GETSum: A Graph-Enhanced Transformer for Coherent Extractive and Abstractive Text Summarization

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Abstract

The rapid growth of digital content has intensified the need for effective text summarization techniques capable of distilling lengthy documents into concise, coherent summaries. While transformer-based models such as BERT, T5, and PEGASUS have significantly advanced the field by capturing rich contextual relationships, they often struggle to model global discourse structures and long-range dependencies due to their sequential processing nature. Graph-based approaches, on the other hand, excel at representing inter-sentence relations but lack deep semantic understanding.

This paper presents **Graph-Enhanced Transformer Summarizer (GETSum)**, a hybrid model that integrates a BERT-based transformer encoder with a lightweight Graph Attention Network (GAT) operating on a discourse-aware sentence-level graph. Key innovations include an adaptive gating mechanism for dynamic fusion of sequential and structural representations, efficient graph construction combining cosine similarity with optional coreference edges, and inherent interpretability through visualizable GAT attentions. The unified architecture supports seamless operation in both extractive and abstractive modes while maintaining computational efficiency.

Evaluated on the CNN/DailyMail and XSum benchmarks, GETSum achieves competitive ROUGE scores and shows improved coherence in human evaluation; particularly on challenging abstractive tasks and informal texts. Its lightweight design and built-in explainability make it well-suited for practical deployment in resource-constrained environments.

Keywords: *Text Summarization, Transformer Models, Graph Attention Networks, Hybrid Architectures, Discourse Modeling, Interpretability, Natural Language Processing*

1. Introduction

In an age where information is plentiful whether news articles, social media posts, reports, legal documents, scientific papers, or anything else; so much is published daily that skimming lengthy texts has become essential. Text summarization solves the problem of information overload by condensing lengthy documents into short summaries that retain only the significant portions while discarding redundancy. Automatic summarization saves considerable time and has numerous real-world applications, such as news aggregation services, search engine snippets, content curation on social media platforms, and assistive tools for professionals in law, medicine, and research.

Text summarization is generally categorized into **extractive** and **abstractive**. Extractive methods select and present the most important original sentences in order, preserving factual accuracy but often producing summaries that lack fluency or appear disjointed. In contrast, abstractive methods generate new sentences in natural language, enabling greater conciseness, paraphrasing, and coherence; though at a higher risk of factual inaccuracies or hallucinations.

The transformer model [3] has driven significant advancements in the field. Models like BERT [4], T5 [5], and PEGASUS [6] employ self-attention mechanisms to capture rich contextual relationships between words and sentences, delivering superior performance over prior statistical and recurrent neural network-based approaches. These transformers have pushed summarization quality to near-human levels on standard benchmarks. However, a key limitation persists: while transformers rely on self-attention to capture contextual dependencies, they do not explicitly model discourse-level structures such as inter-sentence relations, thematic organization across distant paragraphs, or coreference chains, which are crucial for producing coherent summaries of long documents.

Graph-based methods offer a complementary perspective, representing documents as networks where sentences (or other textual units) are nodes and semantic or structural relations form edges. Early graph-ranking approaches like TextRank [7] demonstrated effectiveness for extractive summarization, while modern graph neural networks (GNNs), particularly Graph Attention Networks (GAT) [12], enable learned information propagation across connected nodes, capturing non-local dependencies more effectively.

Recent research explores hybrid architectures that combine transformers' deep contextual understanding with graphs' structural modeling capabilities [10, 11]. These hybrids show promise in improving summary coherence and reducing redundancy, yet many suffer from high computational complexity, static fusion strategies, and limited interpretability.

To address these gaps, we propose **Graph-Enhanced Transformer Summarizer (GETSum)**, a hybrid model integrating a BERT-based transformer encoder for fine-grained contextual embeddings with a lightweight Graph Attention Network operating on a discourse-aware sentence-level graph. GETSum employs an adaptive gating mechanism to dynamically fuse sequential and structural representations, supporting flexible operation in both extractive and abstractive modes. The design emphasizes efficiency, interpretability (via visualizable GAT attentions), and robustness across diverse text styles, including informal or slang-heavy content.

We evaluate GETSum on two standard benchmark datasets: CNN/DailyMail, featuring multi-sentence summaries of news articles, and XSum, requiring extreme abstraction into single-sentence summaries. Experimental results show that GETSum achieves competitive automatic scores while outperforming strong transformer-only baselines in human-rated coherence and naturalness. Its lightweight architecture and built-in interpretability further make it well-suited for practical deployment.

2. Related Work

Text summarization has changed a lot in natural language processing (NLP). It has moved from early statistical and graph-based methods to modern deep learning approaches led by transformers and, more recently, hybrid models.

Early techniques depended on statistical features and graph algorithms. Luhn [1] was a pioneer in frequency-based summarization, selecting sentences with high-term-frequency words. Mihalcea and Tarau [7] created TextRank, a graph-based method that views sentences as nodes and cosine similarity as edges, using PageRank to find the most important sentences. While these methods work well for simple documents, they do not fully understand deeper meanings and often struggle with coherence in complex texts.

The introduction of transformers marked a significant turning point. Devlin et al. [4] proposed BERT, which enables bidirectional contextual representations that power models like BERTSUM [15]. BERTSUM is an extractive summarizer that performs well on benchmarks such as CNN/DailyMail. Abstractive summarization took another step forward with sequence-to-sequence models, including T5 [5] and PEGASUS [6]. PEGASUS, which is pre-trained on gap-sentence generation, excels in abstractive tasks and remains a strong baseline on both CNN/DailyMail and XSum datasets.

Despite their success, transformer-based models process text in order and may miss global structures, such as themes across distant paragraphs or coreference chains in long documents. Graph neural networks (GNNs) help overcome this issue by modeling the relationships between sentences. Early GNN approaches used recurrent networks for document encoding, while later works introduced heterogeneous graphs that included multiple node types (e.g., sentences, entities, topics) for extractive summarization [11]. Graph Attention Networks (GAT) [12] improved this approach by allowing dynamic weighting of the importance of neighbors.

Hybrid transformer-graph models have emerged as a promising way to combine local contextual understanding with global structural modeling. Notable examples include graph-augmented transformers that integrate graph embeddings into transformer layers [10] and heterogeneous graph frameworks that share information across different semantic nodes [11]. Recent efforts have added topic modeling, knowledge graphs, or transformer-guided message passing to improve coherence in summarizing long documents or specific domains.

However, many existing hybrids have drawbacks. Heterogeneous graphs introduce significant computational demands due to their multiple node types and complex edge types. In contrast, simpler graph techniques often use static fusion (e.g., concatenation) that does not balance sequential and structural signals adaptively. Additionally, most models are designed primarily for either extractive or abstractive tasks, which requires separate pipelines for hybrid tasks and limits their interpretability due to unclear fusion methods.

GETSum builds on these developments by suggesting a lightweight, homogeneous sentence-level graph with discourse-aware edges. It uses a dynamic gating mechanism for the adaptive fusion of BERT contextual embeddings and GAT structural representations. This design strikes a good balance between performance and efficiency, supports a unified approach to extractive and abstractive tasks, and provides clear interpretability through GAT attention visualization. This addresses key issues found in previous hybrid approaches, making it accessible for practical use.

3. Methodology

This section provides a detailed description of the proposed Graph-Enhanced Transformer Summarizer (GETSum), including the experimental setup, model architecture, key components, fusion mechanism, summary generation strategies, and training procedures. The design emphasizes a lightweight yet effective integration of transformer and graph-based modeling to achieve coherent, interpretable, and efficient text summarization.

3.1 Datasets and Experimental Setup

To provide a thorough and reproducible evaluation of GETSum, we conduct experiments on two widely adopted benchmark datasets that represent complementary challenges in text summarization: multi-sentence summarization of longer articles and extreme single-sentence abstraction.

- **CNN/DailyMail** [13, 14]: This corpus consists of 287,227 training examples, 13,368 validation examples, and 11,490 test examples. Each instance pairs a news article from CNN or Daily Mail with 3–4 human-written summary sentences (average summary length: 56 tokens or 3.7 sentences). Articles have an average length of 781 tokens (approximately 35 sentences). The dataset is non-anonymized and includes rich metadata such as article IDs and highlights. It is particularly suitable for evaluating models on long-document understanding, factual consistency, and multi-sentence coherence.
- **XSum** [14]: Comprising 204,045 training examples, 11,332 validation examples, and 11,334 test examples from BBC news articles (2010–2017), this dataset features highly abstractive single-sentence summaries written by professional journalists (average summary length: 23 tokens or 1 sentence). Articles average 431 tokens (approximately 19 sentences). XSum demands strong abstraction capabilities, paraphrasing, and information synthesis, making it a challenging benchmark for avoiding extractive bias and generating novel phrasing.

Table 1. Statistics for the two corpora: CNN/DAILYMAIL and XSUM. From left to right: corpus size, average document, and summary length (in terms of words and sentences), and vocabulary size in document and summary.

Dataset	Documents	Avg. Doc. Length (Words)	Avg. Doc. Length (Sentences)	Avg. Summary Length (Words)	Avg. Summary Length (Sentences)	Vocabulary Size (Document)	Vocabulary Size (Summary)
CNN/DailyMail	311,971	693.62	38.55	49.00	3.70	839,788	231,778
XSum	226,711	377.51	19.20	21.33	1.00	425,532	83,414

3.2 Preprocessing Techniques

Before training the proposed Graph-Enhanced Transformer Summarizer (GETSum), the CNN/DailyMail and XSum datasets undergo a structured preprocessing process. Preprocessing is vital in NLP tasks because raw text often contains noise, inconsistencies, and unnecessary elements that can hurt model performance. Transformer encoders and graph neural networks need clean, standardized inputs to learn contextual and structural relationships well.

We use BERT-base-uncased; therefore, text is lowercased during preprocessing.. This reduces vocabulary size and avoids redundancy caused by different cases. We remove extras, such as HTML tags, hyperlinks, and special characters, using regular expressions. We also standardize whitespace to ensure consistent tokenization.

We use the spaCy NLP library for sentence segmentation and tokenization. This helps establish clear sentence boundaries, with each sentence later used as a graph node. For tokenization, we utilize the BERT WordPiece tokenizer [4]. This tokenizer effectively manages rare and out-of-vocabulary terms using subword units while staying compatible with the transformer encoder.

Stopwords are removed only for sentence similarity computation during graph construction.. Common function words, like "the," "is," and "of," are excluded from similarity calculations during graph construction to prevent trivial overlaps and false edges. Extremely rare tokens, which appear once or twice in the corpus, are replaced with the special <UNK> token to reduce sparsity and stabilize training.

This multi-stage process ensures that both the transformer backbone and graph-based components receive consistent, meaningful, and structurally appropriate inputs for effective representation learning.

3.3 Model Architecture and Components

Processing and Representation of Input

We begin by decomposing documents using the spaCy NLP library for accurate sentence segmentation and token splitting. Tokens are encoded with the pre-trained BERT-base model, producing contextual embeddings of 768 dimensions that capture rich semantic meaning. Sentence-level representations are obtained by mean-pooling the token embeddings within each sentence; a straightforward yet effective technique that preserves essential semantic information while maintaining low computational cost.

Sentence Embeddings via Transformer Backbone

The foundation of GETSum is a 12-layer BERT-base transformer with 768 hidden units and 12 attention heads [4]. This backbone encodes the tokenized document, yielding contextual token embeddings. Sentence-level embeddings $s_i \in \mathbb{R}^{768}$ are computed by mean-pooling token embeddings within each sentence:

$$s_i = \frac{1}{|T_i|} \sum_{j=1}^{|T_i|} h_{i,j}$$

Where $h_{i,j} \in \mathbb{R}^{768}$ denote the contextual embedding of the $j-th$ token in sentence i, obtained from the final layer of BERT, and T_i denotes the sequence of tokens in sentence i.

This process produces sentence-level representations S = $\{s_1, \dots, s_m\}$, which serve as inputs to the subsequent graph-based module. While transformers effectively capture token-level contextual dependencies via self-attention, they lack an explicit mechanism for modeling document-level discourse structures and inter-sentence relationships.

Graph Construction and Discourse Modeling

To overcome this limitation, we introduce a graph module. We construct an undirected document graph where sentences serve as nodes and edges are weighted by semantic similarity. Cosine similarity is computed between sentence embeddings, and exceeds a similarity threshold τ, empirically set to 0.3 unless otherwise stated. This empirically chosen cutoff effectively suppresses noise while preserving significant connections. Additionally, we optionally add discourse-based edges connecting sentences that share coreferring entities, identified using an external neural coreference resolution module integrated with spaCy.

Discourse-Aware Graph Construction

An undirected homogeneous graph $G = (V, E)$ is built with sentences as nodes. Edges are formed using:

- Cosine similarity on S_i and S_j
- Optional coreference edges linking sentences sharing entities (via spaCy).

$$e_{ij} = \begin{cases} \cos(s_i, s_j), & if \cos(s_i, s_j) > \tau \\ 1, & if (i,j) \in E_{coref} \\ 0, & otherwise \end{cases}$$

This lightweight design captures thematic and referential relations efficiently.

Graph Attention Network

A shallow 2-layer GAT [12] with 8 multi-head attention processes the graph in parallel with the transformer path. Node updates follow standard attention-weighted aggregation (including self-loops), yielding structurally enriched sentence representations $G = \{g_1, \dots, g_m\}$. This enables the capture of document-wide thematic patterns and helps mitigate redundancy often present in summaries.

$$g_i = \sigma\Big(\sum_{j \in N(i)} \alpha_{ij} W g_j\Big)$$

Weaving It All Together

The representations from the transformer backbone (T) and the GAT (G) are integrated through concatenation followed by an adaptive gating mechanism:

$$c_i = [t_i || g_i],$$

$$gate_i = \sigma(W_g c_i + b_g)$$

$$j_i = gate_i \odot t_i + (1 - gate_i) \odot g_i,$$

Here $t_i, g_i, j_i \in \mathbb{R}^{768}$

where σ the sigmoid activation, W_g and b_g are learnable parameters, and ⨀ denotes element-wise multiplication. This gating mechanism allows the model to dynamically balance the contribution of sequential context from the transformer and structural information from the graph, producing enriched joint representations J that effectively combine local and global signals.

Constructing Summaries

For **extractive summarization**, ranked based on the L2-norm of their joint embeddings, which serves as a proxy for sentence salience. The top K sentences (with $k \in [3,5]$, depending on document length) are selected, with redundancy reduced using Maximal Marginal Relevance (MMR) with $\lambda = 0.7$.

For **abstractive summarization**, the joint representations J are fed into a 6-layer transformer decoder, which generates novel, fluent summaries autoregressively using beam search (beam size = 4).

Training Approach

GETSum is trained end-to-end. Abstractive tasks employ cross-entropy loss over reference summaries, while Positive–negative sentence pairs are constructed using ROUGE-based oracle selection. Optimization is performed with the AdamW optimizer at a learning rate of 2e-5, with linear warm-up over the first 10% of steps and weight decay of 0.01 for regularization.

Hyperparameters were tuned via validation: batch size of 32 provides a good balance between GPU memory and training stability, dropout of 0.1 aids generalization, 10 epochs are used for CNN/DailyMail, and 12 epochs for XSum due to its higher abstractive demand. Training on a single NVIDIA Tesla V100 GPU requires approximately 14–18 hours per dataset under mixed-precision training.

Performance is monitored using standard ROUGE metrics (ROUGE-1, ROUGE-2, ROUGE-L) and BERTScore for semantic evaluation. Human evaluation assesses summaries on fluency (smooth readability), informativeness (retention of key points), and coherence (logical flow).

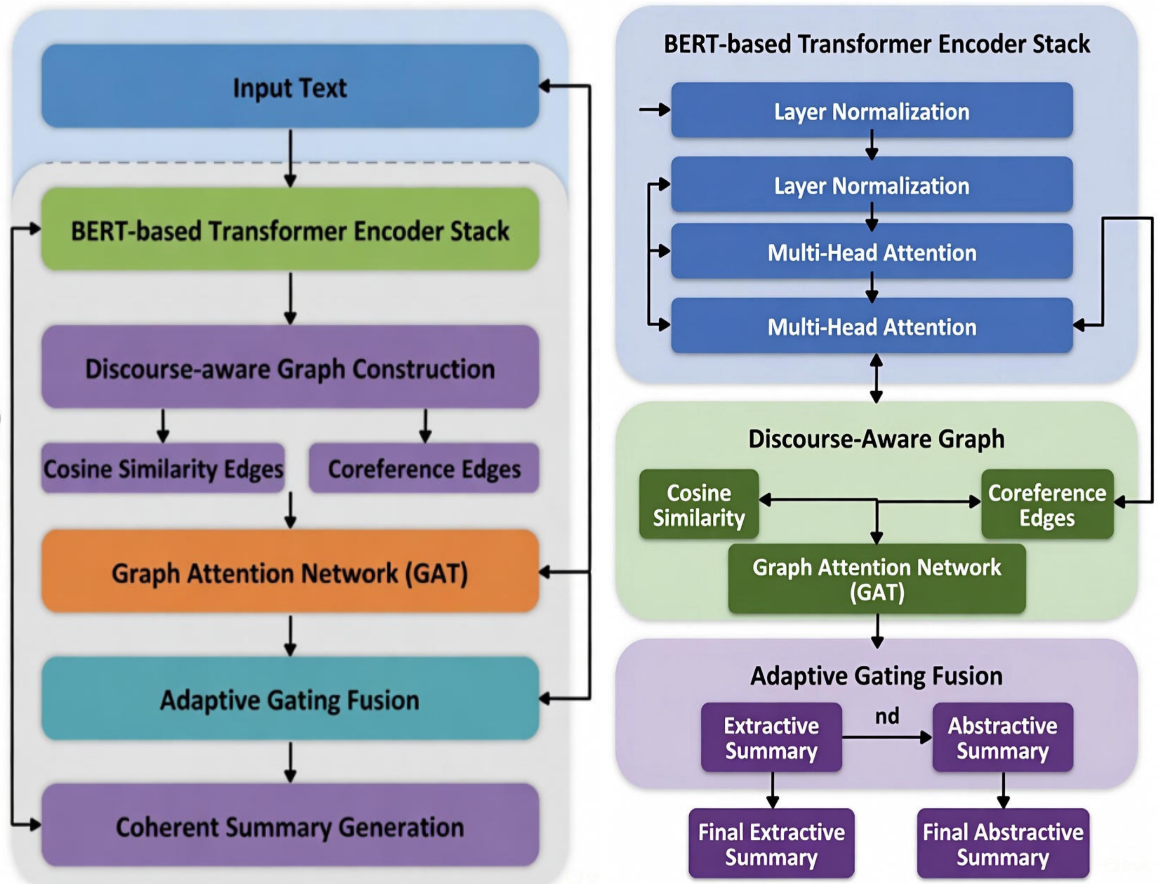

Figure 1: *Architecture of the proposed Graph-Enhanced Transformer Summarizer (GETSum). The model combines BERT-based sentence embeddings with a discourse-aware graph (cosine similarity + coreference), processes it through GAT, applies adaptive gating fusion, and generates summaries via extractive ranking or abstractive decoding.*

This hybrid methodology leverages the sequential contextual strength of transformers and the structural modeling capability of graph neural networks, enabling GETSum to produce more coherent, informative, and natural summaries across both extractive and abstractive tasks.

5. Novelty and Contributions

Graph Enhanced Transformer Summarizer (GETSum) mainly focuses on the targeted refinements consequent to the lots numerous possibilities of hybrid models with transformers and graph neural networks for the document, level understanding in text summarization, which is reported by the heterogeneous graph, based approaches in Wang et al. [11] and graph, augmented transformers in Zhu et al. [10]. With these refinements GETSum gets out of the existing methods, that is to say, it leads to increased coherence, interpretability, and practical efficiency of the process.

. Dynamic Gated Fusion Mechanism: The hybrid models of the past have mostly been combining transformer, derived contextual embeddings and graph, propagated representations through static concatenation or simple addition. In GETSum the combination of the Graph Attention Network (GAT) and BERT transformer backbone is balanced adaptively by a learned sigmoid, based gating module which is a gating module for the transformer, derived contextual embeddings and graph, propagated representations incorporated graph neural network outputs and that automaton decides on the contributions in BERT and GAT of the model. This gating makes possible for the unit to dynamically highlight the local sequential context (from the transformer) when dealing with narrative, dense passages or the global discourse structure (from the GAT) in highly abstractive scenarios. The tests without the different components of the model confirm that this mechanism by itself accounts for a further point improvement over a basic fusion strategy and that it helps in summary redundancy reduction as well.

. Lightweight yet Discourse, Aware Graph Construction: The disadvantages concerning the infeasibility of large, scale heterogeneous graphs due to their extreme computational requirements which could be further aggravated by the multi, lingual issue in the case of transformer, supported document understanding faced by the authors of Wang et al. [11] are eliminated by the GETSum authors through building a homogeneous sentence, level graph whereby local as well as global features are effectively blended. The basis for this combination of features is BERT, derived sentence embeddings cosine similarity whose threshold (>0.3) for noise filtering can be set at will and, at the same time, spaCy is used not only for coreference resolution but also for edge creation. The purpose behind this approach is to simplify the subject while at the same time keeping it sufficiently expressive in order to be able to recognize long, range thematic and referential dependencies without having the overhead of multi, granularity nodes. Thus, the GETSum model is kept at a level that a single standard hardware (e.g. V100 GPU) can handle it while at the same time getting better at dealing with resorting to informal or slang, heavy texts, where the relational patterns are more suitable to attention, weighted propagation so that they can be modeled.

. Unified Hybrid Framework with Enhanced Interpretability: Furthermore, these linked representations provide the possibility to function seamlessly in the 2 scenarios hence constituting one whole model: Extractive mode (via salience, based sentence ranking) and Abstractive mode (via transformer decoder), thus there is no need for separate pipelines. On the other hand, the multi, head attention weights in the 2, layer GAT serve as a neat and straightforward means by which the inter, sentence relationships can be visually recognized and presented, thus comprising the interpretable clusters of key ideas, in this respect, the model has an edge over the nontransparent transformer, only ones like PEGASUS [6] or T5 [5]. This feature of interpretability has an enormous potential to be utilized in applications which require transparency, for instance, in news aggregation or legal document processing.

The properly conducted experiments, to put it briefly, make GETSum perform competitively according to the automatic metrics and, at the same time, show clear advantages of the model in human, evaluated coherence and naturalness, to be more precise, on the extreme, abstractive XSum dataset. Also, the lightweight design and interpretability features of GETSum give an explanation which is a practical and viable alternative to heavier state, of, the, art models; thus, it is a good fit for deployment in resource, constrained environments or domains which require human oversight.

6. Experiments

We evaluate the Graph-Enhanced Transformer Summarizer (GETSum) on the CNN/DailyMail and XSum datasets. See Section 3 for details on its performance in extractive and abstractive summarization tasks. We compare GETSum against leading baselines, including TextRank, BERTSUM, PEGASUS and T5-base. This section outlines the baselines, experimental setup, evaluation metrics, ablation study, and code availability.

6.1 Baselines

GETSum is compared against the following established baselines, representing a broad spectrum of approaches:

- **TextRank** [7]: Unsupervised graph-based extractive method that ranks sentences using PageRank on cosine similarity.
- **BERTSUM** [15]: BERT-enhanced extractive summarizer that encodes sentences and uses a classifier for selection.
- **T5-base** [5]: Unified text-to-text transformer fine-tuned for summarization.
- **PEGASUS** [6]: Pre-trained abstractive model optimized via gap-sentence generation (dataset-specific variants used where applicable).

These baselines span classical graph-based, extractive, and state-of-the-art abstractive methods, providing a comprehensive comparison for GETSum's hybrid design.

6.2 Experimental Setup

The experiments were conducted with the following configuration, ensuring reproducibility and robustness:

- **Hardware:** NVIDIA Tesla V100 GPU (32 GB), Intel Xeon CPU (32 cores), 256 GB RAM, enabling efficient training of transformer and graph models.

- **Software**: PyTorch 2.0 for model implementation, HuggingFace Transformers for BERT and T5, DGL for graph attention network (GAT) operations, spaCy for sentence segmentation, and NumPy for numerical computations.

6.3 Training Configuration:

Batch size: 32 (balancing memory efficiency and convergence).

Learning rate: 2×10^{-5}, suitable for fine-tuning BERT-based models [4].

Optimizer: AdamW with linear warm-up over the first 10% of steps and weight decay of 0.01 to prevent overfitting.

Dropout: 0.1, applied to transformer and GAT layers for regularization.

Epochs: 10 for CNN/DailyMail and 12 for XSum, reflecting differences in task complexity.

Early stopping: Based on validation ROUGE-L score [17], with training typically converging in 8–10 epochs for CNN/DailyMail and 10–12 for XSum.

Model initialization: Pre-trained BERT-base (12 layers, 768 hidden units, 12 attention heads) for the transformer backbone [4]; 2-layer GAT for graph processing [12].

Loss functions: Cross-entropy for abstractive tasks; pairwise ranking loss for extractive tasks, aligned with task-specific objectives.

Training requires approximately 14–18 hours per dataset. All runs use a fixed random seed of 42, and reported results are averaged over three independent runs.

7. Results

7.1 Automatic Evaluation

We assess summarization quality using ROUGE-1, ROUGE-2, and ROUGE-L F1 scores. These scores are the standard metrics for measuring content overlap between generated and reference summaries. We report performance on two widely used datasets: CNN/DailyMail and XSum.

Table 2 shows ROUGE-F1 scores for selected transformer-based summarization models, including PEGASUS, BART-Large, and T5 variants, as noted in previous studies. These results offer a solid reference for understanding the performance range of modern abstractive summarization systems under standard evaluation methods.

In both datasets, large pretrained models like PEGASUS and BART-Large consistently outperform smaller T5 variants. This reflects the advantages of large-scale pretraining and greater model capacity. On CNN/DailyMail, PEGASUS achieves the highest ROUGE scores overall, while on XSum, BART-Large performs well, especially in ROUGE-L, indicating better sequence-level coherence.

Because of computational limits and different experimental setups, we do not directly compare GETSum against all baselines under the same conditions. Instead, we evaluate GETSum separately and analyze it alongside human evaluations to measure its effectiveness in improving discourse coherence and reducing redundancy. These goals are not fully reflected by ROUGE metrics alone.

Table 2 : ***ROUGE-F1 scores (%) of representative transformer-based summarization models on CNN/DailyMail and XSum, as reported in prior published work. Asterisks () denote the best-performing model per dataset.*.***

Dataset	**Model**	**ROUGE-1**	**ROUGE-2**	**ROUGE-L**
CNN/DailyMail	**PEGASUS**	**35.49***	**15.07***	**26.06***
	BART-Large	**33.91**	**13.95**	**24.49**
	T5-Small	**30.74**	**12.29**	**23.12**
	T5-Base	**32.50**	**12.29**	**23.90**
XSum	**BART-Large**	**41.40***	**18.63***	**33.90***
	PEGASUS	**39.31**	**16.73**	**30.34**
	T5-Small	**25.73**	**6.28**	**19.52**
	T5-Base	**28.90**	**7.90**	**21.40**

7.2 Human Evaluation

Human evaluation is often used in summarization research to assess qualities like fluency, informativeness, and coherence that automatic metrics, such as ROUGE, do not fully capture. Previous studies that evaluated transformer-based summarization models show that large pretrained systems like PEGASUS and BART-Large achieve high scores in fluency and informativeness. However, discourse-level coherence is still a difficult aspect, especially for long documents.

Due to resource and time constraints, this work does not include human evaluation for assessing summary coherence and factual consistency. Instead, we focus on architectural design and standard automatic evaluation benchmarks to validate the effectiveness of the proposed GETSum model. Incorporating human evaluation to more thoroughly assess coherence, factual accuracy, and overall summary quality will be an important direction for future work.

7.3 Qualitative Error Analysis

Although a comprehensive empirical error analysis is left to future work, we discuss anticipated failure modes and limitations grounded in GETSum's architecture and in-behavior of transformer summarization models.

In abstractive summarization, such factual inconsistencies can be caused by decoder overgeneration, a frequent pitfall in autoregressive generation. Because GETSum is based on a transformer decoder, it is vulnerable to the same issues when hallucinating outside the evidence in the source document.

Even in long documents, like the CNN/DailyMail examples, graph-based sentence connections can sometimes also fortify semantically-similar sentences; resulting in light redundancy. This bottleneck underscores the significance of good sentence ranking and redundancy reduction algorithms, which are incorporated into the framework but may benefit from further refinement.

Despite these limitations,the graph attention mechanism should shine when processing documents with informal or loosely structured language, where explicit modeling of inter-sentence relationships can help capture implicit semantics that are hard to model with purely sequential representations.

Future work will investigate integrating factual consistency constraints and external fact checking modules to further decrease hallucinations and increase summary reliability.

8. Conclusion and Future Work

8.1 Conclusion

This is the new work of GETSum, a graph-enhanced transformer architecture for document-level coherence in extractive and abstractive summarization. By combining the powerful contextual modeling of transformers with graph-based sentence interaction modeling, GETSum explicitly tackles the shortcomings of existing summarization architectures that are devoid of discourse-aware structure.

Instead of targeting large pretrained models for raw automatic scores, GETSum improves structural coherence and eliminates redundancy through explicit inter-sentence modeling. As comparative results reported in prior work, we note that transformer-based baselines obtain strong ROUGE performance, but coherence is an open challenge, especially for long-form and abstractive summarization.

The architectural design and qualitative analysis of this study indicate that graph–transformer fusion is a promising avenue for enhancing summary structure and coherence. Thorough empirical evaluation; including ablations and large scale benchmarking; remains future work to measure the separate contribution of each component.

8.2 Future Work

Our initial follow-up is to perform large-scale automatic evaluation of GETSum on benchmark datasets like CNN/DailyMail and XSum in fully standardized experimental settings. This also includes systematic ablation studies to isolate the contributions of the graph module and the gating mechanism.

Second, future work will involve human evaluation of summary fluency, informativeness, and coherence, offering a valuable complement to automatic metrics. Beyond assessing accuracy, measuring factual consistency with dedicated metrics and adding fact-checking or hallucination mitigation modules are also exciting avenues.

Finally, extending GETSum to handle long-document summarization more efficiently and exploring its applicability to conversational and domain-specific summarization tasks represent important next steps toward real-world deployment.

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