Jin et al. proposed a comprehensive survey on Automatic Text Summarization (ATS) methods with a focus on Large Language Models (LLMs) and a “Process-Oriented Schema” perspective. The problem addressed is the limited practical applicability of previous ATS methods and the need for up-to-date evaluations of LLM-based techniques. Their research contribution includes presenting a “Process-Oriented Schema” for ATS that aligns with real-world implementations, reviewing the latest LLM-based ATS approaches, and bridging a two-year gap in the literature. They provide a structured overview of ATS components including data acquisition, text pre-processing, language modeling, and evaluation metrics, and highlight the advantages of LLMs over traditional methods. The study concludes that LLMs significantly enhance summarization quality and flexibility, with future research directions focusing on effective prompt design, domain-specific training, and stabilization of summarization outputs [1].

Işıkdemir proposed a comparative analysis of traditional text summarization approaches and modern NLP transformers. The problem is the growing challenge of extracting relevant information from extensive textual data and choosing the most effective summarization technique. This research evaluates various methods, including unsupervised, supervised, and deep learning techniques, using datasets such as BBC News and CNN/DailyMail. The paper concludes that while traditional methods like LSA can still be effective in specific contexts, transformer-based architectures generally offer superior performance due to their ability to understand complex relationships in text. The findings emphasize the importance of selecting summarization techniques tailored to specific domain requirements and highlight the ongoing need for further advancements in the field [2].

Fecht proposed a thesis on the application of transfer learning techniques to neural text summarization systems. The problem addressed is the limited exploration of transfer learning within text summarization and its potential to enhance summarization performance. The research involves developing a workflow to integrate pre-trained language models into neural summarization tasks and evaluates their effectiveness using the CNN/DailyMail dataset and the CopyNet model. The study demonstrates that transfer learning can improve summarization results, particularly for datasets with fewer historical data, though current models still face limitations due to task-specific components. The thesis concludes that while transfer learning shows promise, further research is needed to adapt these techniques for sequence-to-sequence tasks and explore multi-task learning approaches [3].

Challagundla and Peddavenkatagari proposed a novel framework for abstractive text summarization integrating structural, semantic, and neural approaches. The problem is creating coherent and concise summaries from large volumes of text while handling rare and out-of-vocabulary words effectively. Their framework includes pre-processing with Word Sense Disambiguation, semantic content generalization, and the use of deep sequence-to-sequence models with attention mechanisms. Experimental results on datasets like Gigaword and CNN/DailyMail show that the framework significantly improves handling rare words and outperforms existing deep learning methods. The study concludes that the proposed approach offers a unified and effective solution for abstractive summarization, though future work should focus on refining the model and exploring additional datasets [4].

Kouris et al. proposed a framework for abstractive text summarization using semantic graph representations combined with deep learning techniques. The problem addressed is the challenge of generating summaries from unstructured text in a machine-readable format. Their framework involves semantic graph parsing, construction, and transformation, and evaluates various deep learning models including sequence-to-sequence networks, reinforcement learning, and transformer architectures. The study introduces a novel graph-to-summary prediction approach and a measure for assessing factual consistency in summaries. Experimental results using Gigaword and CNN/DailyMail datasets show promising performance, suggesting that semantic graph-based methods can effectively enhance summarization. The paper concludes that while the framework shows strong potential, further research is needed to improve semantic representation quality and explore more advanced deep learning architectures [5].

**Citations:**

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