Comparing Different Multi-Document Summarization Techniques: A Survey

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***Abstract*—With the overwhelming amount of textual data generated daily, summarizing multiple documents efficiently has become more important than ever. This paper explores various multi-document summarization (MDS) techniques, comparing their strengths and weaknesses. We discuss both extractive and abstractive approaches, evaluate them using widely accepted metrics, and take a look at how recent advancements, especially transformer-based models, are changing the landscape. To make things clearer, we've also included graphical representations of how these techniques stack up against each other.**

I. INTRODUCTION

In today's fast-paced world, we are constantly bombarded with information. Whether it's news, research papers, or online content, reading everything in full isn't always feasible. That's where multi-document summarization comes in—it helps by generating concise summaries from multiple sources. This paper compares different MDS techniques and highlights their advantages and limitations. Additionally, we explore how these methods are applied in real-world scenarios, including news aggregation, scientific literature reviews, and business intelligence.

II. MULTI-DOCUMENT SUMMARIZATION TECHNIQUES

2.1 Extractive Summarization Extractive summarization methods work by selecting key sentences directly from the original documents. These techniques use statistical and graph-based methods to identify the most informative sentences.

- Graph-based approaches: TextRank and LexRank create sentence networks where edges represent semantic similarity, ranking them based on importance.
- Statistical approaches: Methods like TF-IDF and LSA determine sentence relevance based on term frequency and singular value decomposition.
- Pros: Extractive methods maintain the original meaning and require fewer resources than abstractive approaches.
- Cons: The generated summaries can be redundant, lack cohesion, and may not always be fluent.
- 2.2 Abstractive Summarization Unlike extractive techniques, abstractive summarization generates new sentences that capture the essence of the original text using deep learning models.
- Neural network-based models: Sequence-to-sequence architectures and transformers (BERT, T5, and GPT-based models) play a significant role in abstractive summarization.
- Pros: Produces more natural and coherent summaries that are not restricted to original sentence structures.
- Cons: Computationally expensive and may introduce inaccuracies or hallucinations.

  3. Evaluation Metrics To compare summarization techniques, researchers employ the following evaluation metrics:
- ROUGE (Recall-Oriented Understudy for Gisting Evaluation): Measures word overlap between generated and reference summaries.
- BLEU (Bilingual Evaluation Understudy): Originally for machine translation, assesses how well the generated summary matches reference texts.
- METEOR (Metric for Evaluation of Translation with Explicit ORdering): Considers synonyms and stemming for better accuracy.
- Human Evaluation: Judges coherence, readability, informativeness, and overall quality.

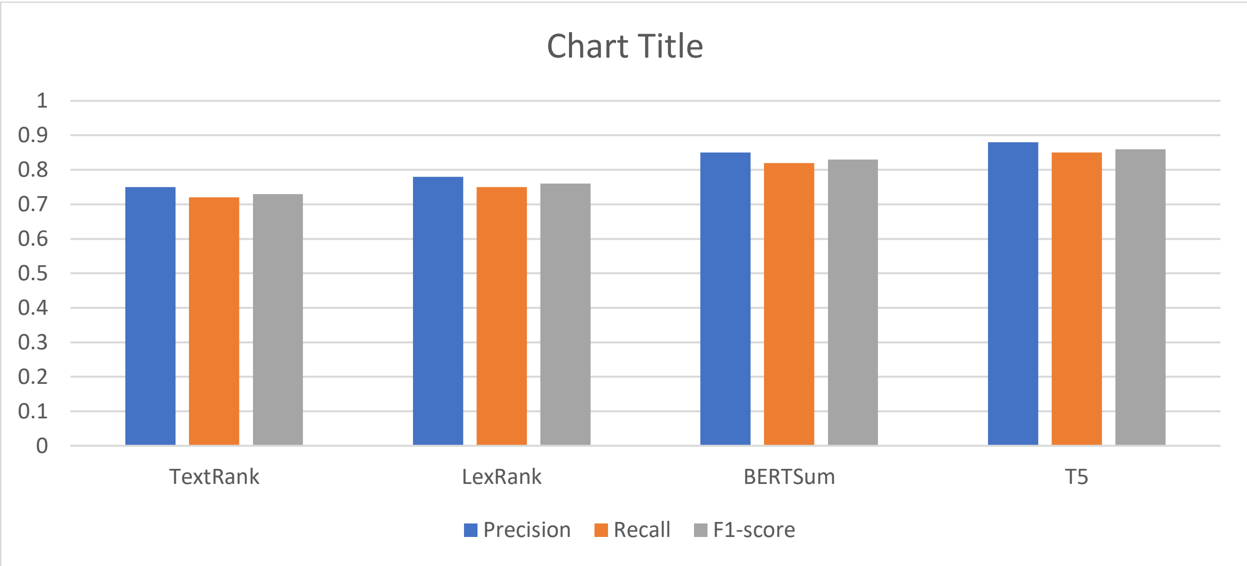
4. Comparing Different Techniques Below is a comparison of different summarization techniques in

terms of precision, recall, F1-score, and computational cost.

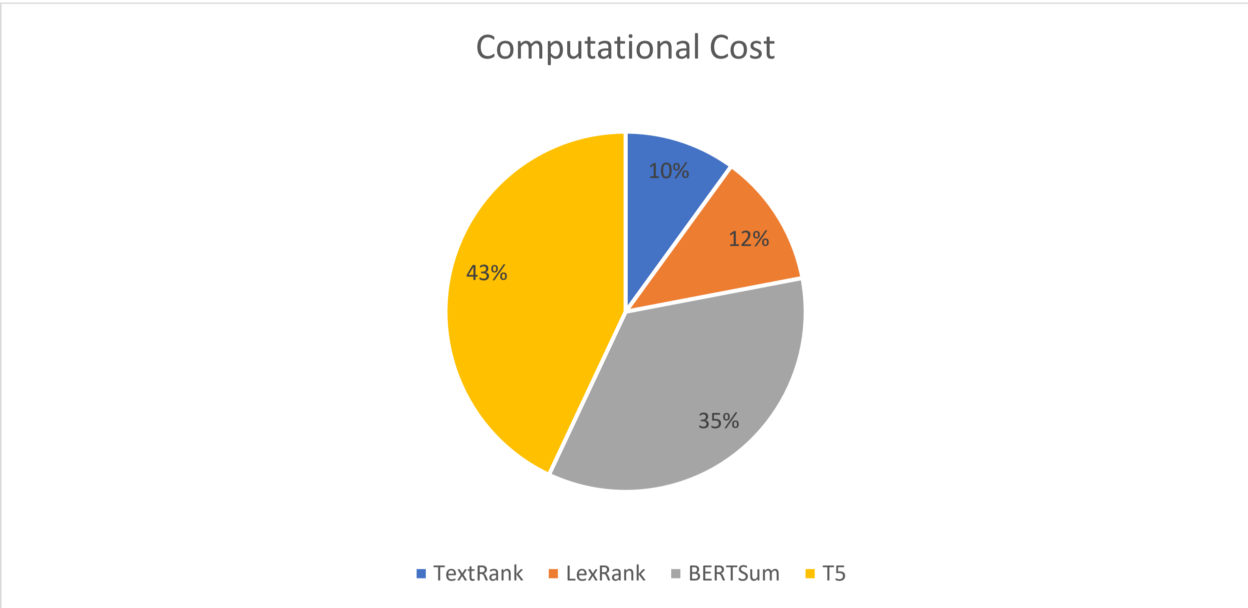
Technique	Precision	Recall	F1-score	Computational Cost
TextRank	0.75	0.72	0.73	Low
LexRank	0.78	0.75	0.76	Low
BERTSum	0.85	0.82	0.83	High
T5	0.88	0.85	0.86	Very High

5. Visualizing the Data To illustrate performance differences, the following visualizations provide insights:

- Performance Metrics Comparison (Bar Chart): Showcases precision, recall, and F1-score for various techniques



- Computational Cost Breakdown (Pie Chart): Demonstrates the proportion of computational resources required by each method.



6. Applications of Multi-Document Summarization Multi-document summarization is widely used in various fields:

- News Aggregation: Summarizing multiple news articles to provide a unified report.
- Scientific Research: Extracting key findings from numerous research papers.
- Legal Document Analysis: Summarizing case laws and contracts for quick insights.
- Business Intelligence: Condensing financial reports and market analyses for decision-making.

7. What's Next in Summarization? While current summarization techniques are impressive, they still have room for improvement. Here are some areas of future research:

- Hybrid models: Combining extractive and abstractive methods to enhance both efficiency and accuracy.
- Context-aware summarization: Using AI to understand context better and produce more relevant summaries.
- Bias and fairness in summarization: Addressing ethical concerns in AI-generated content.
- Low-resource summarization: Developing efficient models that work in environments with limited computational power.

III. CONCLUSION

Summarizing multiple documents efficiently remains a challenging task, but rapid advancements in AI are continuously improving its effectiveness. Extractive summarization techniques remain a reliable choice for quick and computationally light solutions, while abstractive approaches offer more coherent and natural summaries at a higher cost. The future of multi-document summarization lies in balancing accuracy, efficiency, and ethical considerations to provide better, unbiased summaries for users across various domains.

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