LLM-Powered Synthetic Environments for Self-Driving Scenarios

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Abstract

This paper outlines a proposal exploring the potential use of large language models (LLMs), particularly GPT-4, in crafting realistic synthetic environments for self-driving scenarios. The envisioned approach involves dynamic scene generation within game engines, leveraging LLMs to introduce challenging elements for autonomous vehicles. The proposed evaluation process outlines assessments such as realistic testing, safety metrics, and user interaction, aiming to set the stage for potential improvements in self-driving system performance.

The paper aims to contribute to the AI field by discussing how LLMs could be utilized to create valuable testing grounds for autonomous vehicles, potentially fostering the development of more robust self-driving technology. The envisioned impact is the eventual enhancement of road safety and the possible acceleration of the adoption of autonomous vehicles, paving the way for a future with safer and more efficient transportation.

Introduction

This proposal is driven by a keen interest in harnessing AI, specifically Large Language Models (LLMs), to craft synthetic environments tailored for self-driving scenarios. The conceptual framework involves AI-driven construction of intricate virtual environments challenging autonomous vehicles. The aim is to instruct AI systems to dynamically generate lifelike scenes, simulating complex real-world driving scenarios, including rare and challenging edge cases.

Beyond mere curiosity, this vision acknowledges AI's transformative potential.

The proposal charts a groundbreaking research trajectory in the field of self-driving cars, pushing the boundaries of Artificial Intelligence (AI). It places a strong emphasis on the societal impact of AI by enhancing safety and reliability in autonomous vehicles, contributing significantly to the advancement of transportation technology.

The methodology, utilizing text-to-text generation AI, involves inputting textual descriptions into LLMs to generate configuration parameters for game engines like Unity and Unreal. The proposal includes creating a dataset comprising validated scenarios generated through this methodology.

Background

AI's landscape has witnessed remarkable advances with Large Language Models (LLMs), extending to diverse domains like synthetic scenario creation. Mass et al.'s (2023) "To Infinity and Beyond: SHOW-1 and Showrunner Agents in Multi-Agent Simulations" illustrates the effectiveness of multi-agent simulations and LLMs in immersive content generation. This integrates simulations and language models, laying the groundwork for immersive storytelling—a central premise of this proposal.

S. Tan et al.'s (2023) recent paper, "SceneGen: Learning to Generate Realistic Traffic Scenes," introduces SceneGen, a neural autoregressive model for realistic traffic scene generation. SceneGen differs by eschewing rules or heuristics, offering flexibility and scalability. Aligned with my research, it emphasizes LLM utilization for intricate self-driving scenarios, fostering a paradigm shift towards safer and scalable autonomous systems.

Approach

In my research, I will leverage Large Language Models (LLMs) like GPT-4 to create dynamic synthetic environments in game engines for self-driving scenarios. The approach involves:

1. **User-Generated or Automatic Scenarios:** Users describe self-driving scenarios, or the system autonomously generates diverse scenarios for a comprehensive training dataset.
2. **Parameter Extraction for Game Engine:** Extract configuration parameters (e.g., vehicle dynamics,

environmental conditions) from the scenario for game engine configuration.

3. **Dynamic Game Engine Configuration:** Dynamically configure game engine settings using extracted parameters to replicate specified or generated scenarios realistically.
4. **User-Involved Simulation Execution:** Users interact with the simulated environment, enhancing user involvement and providing valuable data.
5. **Evaluation through User Feedback:** Users provide feedback on simulated scenarios, guiding improvements to enhance the system's ability to generate diverse and challenging environments.
6. **Integration with Autonomous Systems:** Synthetic environments serve as realistic training grounds for autonomous systems, facilitating seamless integration and improving self-driving algorithms' adaptability.

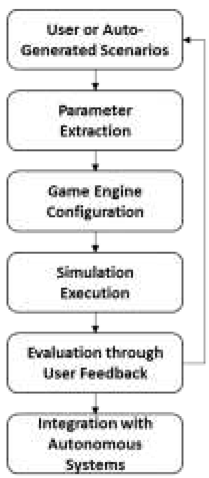

Figure 1: Flow Chart of Approach.

Evaluation

Assessing the quality of generated synthetic environments is crucial for this research. The evaluation focuses on the efficacy of synthetic scenarios, emphasizing key components:

1. **Realism Testing:** Synthetic scenarios undergo rigorous testing using real-world self-driving systems. Human evaluators familiar with real-world driving scenarios assess realism, emphasizing authentic navigation within synthetic scenes.
2. **Safety Metrics:** Safety metrics, including collision rates, emergency braking incidents, and responses to unpredictable events, quantify the safety performance of synthetic environments.
3. **Complexity and Unpredictability Assessment:** Intentionally designed synthetic scenarios introduce complexity and unpredictability to challenge self-driving technology. Evaluation centers on realistic and dynamic testing, utilizing a complexity index based on the diversity of dynamic elements for assessment.
4. **User Feedback on Environment Realism:** A user satisfaction survey, focusing on perceived realism and engagement levels, will be administered.
5. **Performance Improvement of Self-Driving Systems:** Success hinges on self-driving systems enhancing their performance in synthetic environments, gauged through adaptability and efficacy in managing rare edge cases. Metrics, such as decision-making speed and adaptability, are assessed before and after exposure to synthetic scenarios.

Discussion

This research aims to achieve two pivotal outcomes. Firstly, it highlights the potential of Large Language Models (LLMs) in crafting synthetic self-driving scenarios, playing a crucial role in advancing autonomous vehicle development and safety. Secondly, it strives to propel more robust self-driving technology, fostering widespread adoption for safer roads. However, potential challenges, such as Bias in Scenario Generation and the comprehension of complex scenarios by LLMs, may emerge. These challenges will be effectively addressed through a feedback loop for continuous refinement based on user feedback and the integration of real-world data into LLMs with meticulous prompt engineering. These measures not only enhance accuracy but also minimize biases in synthetic scenario generation.

Conclusion

In conclusion, my research is dedicated to harnessing the power of LLMs to create synthetic environments for self-driving scenarios. By pushing the boundaries of AI and self-driving technology, this research has the potential to revolutionize the way we develop and test autonomous vehicles. The ultimate benefit to society is enhanced road safety and the accelerated adoption of autonomous vehicles, promising a future with safer and more efficient transportation.

References

Fable Studio. 2023. To Infinity and Beyond: SHOW-1 and Showrunner Agents in Multi-Agent Simulations. https://fablestudio.github.io/showrunner-agents/. Accessed: 2024-01-01

S. Tan, et al. 2021. SceneGen: Learning to Generate Realistic Traffic Scenes. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR): 892-901. doi.org/10.1109/CVPR46437.2021.00095