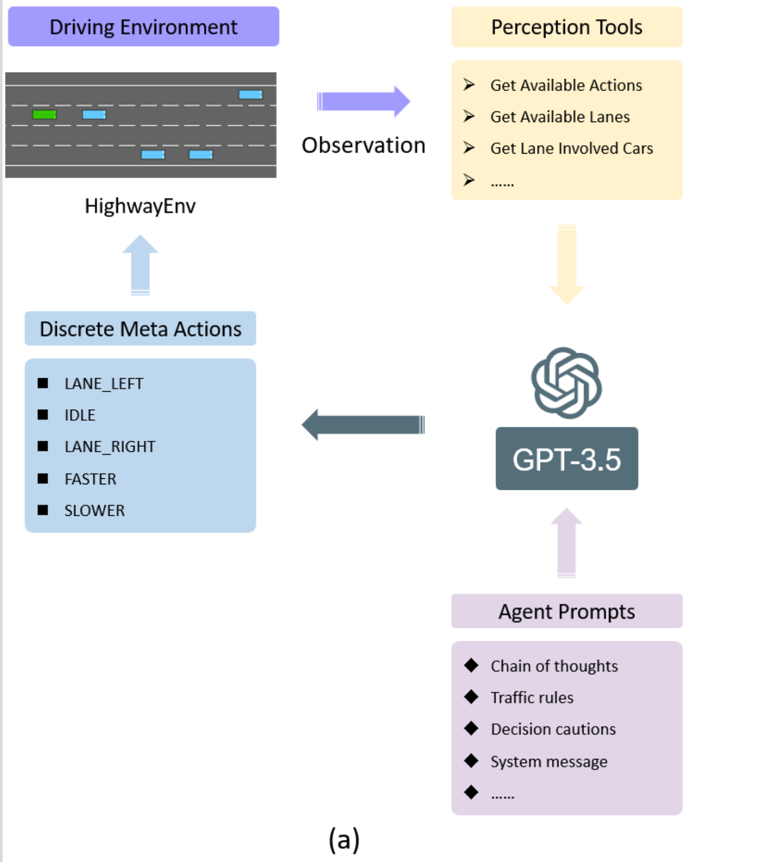



**Image 1.** End-to-end architecture of the LLM-driven highway agent. It shows how the layers are connected to each other in the system.

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# Methods & Details: HELLM.py- Main Control Loop

- **Central orchestrator**: HELLM.py is the **top-level script** that coordinates all components of the driving stack for each simulation episode.
- **Initialization**: It configures **HighwayEnv**, initializes the chosen **scenario configuration**, and loads the **LLM model and associated tools** (safety checks, prediction tools, memory modules).
- **Per-timestep workflow**: On every timestep, it
  - extracts the latest observation from HighwayEnv,
  - updates the scenario JSON using the Scenario Engine,
  - calls LLMDriver.agentRun() to obtain a high-level action,
  - applies the safety wrapper to refine or veto that action, and
  - executes the final action in the environment.
- **Logging and termination**: Each step is **logged into SQLite**, and the loop terminates when a **collision** or **timeout** is detected, enabling detailed post-episode analysis.

```
# environment setting
config = {
    "observation": {
        "type": "Kinematics",
        "features": ["presence", "x", "y", "vx", "vy"],
        "absolute": True,
        "normalize": False,
        "vehicles_count": vehicleCount,
        "see_behind": True,
    },
    "action": {
        "type": "DiscreteMetaAction",
        "target_speeds": np.linspace(0, 32, 9),
    },
    "duration": 40,
    "vehicles_density": 2,
    "show_trajectories": True,
    "render_agent": True,
}
```

**Image 2.** After configing the LLM, Environment configuration for highway-v0, defining kinematic observations, discrete meta-action target speeds, and simulation settings such as duration, vehicle density, and visualization options.

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# Methods & Details: Scenario Engine (scenario.py)

- **Lane graph construction**: Builds a **lane graph** tailored to each scenario (highway, merge, intersection, roundabout), capturing connectivity, allowed transitions, and lane adjacency.
- **Vehicle objects**: Creates **Vehicle objects** for both the **ego car** and **neighboring vehicles**, tracking their lane positions, velocities, and IDs.
- **JSON state representation**: Converts raw HighwayEnv observations into a **compact JSON tuple** containing lane index, longitudinal position, speed, neighbor relationships, and scenario-level metadata.
- **Database logging**: For each frame, the Scenario Engine saves the structured state into a **SQLite database**, providing a convenient backend for failure analysis and memory building.
- **Replay and visualization**: Supports **scenario replay** via scenarioReplay.py, allowing us to reconstruct and visualize episodes when studying failures and long-tail cases.


**Image 3.** Defining the Scenario class: it builds the 4-lane road graph and vehicle objects, initializes the SQLite database tables for vehicle states and LLM decisions, and starts the frame counter for logging the driving episode.

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# Methods & Details: LLMDriver (Reasoning + Tools)

- **Core responsibilities**: LLMDriver orchestrates **high-level reasoning** about the scene and decides the ego vehicle's next maneuver.
- **agentRun() pipeline**
    - Builds a **system prompt** that includes traffic rules, scenario descriptions, and decision-making cautions.
    - Injects the **current scenario JSON** with lane/topology information.
    - Performs **tool calls** (e.g., lane checks, collision checks, speed checks, multi-step prediction).
    - Integrates **memory retrieval** from the Failure Memory Bank (when enabled).
    - Outputs a final action in a strict format (e.g., Final Answer: <ACTION>).
- **exportThoughts()**: Extracts the LLM's **chain-of-thought** and saves it for later analysis, giving a window into *why* certain decisions were made.

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# Experiment and Results: Setup

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# Setup Overview

**Perception**
- Kinematics (x, y, vx, vy, presence)
- Front Gap, Lane-Clearance, TTC

**Context Enhancement Layer**
- Failure Memory Bank

**LLM Decision Layer (SDG)**
- LLM outputs a Structured Decision Graph:
  - Hazard_assessment
  - Gap_change_prediction
  - Lane_feasibility
  - Collision_risk & TTC recommended action

**Action Execution**
- Final safe action → Environments
- Vehicle moves based on SDG + safety rules

**Metrics & Behavior Analysis**
- Ego Speed, Front Gap, Min TTC
- Lane Scores + Best Lane
- Raw vs Safe Actions, Collision Risk

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# Extension 1: Failure Memory Bank + Case-based reasoning

- **Purpose**: Enable the agent to **accumulate driving experience** over time by storing structured memories of **failures** (crashes or near-misses) and reusing them in future episodes.
- **On failure**: When a crash occurs, we log
    - scenario type and difficulty,
    - ego and nearby vehicle states,
    - the LLM's thought process leading up to the failure, and
    - reward and outcome statistics.
- **LLM reflection**: After the crash, we prompt the LLM to **diagnose its own mistake**—identify root causes and summarize a **lesson** that should be remembered.
- **Case abstraction**: Each failure is stored as a **case** with a compact description and a textual "lesson," forming the core of the **Failure Memory Bank.**

# Extension: Current Memory Implemented (Baseline Imitation Memory)

- **Baseline memory mechanism:** The current repository's "memory" is implemented as a **simple lookup table** mapping an observation to a **human driver action.**
- **Data source:** For states encountered during training, the human driver's ground-truth actions are **stored as reference entries.**
- **Decision improvement:** At runtime, when the agent sees a state similar to one in the memory, it **imitates the human action**, often correcting poor LLM decisions in those repeated states.
- **Limitations:** This approach relies heavily on **human-provided corrections** and does not generalize well beyond **exactly encountered states**, motivating our case-based Failure Memory Bank.

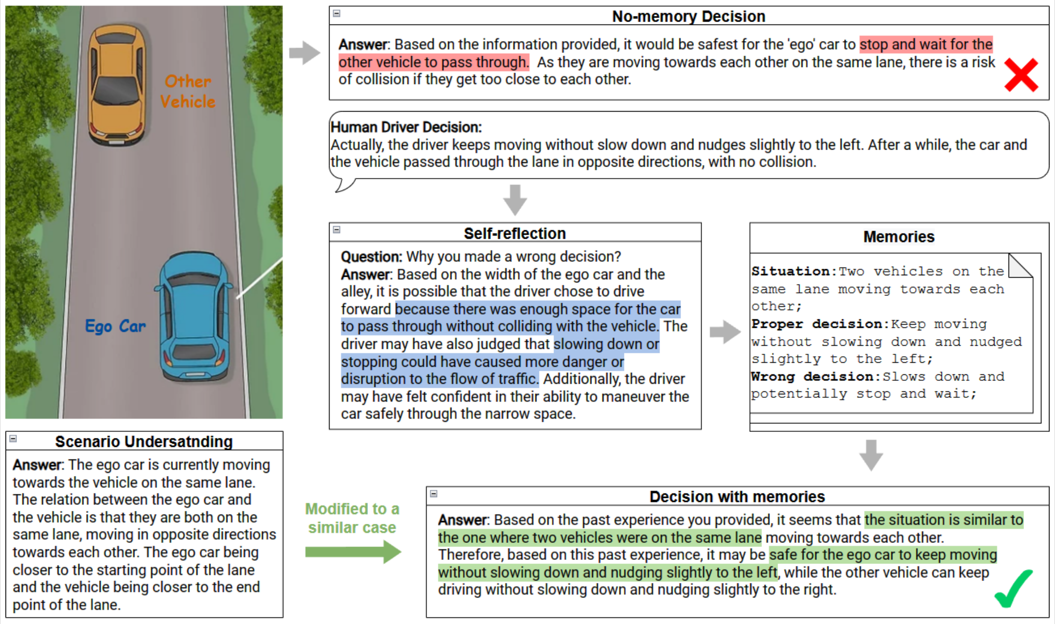


**Image 4.** Illustration of the baseline memory mechanism that compares the LLM's proposed action ('no-memory decision') with the human driver's ground-truth behavior. For each observed traffic scene, the human action is stored as a memory entry. When a similar situation recurs, the system retrieves the stored action and adjusts the LLM's output, yielding an 'improved decision with memory' that better matches human driving behavior."

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# Extension : Failure Memory Bank: Logging Layer

- **Lightweight logging**: Each episode writes a collection of **key fields** into a simple SQLite/JSON store, allowing us to systematically catalogue failures.
- **Stored attributes**: We record **scenario ID**, observation summaries, actions taken, rewards, whether a crash occurred, and additional episode context.
- **Failure-centric design**: The logging layer is optimized to make **failed or risky episodes** easy to query so that we can build and refine memory entries from them.
- **Scalability**: Because entries are stored as **compact records**, the Failure Memory Bank can scale to many episodes without becoming unwieldy.

```
        reflection_prompt = f"""We executed a highway-driving episode in scenario_type={scenario_type},
difficulty={difficulty}, and the episode ended with a crash.

Crash reason from the environment or evaluator:
{crash_reason}

Here is a brief log of the last steps before the crash:
{episode_summary}

You are an expert driving instructor for an autonomous agent.
In 1▯2 sentences, explain the root cause of this failure.
Then, in another 1▯2 sentences, state a concise LESSON the agent should
remember to avoid this in the future.

Respond in the following JSON format:
{{"root_cause": "...", "lesson": "..."}}
"""

        messages = [
            {"role": "system", "content": "You analyse failures and extract lessons."},
            {"role": "user", "content": reflection_prompt},
        ]
```

**Image 5.** Prompting template that asks the LLM to analyze its own mistake. After a crash, we feed a compact log of the last steps to the LLM and ask it to identify the root cause and articulate a concise lesson that should be remembered for similar future situations

```
    def __init__(self, path: str = "results-db/memory_bank.jsonl"):
        self.path = path
        os.makedirs(os.path.dirname(self.path), exist_ok=True)
        self._memories: List[EpisodeMemory] = []
        self._load()

    def _load(self) -> None:
        if not os.path.exists(self.path):
            return
        with open(self.path, "r", encoding="utf-8") as f:
            for line in f:
                line = line.strip()
                if not line:
                    continue
                data = json.loads(line)
                self._memories.append(EpisodeMemory(**data))

    def _save_append(self, memory: EpisodeMemory) -> None:
        with open(self.path, "a", encoding="utf-8") as f:
            f.write(json.dumps(asdict(memory)) + "\n")

    def add(self, memory: EpisodeMemory) -> None:
        self._memories.append(memory)
        self._save_append(memory)
```

**Image 6.** Lightweight logging layer for the Failure Memory Bank. Each episode writes key fields, scenario ID, observation summary, action, reward, crash flag, and additional context, into a simple SQLite / JSON store, making failures easy to query and analyze later.

# Extension: Using the memory (case retrieval)

- **Structured memory entries**: After our extensions, every failure is transformed into a **rich memory record** containing scenario type, difficulty, outcome statistics, and a textual lesson.
- **Similarity search**: Before choosing an action, the agent queries the Failure Memory Bank for **similar past episodes** based on scenario metadata and observation summaries.
- **Prompt augmentation**: Retrieved cases are injected into the LLM prompt as **“previous similar failures and their lessons”**, biasing the agent toward safer, more cautious actions in analogous situations.
- **From one-off mistakes to experience**: This effectively turns repeated exposure to long-tail scenarios into **incremental experience accumulation**, moving toward an agent that “drives like a human and learns from its own mistakes.”

```
=== Memory 299 ===
 Episode ID   : cones_high_density-1-seed1
 Scenario     : cones_high_density
 Difficulty   : 1
 Steps        : 1
 Total reward : 0.033
 Time         : 2025-11-29 13:14:10.627104
 Failure reason:
   The root cause of the failure was the ego vehicle's inability to react quickly enough to the high-densit
y cones scenario, resulting in a collision or offroad incident.
 Lesson:
   The agent should remember to anticipate and react promptly to changes in the environment, especially in
high-density scenarios, to avoid collisions or offroad incidents in the future.

=== Memory 300 ===
 Episode ID   : cones_high_density-1-seed2
 Scenario     : cones_high_density
 Difficulty   : 1
 Steps        : 4
 Total reward : 2.294
 Time         : 2025-11-29 13:14:13.989392
 Failure reason:
   The ego vehicle was driving too slowly, which may have caused other vehicles to approach too closely and
 resulted in a collision or offroad incident.
 Lesson:
   The agent should maintain a safe and appropriate speed for the given scenario to avoid potential collisi
ons or offroad incidents.
```

**Image 7.** Example of a stored failure case. The record includes the episode ID, descriptive scenario label, performance metrics, a textual summary of the final states and actions, and LLM-generated ‘root cause’ and ‘lesson’ fields. This case can be retrieved later to remind the agent of what went wrong and how to avoid repeating the same mistake.

# Experiment and Results: Evaluation Metrics

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# Metrics Details

- Extension 1,3,4 – Failure Memory Bank + Case-Based Reasoning
  - **Collision Rate:** Share of episodes that end in a crash before/after enabling the Failure Memory Bank. Lower = fewer repeated mistakes.
  - **Average Episodic Reward:** Mean HighwayEnv reward per episode (speed, lane-keeping, penalties, collisions). Higher = safer yet efficient driving.
  - **Average Speed:** Mean ego-vehicle speed per episode. Checks that safety gains do not come from driving unrealistically slowly.

# Experiment and Results: Quantitative & Qualitative

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# Quantitative Results – Extension 1,3,4

- We evaluate all driver variants on a **mixture of long-tail highway scenarios**, each designed to stress the decision-making of the LLM:
  - **High-speed cut-in** – a fast vehicle suddenly merges into the ego lane with a small gap.
  - **Partial occlusion** – the ego's view of a nearby vehicle is blocked by a larger car until late.
  - **Erratic braking** – the lead vehicle brakes unpredictably, forcing rapid reassessment of safe headway.
  - **Multi-vehicle merge** – several vehicles compete to join the same lane, creating complex interactions.
  - **Truck-debris scenario** – a slow truck and static obstacle/debris force the ego vehicle to make a timely lane change.
- Reward and metrics

We use the **HighwayEnv default reward function**, which jointly encourages **high average speed, staying on the road, lane-keeping discipline, and avoiding collisions.**

For each driver kind we report two aggregate metrics over many episodes:

  - **Crash rate** – fraction of episodes in which the ego vehicle collides with another vehicle or obstacle (lower is better).
  - **Total reward** – mean cumulative reward per episode under the default HighwayEnv reward (higher is better).

| Driver kind | Crash rate(100 episodes) | Total reward | Average speed |
|---|---|---|---|
| Base LLM | 65.7% | 10.327 | 28.8 |
| LLM with memory | 20.4% | 26.936 | 20.4 |

**Table 1.** Quantitative comparison of different driver configurations on a mixture of long-tail highway scenarios (high-speed cut-ins, partial occlusions, erratic braking, multi-vehicle merges, and truck-debris situations).

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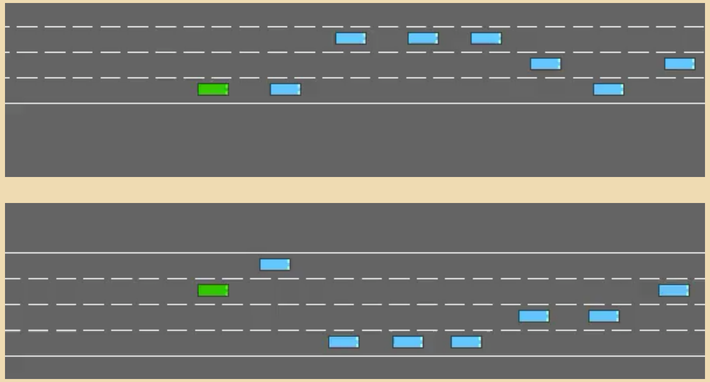
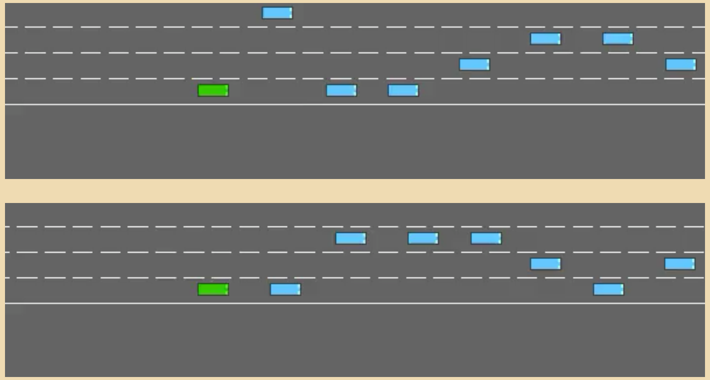
# Qualitative Results – Extension

- Here are some example of failure and success in each driver kind:

- Base LLM



- LLM with memory



# Discussion

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# Discussion and Next steps

1. Key Findings & conclusion

• Combining LLM reasoning with our four extensions – Failure Memory Bank helped to reduce the collision rate in long tail scenarios.

2. Limitations and drawbacks

• Simulator limits: HighwayEnv offers clean, fully observable scenes and limited control over truly adversarial long-tail setups, which caps how hard we can stress-test the stack and may overestimate real-world robustness.

• Prediction & memory brittleness: When rollouts are ambiguous, the LLM can overreact (e.g., unnecessary hard braking), and memory retrieval is still coarse, relying on simple similarity rather than rich semantic search.

# Future works

- More challenging scenarios:
  - Emergency vehicles (ambulance approaching, all lanes stopped)
  - Stalled cars and work zones would better probe the agent's ability to handle rare but safety-critical events.
  - Pedestrians gesturing at 4-way stops
  - Multi-agent negotiation (merging, cut-ins, aggressive drivers)
  - Limited Sensor / Partial Observability Parking with blind spots
- Adding more sensors
- Integrate with platforms like CARLA, MetaDrive, DriveArena, LimSim or DiLu-style frameworks.

Sample Approach

- Choose one vehicle as the "ambulance".
- Add new scenario with semantics, is_emergency = True.
- Spawn or position the ambulance behind the ego.
- Script background traffic to stop (all lanes) or slow down.
- Keep the ambulance moving faster than traffic.
- Inform RL agent about the ambulance.

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# References

1. 1. Hu, Y., Yang, J., Chen, L., Li, K., Sima, C., Zhu, X., ... & Li, H. (2023). Planning-oriented autonomous driving. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 17853-17862).
2. 2. Chen, L., Wu, P., Chitta, K., Jaeger, B., Geiger, A., & Li, H. (2024). End-to-end autonomous driving: Challenges and frontiers. IEEE Transactions on Pattern Analysis and Machine Intelligence.
3. 3. Deng, H., Zhao, Y., Wang, Q., & Nguyen, A. T. (2023). Deep reinforcement learning based decision-making strategy of autonomous vehicle in highway uncertain driving environments. Automotive Innovation, 6(3), 438-452.
4. 4. Yang, Z., Jia, X., Li, H., & Yan, J. (2023). Llm4drive: A survey of large language models for autonomous driving. arXiv preprint arXiv:2311.01043.
5. 5. Fu, D., Li, X., Wen, L., Dou, M., Cai, P., Shi, B., & Qiao, Y. (2024, January). Drive like a human: Rethinking autonomous driving with large language models. In 2024 IEEE/CVF Winter Conference on Applications of Computer VisionWorkshops (WACVW) (pp. 910-919). IEEE
6. Fu, D., Li, X., Wen, L., Dou, M., Cai, P., Shi, B., & Qiao, Y. (2024, January). Drive like ahuman: Rethinking autonomous driving with large language models. In 2024IEEE/CVF Winter Conference on Applications of Computer Vision Workshops(WACVW) (pp. 910-919). IEEE
7. Wang, Y., Jiao, R., Lang, C., Huang, C., Wang, Z., Yang, Z., & Zhu, Q. (2023).Empowering autonomous driving with large language models: A safety perspective.arXiv. 2023. arXiv preprint arXiv:2312.00812.

# Thank you for your attention!

# Questions?