Adaptive Evolution Framework: Enhancing Multi-Agent Systems through Continuous Learning and Behavioral Evolution

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Abstract

This framework introduces adaptive learning and behavioral evolution for multi-agent systems. Leveraging large language models (LLMs) to dynamically modify strategies based on real-time feedback and evolving task requirements, it aims to enhance resilience and adaptability. The framework creates a simulation environment with unpredictable task changes, where agents utilize a feedback loop mechanism to continuously learn and adapt using reinforcement learning principles such as Q-learning and policy gradient methods.

In this feedback loop, agents interact with the environment, receive performance metrics, and adjust their strategies accordingly. Evaluations will be conducted on tasks such as resource management, collaborative problem-solving, and real-time strategy games, measuring metrics like task completion time, accuracy, and adaptability. Detailed experimental results will be provided to substantiate claims and demonstrate significant improvements in agent performance over time in dynamic environments.

Example scenarios include dynamic resource allocation and real-time adjustments in team-based problem-solving. Specific experimental setups and evaluation metrics, such as task completion time, accuracy, and adaptability, will be outlined. Theoretical grounding for the integration of LLMs and their impact on strategy modification will be discussed. Potential challenges include efficient processing of feedback and avoiding overfitting, which will be addressed through described methodologies.

Limitations of using LLMs, particularly in terms of computational complexity and scalability, as well as potential negative societal impacts, will also be examined. The framework aims to present a comprehensive evaluation while ensuring ethical considerations are met in deploying adaptive multi-agent systems.

1 Introduction

The Adaptive Evolution Framework is designed to enhance the capabilities of multi-agent systems through adaptive learning and behavioral evolution. Such enhancements are essential in dynamic environments where adaptability to changing conditions is crucial for effective performance. Traditional multi-agent systems often struggle with adaptability and robustness when faced with unpredictable task requirements and environmental changes.

Achieving adaptive and robust multi-agent systems presents significant challenges, particularly in the ability to continuously learn from real-time feedback and dynamically evolve strategies. This necessitates sophisticated mechanisms to seamlessly integrate learning algorithms with behavioral adaptations, ensuring that agents remain effective under varying conditions without overfitting to specific scenarios.

To overcome these challenges, our framework leverages large language models (LLMs) to dynamically modify agent strategies based on real-time feedback and evolving task requirements. The framework creates a simulation environment characterized by unpredictable task changes, enabling agents to utilize a feedback loop mechanism for continuous learning and adaptation. Reinforcement learning principles, including Q-learning and policy gradient methods, form the foundation of the learning processes within this feedback loop.

Our evaluations include diverse tasks such as resource management, collaborative problem-solving, and real-time strategy games. Metrics like task completion time, accuracy, and adaptability are used to assess improvements. Example scenarios cover dynamic resource allocation and real-time adjustments in team-based problem-solving tasks. Comprehensive experimental results will be detailed to support our claims, ensuring our framework demonstrates substantial enhancements in agent performance within dynamic environments.

To address potential overfitting, we implement various reinforcement learning methods, including regularization techniques and multi-epoch training to ensure adaptability and resilience. We also outline measures to improve feedback processing efficiency by optimizing the feedback loop mechanism with parallel processing and batch updates. Finally, detailed ablation studies and comparisons with existing methods will be provided to validate the effectiveness of our approach.

Our contributions include:

- Development of an adaptive learning and behavioral evolution framework for multi-agent systems.
- Integration of large language models to modify strategies based on real-time feedback.
- Creation of a simulation environment for dynamic task changes and continuous learning.
- Implementation of a feedback loop mechanism utilizing reinforcement learning techniques.
- Comprehensive evaluation of the framework across various tasks to measure improvements in performance.

Future work will focus on refining the feedback loop to enhance processing efficiency and exploring additional reinforcement learning methods to mitigate overfitting risks. We will extend our evaluations to more complex and varied tasks to further validate the robustness of our framework. Moreover, we will address ethical considerations and societal impacts, ensuring that autonomous agent behaviors align with ethical standards and contribute positively to societal needs.

References