Abstractive Text Summarization

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***Abstract*—In this paper, we propose an adversarial process for abstract - Live text summarization, The explosive growth of digital data necessitates efficient text summarization techniques. This paper reviews recent advances in deep learning models for text summarization, focusing on Arabic's unique challenges due to morphology, dialects, and limited data sources. It analyzes issues like lacking gold-standard test data, handling out-of-vocabulary terms, and repetitive sentences, and offering potential solutions.**

I. Introduction

The essence of text summarization lies in its capacity to condense extensive textual content while preserving the essence of the original material. By facilitating the rapid delivery of high-quality and succinct content, these techniques have played a pivotal role in managing the ever-expanding digital landscape. Despite their effectiveness, the application of text summarization to the Arabic language presents a unique set of challenges and complexities. Arabic, as one of the most widely spoken languages globally, is a prominent medium for online content sharing. Nevertheless, the field of Arabic text summarization remains relatively underdeveloped, hindered by factors such as the intricate morphological structure of the language, the diversity of its dialects, and the limited availability of reliable data sources. This paper delves into the specific challenges that arise when applying text The true potential of mBART emerges during the fine-tuning process for specific tasks like Arabic text summarization. Researchers can adapt the model to Arabic's nuances by fine-tuning it on relevant datasets , enabling it to generate contextually rich summaries that faithfully capture the source text's essence. Over the past two decades, the internet has witnessed an explosive surge in available data, comprising a vast array of sources such as news articles, journals, book reviews, and more. In this era of information abundance, the need for automated text summarization systems has become paramount. These systems serve as indispensable tools for extracting critical insights from the deluge of text data, sparing users the need to navigate through extensive documents [1]. Text summarization, in essence, is the process of generating concise summaries from longer textual documents using specialized software. These summaries encapsulate the pivotal elements of the original content, making information consumption more efficient and accessible [2]. The practice of text summarization can be classified from several vantage points.

II. Our Model

Leveraging mBART for Enhanced Arabic Text Summarization Recent strides in text summarization owe much to the introduction of Facebook AI's mBART (Multilingual BART) model. This extension of the BART framework has brought about a revolution in natural language processing (NLP) and abstractive summarization. Multilingual Prowess: mBART's standout feature is its exceptional multilingual competence. It undergoes comprehensive pre-training on a diverse textual corpus, equipping it to excel not only in major languages but also in those with limited resources, including Arabic. Zero-Shot Translation: A remarkable attribute of mBART is its zero-shot translation capability. This means it can generate summaries in languages it has never explicitly been trained for. In the realm of Arabic text summarization, this versatility is particularly valuable given the language's intricacies and data scarcity compared to more widely studied languages. Fine-Tuning for Arabic: The true potential of mBART emerges when fine-tuned for specific tasks like Arabic text summarization. Through fine-tuning on relevant datasets, it becomes adept at generating contextually rich summaries that faithfully capture the essence of the source text.

III. Approach

In the pursuit of refining our text summarization model, we harnessed advanced training techniques to boost both efficiency and performance. Two key methodologies that significantly influenced our model's training process are Mixed Precision Training and Layer-wise Optimized Rate Adaptation (LorA)

A. Mixed Precision Training

The training of large-scale neural networks for text summarization often poses computational challenges due to the immense memory requirements and processing power demanded by these models. To address this, we leveraged Mixed Precision Training, a technique that combines reduced-precision numerical representations with the maintenance of model accuracy. In Mixed Precision Training, numerical values are stored and computed using lower-precision data types, typically 16-bit floating-point numbers (half-precision), to expedite computations and economize memory. However, certain operations critical for model stability and convergence are executed in full precision (32-bit floating-point numbers). This approach led to substantial reductions in training times while

preserving the desired level of model accuracy. Furthermore, the compatibility of Mixed Precision Training with modern hardware, such as GPUs optimized for mixed precision operations, further amplified its effectiveness.

B. Layer-wise Optimized Rate Adaptation (LorA)

Enhancing training efficiency and convergence dynamics in deep neural networks is pivotal for achieving superior model performance. To accomplish this, we integrated Layer-wise Optimized Rate Adaptation (LorA) into our training regimen. LorA is a dynamic optimization technique that intelligently adjusts learning rates for individual layers of the neural network during training. It capitalizes on the understanding that different layers may converge at varying rates, and thus, applying a uniform learning rate across all layers may not be optimal. Through continuous monitoring of loss and gradient information for each layer, LorA adapts learning rates on a layer-by-layer basis. Layers converging slowly may experience increased learning rates to expedite their progress, while layers converging rapidly may witness reduced learning rates to prevent overshooting. The implementation of LorA facilitated more efficient training dynamics and heightened convergence, translating into improved model performance and stability.

IV. Data Preprocessing

Effective Arabic text summarization relies on high-quality input data. To ensure data consistency and quality, we apply a series of preprocessing functions: - Remove Diacritics: Eliminate diacritics for text uniformity.- Remove Extra Spaces: Enhance text formatting by eliminating extra spaces. - Add Spaces to Special Characters: Ensure proper handling of punctuation marks.- Remove Repeated Characters: Improve readability by reducing consecutive character duplication. - Remove Quotes and Punctuation: Eliminate quotes and punctuation marks to avoid interference.- Uniform Punctuation: Standardize punctuation marks. We employ a Sequential function for the sequential application of these steps, ensuring clean and standardized text data for our Arabic text summarization models. — This streamlined version maintains the essential information about data preprocessing while making it efficient for inclusion in your paper.

V. Datasets

In this section, we introduce the datasets that serve as the foundation of our research in Arabic text summarization. These datasets are carefully chosen to provide diversity and challenge, enabling a comprehensive evaluation of our summarization models.

- LANS (Local Arabic News Summarization): Handling regional variations, dialects, and specific named entities presents distinct summarization intricacies.
- XLSum (XLNet Summarization): XLSum's diversity, including both extractive and abstractive summaries, necessitates methodical model handling.
- WikiHow: Adaptation is essential due to structural and stylistic differences compared to news articles.

VI. Results

- Rouge L: 22,04
- Mean: 81,78
- INV-Norm-KL-DIV: 98,08
- Compression Ratio: 40,15
- Final Score: 83,59

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