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DILU: A KNOWLEDGE-DRIVEN APPROACH TO AUTONOMOUS DRIVING WITH LARGE LANGUAGE MODELS

1. INTRODUCTION

In this research paper, the authors address the limitations of data-driven algorithms in autonomous driving, such as dataset bias and overfitting, by proposing a knowledge-driven approach that mirrors human reasoning and common-sense knowledge. They introduce a novel framework called DiLu that integrates large language models (LLMs) to improve decision-making and enhance generalization in autonomous systems. This framework comprises a reasoning module, a reflection module, and a memory component, facilitating continuous learning and decision-making refinement. DiLu demonstrates superior performance and generalization in a closed-loop driving environment, suggesting significant potential for practical implementations in autonomous driving technologies.

2. RELATED WORKS

The paper reviews advancements in large language models (LLMs) such as GPT-3, PaLM, LLaMA, and GPT-4, highlighting their significant abilities in text generation, comprehension, in-context learning, and reasoning. These models, especially with capabilities such as instruction following and chain-of-thought reasoning, have pushed the boundaries towards Artificial General Intelligence (AGI). The paper also discusses the application of LLMs in creating autonomous agents with human-like capabilities, emphasizing their role in tasks requiring common-sense knowledge, reasoning, and planning. Examples include embodied language models that integrate sensor data, lifelong learning systems like Voyager, and robotic manipulation with Voxposer. Furthermore, the paper mentions the application of LLMs in autonomous driving, such as the LINGO-1 system, which combines vision and language for better driving model training. The section concludes by proposing a novel knowledge-driven paradigm and the DiLu framework to enable LLMs to better understand and navigate driving environments by incorporating human-like knowledge.

3. METHODOLOGY

3.1 OVERVIEW

The paper presents DiLu, a knowledge-driven framework for autonomous driving, comprised of four main modules: Environment, Reasoning, Reflection, and Memory. The process involves observing the environment, generating decision-making prompts using a few-shot approach from the Memory module, processing these through an LLM, and refining decisions in a cycle that involves continuous learning and updating.

3.2 MEMORY MODULE

The Memory module functions as the knowledge base, storing experiences and decision processes from past driving scenarios. It operates through three phases: initialization, recall, and storage. Initial memories are created based on predefined correct decisions, while ongoing driving experiences are dynamically encoded and stored, enhancing the system's decision-making capabilities.

3.3 REASONING MODULE

This module integrates inputs from the Memory module and employs the LLM's common-sense knowledge to make decisions about current traffic scenarios. It involves encoding the scenario, recalling related experiences, generating tailored prompts, and decoding actions from the LLM’s responses. The use of Chain-of-Thought prompting ensures a structured reasoning process.

3.4 REFLECTION MODULE

The Reflection module evaluates past decisions and improves future performance by learning from both successful outcomes and mistakes. It uses a continuous feedback loop to analyze decision sequences, refine unsafe decisions, and update the Memory module. This self-improvement process mimics the way humans learn from experience, enhancing the system’s reliability over time.

4. EXPERIMENTS

4.1 THE VALIDATION OF THE DILU FRAMEWORK

Experiments validate the DiLu framework using the Highway-env simulation, focusing on the importance of memory experiences. The framework's performance improves with the accumulation of experiences, as evidenced by experiments showing increased success steps (SS) with the number of few-shot experiences used. Notably, with 40 experiences, DiLu consistently demonstrates superior closed-loop driving performance compared to the 0-shot baseline, which shows minimal success without memory support.

4.2 COMPARISON WITH REINFORCEMENT LEARNING METHOD

DiLu is compared to a state-of-the-art reinforcement learning method, GRAD, in a standardized environment. DiLu achieves comparable success rates with significantly fewer training instances and exhibits better generalization across different traffic densities and lane counts. This indicates DiLu’s stronger adaptation and generalization capabilities over traditional reinforcement learning approaches, which tend to overfit specific training environments.

4.3 EXPERIMENTS ON GENERALIZATION AND TRANSFORMATION

Further experiments assess DiLu's generalization and transformation abilities. DiLu shows effective generalization across different settings, with performance correlating positively with the number of few-shot experiences used. The framework also demonstrates robust transformation capabilities, effectively utilizing experiences transferred from real-world datasets, which perform better than those solely from simulated environments.

4.4 EFFECTIVENESS OF TWO MEMORY TYPES IN THE REFLECTION MODULE

An ablation study explores the impact of incorporating successful and revised unsafe experiences in the Reflection module. Adding both types of experiences significantly enhances performance, indicating that the integration of diverse memory types facilitates better learning and decision-making in autonomous driving tasks.

5. CONCLUSION

This paper introduces the DiLu framework, a knowledge-driven approach for autonomous driving systems, integrating a memory module and employing reasoning and reflection modules. Extensive testing demonstrates DiLu's ability to accumulate experiences and its superior generalization capabilities compared to state-of-the-art reinforcement learning methods. DiLu also effectively incorporates real-world data, enhancing its applicability in practical scenarios. Despite its strengths, DiLu faces challenges such as decision-making latency and occasional hallucinations from LLMs. Future work will focus on optimizing LLM efficiency and reducing errors to improve the framework's overall performance.

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