NewsSumm-MDS: A Hierarchical Graph-Planner for Multi-Document Abstractive Summarization of Indian English News

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Abstract

Multi-document abstractive summarization aims to generate a concise and coherent summary from multiple documents describing the same event, a task that is particularly challenging for news data due to redundancy, factual consistency, and cross-document entity alignment. The recently introduced NewsSumm dataset provides a large-scale, human-annotated benchmark for Indian English multi-document news summarization, enabling systematic evaluation of long-context and large language models. This project focuses on implementing and fine-tuning a suite of open-weight summarization models and proposes a novel Hierarchical Graph-Planner (HGP) architecture that integrates sentence- and document-level encoders with a cross-document graph aggregator and planning module to guide abstractive decoding. The proposed approach aims to improve factual coverage, reduce redundancy, and enhance coherence across multiple news sources. Evaluation is conducted using ROUGE-1, ROUGE-2, ROUGE-L, and BERTScore matrices with statistical confidence intervals to establish strong baselines and assess the effectiveness of structured planning for multi-document news summarization.

Introduction

Abstractive summarization has made significant progress with the development of pre-trained transformer models; however, most existing research has primarily focused on single-document summarization. Multi-document summarization (MDS) remains a challenging task due to the need for effective information fusion, redundancy reduction, and factual consistency across multiple documents describing the same event. News articles often contain overlapping yet complementary information, temporal updates, and diverse viewpoints, making simple document concatenation insufficient for high-quality summary generation.

Indian English news introduces additional challenges, including region-specific entities, diverse geographic references, and domain-specific writing styles. The recently proposed **NewsSumm** dataset addresses a major gap in this area by providing a large-scale, human-annotated benchmark for multi-document news summarization in Indian English. The dataset organizes multiple articles into event-based clusters, each paired with a professionally written reference summary, enabling systematic evaluation of multi-document summarization models.

This project aims to systematically evaluate modern open-weight summarization models on the NewsSumm dataset and propose a novel architecture tailored for multi-document news synthesis. We investigate long-context encoder–decoder models such as PRIMERA, LED, and LongT5, along with instruction-tuned large language models fine-tuned using parameter-efficient techniques. Beyond establishing strong baselines, we introduce a hierarchical graph-based planning model that explicitly captures cross-document relationships and guides the abstractive generation process. Through rigorous evaluation and analysis, this work seeks to advance multi-document abstractive summarization for Indian news and provide reproducible benchmarks for future research.

Research Gaps

1. Lack of models specialized for Indian English news summarization
2. Limited exploration of graph-based aggregation for large MDS datasets
3. Insufficient use of planning mechanisms in abstractive MDS
4. Redundancy control across multi-article clusters remains weak
5. Hallucination persists in long-context summarization
6. Limited benchmarking of LoRA-based LLMs for MDS
7. Poor modeling of cross-document entity relationships
8. Absence of cluster-level evaluation confidence intervals
9. Limited reproducibility in large-scale MDS experiments
10. Lack of domain-aware adaptations for regional news data

Research Objectives

1. Study the NewsSumm dataset structure and annotation scheme
2. Implement a unified preprocessing and data loading pipeline
3. Fine-tune long-context encoder–decoder summarization models
4. Fine-tune instruction-tuned LLMs using LoRA
5. Build a unified evaluation framework using ROUGE and BERTScore
6. Design a hierarchical graph-based summarization architecture
7. Integrate a planning module for structured summary generation
8. Reduce redundancy and hallucination via auxiliary losses
9. Benchmark the proposed model against 10 baseline models
10. Perform qualitative error analysis on generated summaries

Proposed Model Architecture

The proposed **Hierarchical Graph-Planner (HGP)** model consists of three main components, as illustrated in **Figure 1**.

1. **Hierarchical Encoder:** Each document within a news cluster is encoded independently using a shared long-context encoder. Both sentence-level and document-level embeddings are extracted to preserve local and global contextual information.

2. **Graph Aggregator:** Sentence- or entity-level embeddings across documents are organized into a graph based on semantic similarity and entity overlap. A graph neural network propagates cross-document information through this structure to compute salience-aware representations.
3. **Planner-Conditioned Decoder:** A planning head predicts key content units or bullet-level guidance from the aggregated graph representations. These planner outputs condition the abstractive decoder, which generates the final summary by attending to both the planner signals and the encoded document representations.

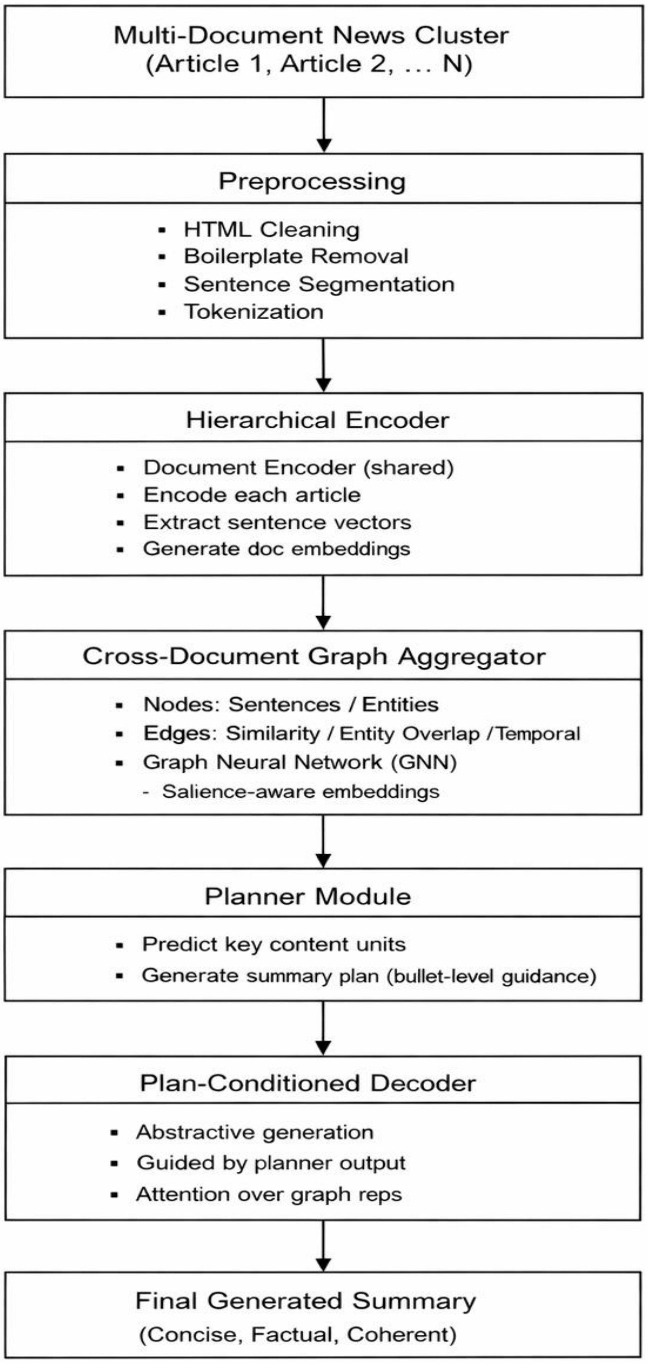

Figure 1. Proposed HGP Architecture

Comparison Methodology

The proposed model is evaluated against ten strong baseline models on the NewsSumm dataset, including PRIMERA, LongT5, LED, Flan-T5-XL, Flan-T5-XXL, Mistral-7B-Instruct, LLaMA-3-8B-Instruct, Qwen2-7B-Instruct, Gemma-2-9B-Instruct, and Mixtral-8x7B-Instruct. All models follow identical preprocessing pipelines, document concatenation strategies, and evaluation settings to ensure a fair comparison. Encoder–decoder models are fine-tuned using full supervised training, while decoder-only large language models are fine-tuned using parameter-efficient LoRA techniques. Evaluation is performed on the official test split using ROUGE-1, ROUGE-2, ROUGE-L, and BERTScore, with mean scores and corresponding confidence intervals reported.

Conclusion

This project presents a comprehensive benchmarking study of open-weight summarization models on the NewsSumm dataset and introduces a novel Hierarchical Graph-Planner architecture for multi-document news summarization. By explicitly modeling cross-document relationships and incorporating structured planning into the generation process, the proposed approach aims to address key limitations of existing methods, including redundancy and hallucination. The expected outcomes include strong baseline benchmarks, reproducible experimental pipelines, and a scalable model design suitable for international journal and conference publications.

Related Work

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