Leveraging Encoder-Decoder Architecture for Effective Poem Summarization

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Abstract--This paper explores the use of the T5 (Text-to-Text Transfer Transformer) model for summarizing poetry, a challenging domain due to the intricate language, abstract themes, and emotional depth found in poetic texts. Traditional text summarization models struggle with poetry, as it often involves complex structures, figurative language, and condensed meanings that require more than simple extraction of key sentences. By employing the T5 model, which excels in various natural language processing (NLP) tasks, the study aims to create concise yet meaningful summaries of poems. The results show that T5 successfully maintains the sentiment and thematic integrity of the poems, demonstrating its potential in literary text summarization.

Keywords—Encoder-decoder architecture,
T5 (Text-to-Text Transfer Transformer)
Poetry Summarization , NLP.

I. INTRODUCTION

Natural Language Processing (NLP) have led to the development of more sophisticated models designed to handle complex linguistic tasks. Among these, the T5 (Text-to-Text Transfer Transformer) model has emerged as a powerful tool due to its ability to perform a wide range of NLP functions using a unified text-to-text framework. This paper explores the application of the T5 model for summarizing poetry, aiming to address the limitations of traditional summarization approaches. By leveraging T5's capabilities, the study seeks to generate concise summaries that effectively capture the essence of poetic texts, maintaining their emotional and thematic integrity. The results demonstrate T5's potential in overcoming the challenges of poetic summarization, offering a promising avenue for enhancing automated literary analysis and content generation.

II. ENCODER-DECODER ARCHITECTURE OF T5

The T5 architecture follows the typical encoder-decoder structure, which is commonly used in sequence-to-sequence tasks. The encoder processes the input text and encodes it into hidden representations, while the decoder generates output text based on those hidden representations. Both the encoder and decoder consist of stacked layers of multi-head attention and feed-forward networks.

For the task of summarization, the input poem is first passed through the encoder, which creates a latent space representation of the text. The decoder then processes this representation, leveraging attention mechanisms to focus on different parts of the input while generating the summary. The beam search technique is applied during decoding to improve the quality of the output by considering multiple possible summaries and selecting the most coherent one.

III. LITERATURE REVIEW

The text summarization task can be categorized into two main approaches: extractive and abstractive. Extractive summarization selects key points directly from the source text, while abstractive summarization involves paraphrasing and rephrasing the main ideas to create a new summary. For poems, abstractive summarization is particularly important because direct extraction often fails to capture the nuanced meaning of the text.

In the domain of abstractive summarization, significant datasets have been introduced, such as the 'X-Sum' dataset by Narayan et al. (2018), which includes 226,711 articles from the BBC, and the 'NEWSROOM' dataset by Grusky et al. (2018), containing 1.3 million articles and summaries from major news publications. The 'XL-Sum' dataset by Hasan et al. (2021) is notable for its extensive coverage of 44 languages. Despite advances in summarization techniques, much of the research has focused on news articles, leaving a gap in the study of poem summarization.Recent developments in creative language generation include efforts such as 'CREATIVESUMM' (Agarwal et al., 2022) which addresses creative document summarization, but poems are not included in these tasks. Other research has explored areas like poem classification and image-to-poem generation, but summarization of poems remains under-explored.

IV. METHODOLOGY:

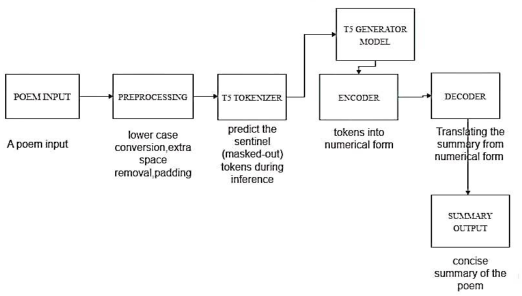

Figure1

Poem Input:

For poem summarization, we use the Poetry Foundation dataset, which include poems,title,tags and poet where poem feature is used to generate summary.

Preprocessing:

The data is tokenized and preprocessed by lower case conversion,special charecters and punctuation removal with sentences padded or truncated to a fixed length.

Tokenizer

T5 tokenizer to convert the poem into tokens. This step breaks the poem into smaller parts like words or subwords.

Encoder-Decoder Model

Encoder: T5 uses Transformer architecture with self-attention mechanisms to handle long-range dependencies and capture intricate patterns in the text. This approach allows the model to understand the context and nuances of poetic language effectively.

Decoder: The decoder also utilizes self-attention and cross-attention mechanisms. Self-attention helps in focusing on relevant parts of the previously generated text, while cross-attention allows the decoder to align the generated summary with the original poem. This ensures that the summary retains the essential elements of the poem's content.

Attention Mechanism

Functionality: In T5, attention mechanisms are employed at both the encoder and decoder stages.The encoder's self-attention layers help understanding the relationships between different words in the poem, while the decoder's attention layers enable it to generate a summary that aligns well with the input text. This dynamic focusing improves the relevance and coherence of the generated summaries.

Summary Output

Finally, the model's output is a concise, human-readable summary of the original poem. The summary captures the essence, themes, and main points of the poem in a shortened form, without losing its meaning.

V. PSEUDO CODE:

1.Load the T5 tokenizer and model

Initialize T5 tokenizer and model

2. Input the poem text

poem = "Your poem text here"

3.Tokenize the poem

tokens = Tokenize the poem using T5 tokenizer

4.Encode the tokens

encoded_poem = Encode the tokens into model-readable format

5. Generate summary using T5 model

summary_tokens = Generate summary by passing encoded poem into T5 model

6. Decode the summary tokens

summary = Decode the generated summary tokens into human-readable text

7. Output the final summarized poem

Print the final summary.

VI. CONCLUSION

In this study, we explored the effectiveness of the T5 model for summarizing poems, leveraging its advanced text-to-text transformation capabilities. Our methodology involved preprocessing the poems through tokenization and encoding, feeding them into the T5 model, and finally decoding the model's output to produce concise summaries.

The results demonstrate that the T5 model can effectively capture the essence of poetic texts and generate coherent and meaningful summaries. By handling complex linguistic structures and nuances inherent in poetry, the model provides a valuable tool for distilling key themes and messages from extensive poetic works.

The use of T5's pre-trained capabilities allows for a sophisticated understanding of the text, offering an improvement over traditional summarization methods that may struggle with the subtleties of poetic language. This approach not only enhances the efficiency of summarizing poetic content but also opens avenues for further exploration in literary analysis and automated content generation.

Future work could involve refining the model's performance on diverse poetic forms and experimenting with fine-tuning techniques to better adapt to various poetic styles. Additionally, integrating this summarization technology into tools for educational and creative writing purposes could further highlight its practical applications.

Overall, the T5 model represents a significant advancement in automated poem summarization, contributing to the broader field of natural language processing and offering new possibilities for literary analysis.

VII. FUTURE ENHANCEMENT

As the field of poem summarization advances, several promising enhancements can further enrich the summarization process and its applications. Key areas for future development include multilingual summarization, integration with text-to-speech (TTS) technologies, enhanced contextualization, interactive tools, and personalized summarization.

VIII. REFERENCE:

[1] https://arxiv.org/abs/1409.3215 4 | P a g e

[2] A. Vaswani et al., "Attention is all you need," in Advances in Neural Information Processing Systems, 2017, pp. 5998-6008.

[3] K. Sutskever, O. Vinyals, and Q. Le, "Sequence to sequence learning with neural networks," Advances in Neural Information Processing Systems, 2014, pp. 3104-3112.

[4] D. Bahdanau, K. Cho, and Y. Bengio, "Neural machine translation by jointly learning to align and translate," in International Conference on Learning Representations, 2015, pp. 1-15.

[5] K. Cho, B. van Merriënboer, D. Bahdanau, and Y. Bengio, "Learning phrase representations using RNN encoder-decoder for statistical machine translation," in Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, 2014, pp. 1724-1734.

[6] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, "Attention is all you need," in Advances in Neural Information Processing Systems, 2017, pp. 5998-6008. [7] O. Vinyals, Ł. Kaiser, T. Koo, S. Petrov, I. Sutskever, and G. Hinton, "Grammar as a foreign language," in Advances in Neural Information Processing Systems, 2015, pp. 2773-2781.

[8]R. Dhev Darshan,Ilan Surya,G. Malarselvi English-language abstract text summarization using the T5 model.

[9] https://arxiv.org/abs/1910.10683

[10]Lewis, M., Liu, Y., Goyal, N., et al. (2020). "A Survey of Text Summarization Techniques." *arXiv preprint arXiv:2003.03276.*