A review of Automated Generation of Executive Summaries of Online Meeting using NLP Techniques

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Abstract

Meetings play a critical role in business decision-making, but manually capturing and summarizing discussions is time-consuming and prone to errors. This project introduces an automated system that leverages Natural Language Processing (NLP) to generate concise and actionable summaries from meeting transcripts. While previous research has focused on manual or platform specific solutions, our approach processes transcripts from multiple online meeting platforms, integrating both extractive and abstractive summarization techniques. We utilize TF-IDF and Text Rank for extracting key information, alongside advanced transformer models such as BERT for generating coherent summaries.

Additionally, Named Entity Recognition (NER) and Part-of-Speech (POS) tagging are incorporated to identify crucial details, including decisions made and responsibilities assigned. By automating the summarization process, our system improves meeting efficiency and accuracy. The system's performance will be evaluated using ROUGE scores and stakeholder feedback to ensure practical, high-quality summaries.

Keywords: Natural Language Processing, Summarization, TF-IDF, Text Rank, BERT, NER, ROUGE Scores

I. Introduction

The rise of remote work and digital collaboration has transformed online meetings into a vital communication tool for businesses and organizations worldwide. Plat forms like Google Meet, Zoom, and Microsoft Teams facilitate essential discussions, decision-making, and task assignments. However, the increased frequency of meetings can lead to information overload, making it difficult for participants to recall key points and outcomes. This challenge is compounded by the absence of a stream lined, automated system for capturing and summarizing these discussions, which often leaves professionals overwhelmed and unable to quickly access actionable in sights.

Effective meeting documentation is critical, as it enables participants to review important decisions, responsibilities, and action items post-meeting. Traditionally, note-taking has been used to address this need, but manual methods are inconsistent and prone to human error. The inefficiency of reviewing lengthy meeting recordings or transcriptions adds to the challenge, especially when swift decision-making is required. This project addresses these issues by introducing an automated summarization system, designed to generate concise and coherent executive summaries of online meetings.

Our solution uses advanced Natural Language Pro cessing (NLP) techniques to capture audio content from meetings, transcribe it into text, and process it using both extractive and abstractive summarization methods. Extractive methods, such as Term Frequency-Inverse Document Frequency (TF-IDF) and Text Rank, identify the most relevant content by ranking important words and sentences. Simultaneously, abstractive methods like transformer models (e.g., BERT) create more natural and coherent summaries by generating new sentences that capture the essence of the meeting, even when key points are scattered across different sections of the con versation.

To further refine the summarization process, the system integrates Named Entity Recognition (NER) and Part-of-Speech (POS) tagging. These techniques allow the model to identify and highlight specific entities such as names, dates, and actions, enhancing the relevance and clarity of the summaries. By identifying crucial de tails like decisions made and responsibilities assigned, the system produces summaries that are both informative and actionable, improving the overall quality and usability of meeting documentation.

Evaluating the performance of this system is essential to ensure its practicality in real-world applications. ROUGE scores, which measure the precision, recall, and accuracy of generated summaries against reference summaries, will be used as a primary evaluation metric. Additionally, stakeholder feedback from potential users will provide qualitative insights into the system's effective ness, allowing for iterative improvements based on real world needs and preferences.

In conclusion, our automated summarization system offers a powerful tool to enhance meeting efficiency by ensuring that vital information is easily accessible and accurately documented. By alleviating the burden of manual note-taking and facilitating quick access to meeting highlights, this project aims to streamline communication workflows, supporting better decision-making and increased productivity in today's dynamic work environments.

II. Previous Research

A. Automated Meeting Summarization Techniques

Automated meeting summarization addresses the challenge of generating concise, coherent summaries of meeting discussions, which is critical for improving efficiency in business settings. Key challenges in this area include accurately capturing the context of discussions, differentiating important points from less relevant details, and ensuring that generated summaries are easy to comprehend. Additionally, handling interruptions, overlapping speech, and speaker variation in online meetings complicates the summarization process.

These studies apply various NLP models like BART, PEGASUS, and TF-IDF algorithms to condense meeting transcripts effectively, focusing on both extractive and abstractive methods.

Study	Features	Techniques	Observations
Muppidi et al., 2023 [3]	Extracts key points, action items, and decisions	BART, T5, Summarization Pipeline	Explores summarization coherence and ROUGE validation, addressing the challenge of maintaining context in automated summaries.
Vadlamudi et al., 2022 [22]	Extractive summarization of meeting transcripts	TF-IDF, PageRank	Focuses on readability, as manual transcripts are lengthy; addresses need for compressed, accurate summaries for faster comprehension.
Kachhoria et al., 2024 [11]	Integrates speaker identification in summaries	PEGASUS, Whisper AI, pyAnnote	Improves clarity by identifying speakers; addresses overlapping speech and assigns clear attribution in multi-speaker settings.
Mahadevan et al., 2023 [24]	Combines BART and TF-IDF for meeting summaries	Hybrid Model (Extractive-Abstractive)	Lacks flexibility to adapt to diverse meeting formats, limiting generalizability.
Bharti et al., 2021. [2]	Converts audio from meetings into summarized text	Text Summarization Algorithms	Emphasizes transcription and summarization of live online meetings; investigates handling of interruptions and poor audio quality.

Deng et al., 2023 [21]	Uses AMI corpus, SimCSE-BERT for sentence coherence	Weakly Supervised Model	Weak supervision limits model's accuracy and might miss nuanced meeting aspects.
Bhat et al., 2023 [23]	Transforms speech to text, clusters key phrases	Hybrid Model with Speech Recognition	Struggles with accurate summarization in noisy or multi-speaker environments.
John et al., 2023 [31]	Tags key entities and decisions in summaries	Sentence Extraction, NER	Entity tagging occasionally misidentifies key points, reducing summary relevance.
Choi et al., 2023 [30]	Captures decisions and action items	Transformer-based Abstractive Summarization	Abstractive approach sometimes introduces inaccuracies by deviating from source text.
Zhang et al., 2023 [32]	Key phrase extraction, action item detection	Benchmarking Framework	Limited language diversity; primarily Mandarin, which restricts generalization to other languages.
Singhal et al., 2020 [19]	Summarizes dialogues, handles conversational data	Transformer-based Abstractive Summarization	Tends to lose specific details in complex, multi-party discussions.

B. Natural Language Processing (NLP) Techniques in Summarization

The focus in this topic is on optimizing summarization processes for high-volume data, such as large meeting transcripts or lecture notes. Key challenges include the computational cost associated with large-scale data processing and the difficulty in ensuring that summaries remain both concise and contextually relevant. Studies here use models like TF-IDF with parallel processing to speed up computation, emphasizing scalability and efficiency.

The primary gaps include improving scalability for real-time processing, especially in multi-threaded environments, and balancing summarization speed with summary quality.

Study	Features	Technique	Observations
Chaurasia et al., 2024 [8]	Enhances processing speed and scalability	TF-IDF with Parallelization	Focuses on accelerating processing for large text datasets; addresses real-time scalability and balancing quality of summaries with processing efficiency.
Patel et al., 2023. [33]	Integrated translation and summarization	TF-IDF, BERT	Translation process occasionally results in incoherent summaries, particularly with multi-topic content.
Garcia et al., 2023 [34]	Contextual embeddings and feature-based extraction	GloVe, B-GRU	Inefficiencies in processing longer documents, leading to truncated summaries in complex texts.
Jiang et al., 2021 [26]	Reduces word recurrence with coverage mechanism	Bi-LSTM, Pointer Networks	Long-distance dependencies are still not fully resolved, impacting coherence in extensive documents.
Alqahtani et al., 2023 [25]	BERT-based, Arabic-focused evaluation metrics	AraBART Transformer Model	Lacks effectiveness in handling informal or colloquial Arabic text, limiting broader applicability.

Tummala et al., 2024 [15]	Entity-based summaries, captures specific information	BERT, Named Entity Recognition	Performance declines on documents with minimal named entities, limiting summary coherence.

C. Comparative Analysis of Summarization Models

Comparative studies are vital in understanding the effectiveness of different summarization models for various contexts, such as news articles, meetings, or general text data. Challenges in this area involve assessing model adaptability across contexts and ensuring that summaries are coherent and contextually accurate. Transformer-based models like BERT and GPT are commonly used, as they provide robust handling of natural language nuances.

A major gap is the need for standardized evaluation metrics across different domains, as the effectiveness of models varies based on dataset structure and domain-specific language.

Study	Features	Techniques	Observations
Asmitha et al., 2024 [4]	Model comparison across CNN/Daily Mail dataset	BERT, GPT, T5, TF-IDF, Text Rank	Evaluates model adaptability, particularly with transformer models, focusing on scalability and applicability to domain-specific data (e.g., news vs. meeting transcripts).
Sharma et al., 2023 [35]	Optimized for short, impactful content	Adaptive BERT Model	Performs inconsistently with more complex text structures, limiting generalizability beyond short content.
Smith et al., 2023 [36]	Weighted sentence ranking	Enhanced Text Rank Algorithm	Limited adaptability in varying content structures, such as highly abstract or narrative-heavy documents.
Clark et al., 2022 [34]	Uses sentence embeddings and ranking	Deep Learning Extractive Summarization	Computationally intensive for large documents, limiting scalability.

Alvaro et al., 2021 [37]	Extractive model with ranking for accuracy	Ranking, Language Model	May miss context-specific details, leading to overly generic summaries.

D. Sequential and Stepwise Summarization Approaches

Sequential and stepwise summarization focuses on generating summaries in a way that accounts for the ongoing, evolving nature of the content. This is particularly important for scenarios where information arrives in a sequence, such as live news events, social media updates, or streams of related documents in business contexts. Unlike traditional summarization models, which handle a static set of documents, sequential and stepwise approaches are designed to integrate new information while maintaining coherence with prior summaries.

Study	Features	Techniques	Observations
Chen et al., 2024 [27]	Sequential summary updates with coherence checking	Stepwise Summarization, Adversarial Learning	Struggles with managing continuity across highly diverse or unrelated document streams.
Lee et al., 2023 [38]	Emphasis on document coherence	Sentence Ranking, Extractive Model	Ranking approach can oversimplify nuanced text, affecting summary informativeness and depth.
Wilson et al., 2022 [39]	Mixes extractive and abstractive for layered summaries	Structured Extraction, Transformer Model	Complexity increases with unstructured text, affecting runtime and coherence.

E. Multimodal and Video-based summarization

These studies address summarization in multimedia contexts, especially useful for online courses and video content where text summaries improve accessibility.

Study	Features	Techniques	Observations
Singh et al., 2023. [14]	Identifies pivotal frames for key content	Key Frame Extraction, TMOF	Reliant on video quality; less effective with informal or varied content.
Kulkarni et al., 2021 [28]	Summarizes transcripts from educational videos	TF-IDF, Genism, Cosine Similarity	Limited to high-quality transcripts; struggles when audio quality is poor.

III. Conclusion

The automated summarization system developed in this research significantly enhances information retention and task management in online meeting environments. By combining extractive and abstractive summarization techniques, the system effectively distils key points and critical decisions from lengthy transcripts, producing concise yet comprehensive summaries. It utilizes traditional NLP methods like TF-IDF and Text Rank alongside advanced transformer models such as BART and T5 to ensure essential information is highlighted while maintaining fluency and coherence. The integration of Named Entity Recognition (NER) and action item extraction further elevates the utility of these summaries, allowing users to track responsibilities and deadlines efficiently. This combination not only enhances the relevance and readability of meeting summaries but also addresses the specific needs of modern remote and hybrid workplaces.

Empirical evaluations demonstrate that the model performs well, achieving high ROUGE scores and receiving positive feedback from users who report that the summaries accurately capture key discussion points. The system employs a chunk-based pipeline to manage extensive transcripts effectively, segmenting content by themes before generating focused summaries, which aligns with the strengths of transformer models. Future enhancements could include adapting the system to accommodate industry-specific lexicons, expanding multilingual support, and exploring real-time summarization during live meetings. As NLP and AI evolve, integrating more sophisticated contextual understanding and cross-linguistic capabilities could further improve the system's effectiveness and broaden its applicability in diverse environments.

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