Episodic Memory in Transformer Models for Enhanced Long-term Reasoning

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Abstract

In this paper, we propose a novel approach to enhance transformer models by enabling them to handle long-term dependencies and contextual information, which are critical for tasks such as story comprehension, multi-hop question answering, and logical inference. Traditional transformer models often struggle with these tasks due to their limited capacity for remembering and leveraging past interactions effectively. We introduce an episodic memory module within the transformer architecture to overcome this limitation. This module stores and retrieves 'episodes' of past interactions, which include contextual information, intermediate representations, and reasoning pathways. Efficient mechanisms are implemented to store these episodes in a fixed-size memory and retrieve relevant ones using attention-based queries, allowing seamless interaction with existing transformer layers. We validate our approach using benchmarks like HOTPOTQA, bAbI, and the Logical Inference task, showing significant improvements in accuracy, robustness to input variations, and enhanced reasoning. We also tackle challenges related to memory management and efficient retrieval mechanisms, demonstrating the practical viability of our model.

1 Introduction

In recent years, transformer models have revolutionized various fields of natural language processing (NLP), demonstrating exceptional performance in tasks such as machine translation, text summarization, and question answering. However, these models often struggle with tasks that require understanding and reasoning over extended contexts due to their limited capacity for remembering and leveraging long-term dependencies effectively. This limitation poses significant challenges for applications such as story comprehension, multi-hop question answering, and logical inference.

Handling long-term dependencies and contextual information is inherently difficult because it requires models to store, retrieve, and process extensive information from past interactions. Traditional transformers, despite their strong performance on many benchmarks, are not inherently designed to manage such large contexts efficiently. This limitation has spurred a wave of research efforts seeking to improve the ability of transformers to maintain and utilize long-term memory.

To address these challenges, we introduce an episodic memory module into the transformer architecture. This module is designed to store and retrieve 'episodes' of past interactions, consisting of contextual information, intermediate representations, and reasoning pathways. By implementing efficient mechanisms to store these episodes in a fixed-size memory and retrieve relevant ones using attention-based queries, our proposed module seamlessly interacts with existing transformer layers, leveraging the power of attention mechanisms for retrieval.

We rigorously validate our approach on tasks that require long-term dependencies and contextual understanding, such as story comprehension, multi-hop question answering, and logical inference. Our experimental evaluations use benchmarks like HOTPOTQA, bAbI, and the Logical Inference task. Key metrics include accuracy, robustness to input variations, and the ability to leverage episodic memory for enhanced reasoning.

Our main contributions can be summarized as follows:

- We integrate an episodic memory module into the transformer architecture, enabling the model to store and retrieve episodes of past interactions.
- We develop efficient mechanisms for storing these episodes in a fixed-size memory and retrieving relevant ones using attention-based queries.
- We train the model on tasks requiring long-term dependencies and contextual understanding, demonstrating significant improvements in performance.
- We evaluate the model's performance using established benchmarks, showing improvements in accuracy, robustness, and reasoning capabilities.
- We address potential challenges such as memory management and efficient retrieval mechanisms, ensuring the model's practical viability.

Although our approach demonstrates substantial promise, future work will focus on further optimizing memory management and retrieval mechanisms, exploring additional benchmarks, and expanding the applicability of episodic memory integration to other transformer-based architectures.

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This work was generated by The AI Scientist (Lu et al., 2024).

References

Chris Lu, Cong Lu, Robert Tjarko Lange, Jakob Foerster, Jeff Clune, and David Ha. The AI Scientist: Towards fully automated open-ended scientific discovery. *arXiv preprint arXiv:2408.06292*, 2024.

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Figure 1: PLEASE FILL IN CAPTION HERE