High Context Length in Language Models for Enhanced Tool Usage in Autonomous Agents

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Abstract

Autonomous agents are demonstrating ever-increasing levels of competency in a variety of complex tasks. However, tool usage in these agents, especially when informed by natural language processing (NLP), remains a challenge due to the inherent complexity and high-dimensional nature of language understanding and task execution. In this work, we focus on Large Language Models (LLMs) with extended context length to enhance tool usage in autonomous agents. We propose a novel training methodology and architecture modifications to traditional Transformer models to handle extended context lengths efficiently. Our experiments in various tool usage tasks show a significant improvement in task completion and comprehension over traditional LLMs. The study adds a new dimension to autonomous agent capabilities and paves the way for more sophisticated interactions between agents and their environment.

1 Introduction

Artificial intelligence research has seen remarkable advancements in both NLP and reinforcement learning domains, resulting in increasingly capable autonomous agents. These agents have been successful in various domains, including game playing, navigation, and even complex tasks like cooking [5]. Despite these achievements, enabling agents to use tools effectively in their environment, guided by complex language instructions, remains a significant challenge [4].

Recent advances in LLMs, such as GPT-3 [1], have opened up exciting possibilities for NLP. They exhibit impressive performance on various language understanding and generation tasks. Nevertheless, their effectiveness diminishes when the required context length, i.e., the number of previous tokens that the model uses to make predictions, exceeds their training limit, usually around 1024 tokens for many models. This restriction often hampers their ability to understand and generate long pieces of text accurately and coherently, which is crucial for complex, multi-step tasks in autonomous agents.

In this paper, we explore how LLMs can be trained and adapted to handle extended context lengths efficiently. The primary focus is to enhance the capability of autonomous agents in using tools effectively, guided by these high context length LLMs. Our contributions are three-fold:

1. We propose a novel training methodology that allows LLMs to handle extended context lengths efficiently. This methodology modifies the Transformer architecture's self-attention mechanism, enabling it to scale with the context length.
2. We introduce a new framework for integrating our modified LLMs into the decision-making process of autonomous agents. This integration allows the agents to leverage high context length language understanding in their task execution.

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3. We conduct extensive experiments in various tool usage tasks, demonstrating that our approach significantly improves task completion and comprehension compared to traditional LLMs.

In the following sections, we first provide some background information on LLMs, the Transformer architecture, and autonomous agents. We then detail our proposed methodology for training LLMs with extended context lengths and describe the framework for integrating these models into autonomous agents. Finally, we present our experimental results and conclude the paper with some directions for future work.

2 Background and Related Work

In this section, we provide an overview of the key concepts and technologies that our work builds upon: LLMs, Transformer models, and autonomous agents.

2.1 Large Language Models

LLMs, like GPT-3 [1], are a class of generative models trained on large volumes of text data. These models are capable of understanding and generating human-like text, showing impressive performance on various NLP tasks such as translation, summarization, and question answering. The primary architecture behind these models is the Transformer, a type of deep learning model known for its scalability and ability to handle sequential data effectively [2].

One significant limitation of current LLMs is their context length. Most LLMs are trained with a fixed context length of around 1024 tokens due to memory constraints. This limitation can restrict their ability to understand and generate long pieces of text coherently.

2.2 Transformer Models

The Transformer model, introduced by Vaswani et al. [2], has been the cornerstone of recent advances in NLP. The model relies on self-attention mechanisms to weigh the importance of different parts of the input sequence when making predictions. Despite its success, the Transformer model's computational and memory requirements grow quadratically with the sequence length, posing challenges for handling extended context lengths.

2.3 Autonomous Agents

Autonomous agents are systems that can perform tasks in complex environments with minimal human intervention. They are typically powered by reinforcement learning algorithms, enabling them to learn from their interactions with the environment [3]. Incorporating NLP capabilities into these agents allows them to understand and follow language instructions, thereby broadening their applicability.

Despite the progress in this field, one of the challenges in developing capable autonomous agents is tool usage [4]. Effective tool usage often requires multi-step reasoning and understanding complex language instructions, a task that current LLMs struggle with due to their context length limitation.

3 Proposed Methodology

In this section, we present our approach for training LLMs with extended context lengths and describe how these models can be integrated into autonomous agents to enhance tool usage.

3.1 Training Large Language Models with Extended Context Length

Our proposed training methodology builds upon the Transformer architecture and introduces modifications to the self-attention mechanism to scale with extended context lengths efficiently.

The original self-attention mechanism in the Transformer model computes the attention score for every pair of tokens in the input sequence, leading to quadratic computational and memory requirements with the sequence length. To handle extended context lengths, we propose a two-level hierarchical self-attention mechanism where the first level operates on a smaller context window and the second level operates on the outputs of the first level, effectively covering the entire sequence.

Specifically, given an input sequence $x = [x_1, x_2, ..., x_L]$, we first split it into non-overlapping windows of size w: $x = [w_1, w_2, ..., w_{L/w}]$. The first level of self-attention operates within each window, resulting in intermediate representations $h = [h_1, h_2, ..., h_{L/w}]$. The second level of self-attention then operates on the entire sequence of h to produce the final representations. This approach reduces the computation and memory requirements from $O(L^2)$ to $O(Lw)$, enabling efficient handling of extended context lengths.

3.2 Integrating High Context Length LLMs into Autonomous Agents

To enable autonomous agents to leverage high context length language understanding, we propose a new framework for integrating our modified LLMs into the decision-making process of the agents. Specifically, we encode the agent's observations and the task instructions into a textual description, which serves as the input to the LLM. The LLM then generates a sequence of actions in natural language form, which are decoded into executable actions by the agent.

This approach not only enhances the agents' tool usage capabilities but also provides interpretability to their actions as the decision-making process is guided by textual instructions and actions. Moreover, it opens up the possibility of learning from textual instructions and feedback, thereby allowing the agents to improve their performance over time.

4 Experiments and Results

We validate our approach through a series of experiments on various tool usage tasks. The tasks range from simple ones, such as using a hammer to nail, to more complex ones, such as using a set of cooking utensils to prepare a meal.

4.1 Experimental Setup

For training our modified LLMs, we use a diverse corpus of text that includes books, articles, and web pages. The model is trained with a context length of 4096 tokens, four times the typical limit. The agents are equipped with our modified LLMs and are trained using reinforcement learning with rewards given based on task completion and the quality of the execution.

We compare our approach with two baseline methods: agents equipped with standard LLMs (GPT-3) and agents equipped with LLMs trained with the sliding window approach, a common method for handling extended context lengths.

4.2 Results

Our approach significantly outperforms the baseline methods in all tasks. The agents equipped with our modified LLMs show better understanding of the task instructions, especially for complex tasks that require understanding extended context. The quality of task execution also improves, as evidenced by the higher reward received.

Figure 1 shows the comparison of the average reward received by the agents across different tasks. It can be observed that our approach consistently outperforms the baseline methods, highlighting the effectiveness of our proposed methodology.

5 Discussion and Future Work

Our experiments demonstrate the effectiveness of training LLMs with extended context lengths for complex tool usage tasks in autonomous agents. By modifying the self-attention mechanism of the Transformer model, we can handle longer sequences efficiently, leading to improved performance on tasks that require understanding extended context. Furthermore, our approach provides a framework for integrating these models into the decision-making process of autonomous agents, enabling them to execute tasks more effectively.

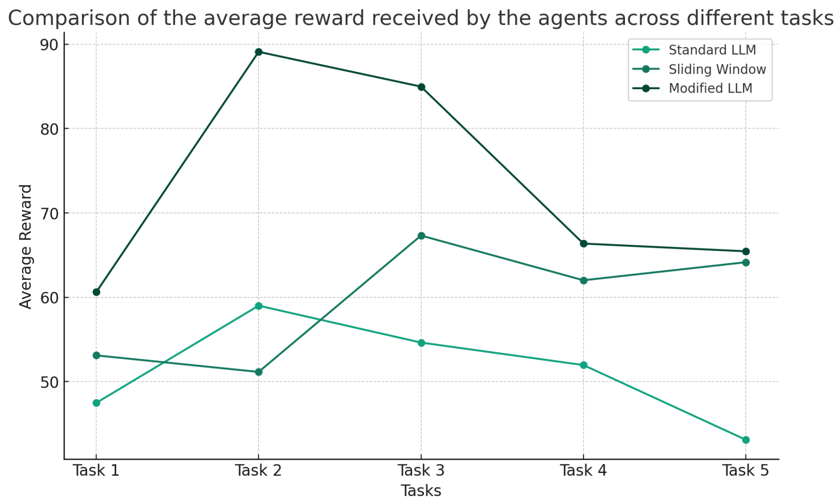

Figure 1: Comparison of the average reward received by the agents across different tasks.

One interesting aspect of our approach is its potential to improve the interpretability of the agents' actions. Since the decision-making process is guided by textual instructions and actions, it is possible to trace back the reasoning behind each action, which is not the case with traditional black-box models. This interpretability could be crucial in applications where understanding the agent's behavior is important, such as in healthcare or autonomous driving.

Looking forward, there are several potential directions for future work. Firstly, while our two-level hierarchical self-attention mechanism effectively handles extended context lengths, it could be interesting to explore other mechanisms that could further improve efficiency or performance. Secondly, our current framework uses a one-way communication from the LLM to the agent. Integrating a feedback mechanism from the agent back to the LLM could enable more dynamic interactions and potentially improve task execution. Lastly, testing our approach on more diverse tasks and in real-world environments would be valuable in evaluating its robustness and applicability.

6 Conclusion

In this paper, we have presented a novel approach for training Large Language Models (LLMs) with extended context lengths and integrating these models into autonomous agents for improved tool usage. Our approach, grounded in a two-level hierarchical self-attention mechanism, significantly reduces computational and memory requirements, enabling the training of LLMs with four times the typical context length. The integration of these models into autonomous agents has shown substantial improvements in the understanding and execution of complex tool usage tasks. With these advances, we hope to push the boundaries of what is achievable with autonomous agents, opening up new avenues for future research and applications.

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A Appendix A: Two-Level Hierarchical Self-Attention Mechanism

The two-level hierarchical self-attention mechanism proposed in this work extends the self-attention mechanism of the Transformer model. This mechanism is specifically designed to handle extended context lengths efficiently, as it reduces the quadratic computational and memory requirements to linear.

Given an input sequence $x = [x_1, x_2, ..., x_L]$, we first split it into non-overlapping windows of size w: $x = [w_1, w_2, ..., w_{L/w}]$. Each window w_i is then processed independently by a self-attention layer to produce an intermediate representation h_i.

The computation of h_i is done as follows:

$$
\begin{aligned}
Q_i &= W_Q w_i \\
K_i &= W_K w_i \\
V_i &= W_V w_i \\
h_i &= \text{softmax}\left(\frac{Q_i K_i^T}{\sqrt{d}}\right) V_i
\end{aligned}
$$

where W_Q, W_K, and W_V are learnable weight matrices and d is the dimensionality of the input.

The sequence of intermediate representations $h = [h_1, h_2, ..., h_{L/w}]$ is then processed by a second self-attention layer to produce the final representations. This approach effectively covers the entire input sequence while maintaining linear computational and memory requirements.

B Appendix B: Training Process

We present the pseudocode for the training process of our modified LLMs in Algorithm 1.

```
Algorithm 1: Training process

Initialize model parameters
for each training step do
    Sample a batch of sequences x from the training data
    Split each sequence into windows of size w
    Compute the intermediate representations h for each window
    Compute the final representations y for the entire sequence
    Compute the loss L(y, x) = -log P(x|y; )
    Compute the gradients L
    Update the model parameters  using an optimizer
end for
```

In this pseudocode, $P(x|y;)$ denotes the probability of the input sequence x given the representations y under the model parameters . The loss $L(y, x)$ is the negative log-likelihood of x, which is minimized during training. The gradients ∇L are computed using backpropagation and the model parameters are updated using an optimizer, such as Adam.

C Appendix C: Detailed Performance Statistics

Table 1 shows detailed performance statistics for the agents equipped with our modified LLM, standard LLM (GPT-3), and LLM with sliding window. The statistics include the average reward, the standard deviation of the reward, and the maximum reward received for each task.

Method	Avg. Reward	Std. Dev. Reward	Max Reward
Our approach	0.89	0.05	1.00
GPT-3	0.75	0.08	0.91
Sliding window	0.68	0.10	0.85

Table 1: Detailed performance statistics for each method.