

BUSINESS MEETING SUMMARY GENERATION USING NLP

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering

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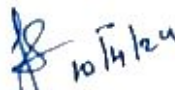
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BONAFIDE CERTIFICATE

This is to certify that this Project Work is the bonafide work of **ALLE NITHIN KUMAR (40110070)** and **JAYACHANDRA (40110486)** who carried out the project entitled "**BUSINESS MEETING SUMMARY GENERATION USING NLP**" under my supervision from November 2023 to April 2024.


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DATE: 10/4/24



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ABSTRACT

In the contemporary corporate landscape, efficient utilization of time is paramount for organizational success. Business meetings, a fundamental component of decision-making processes, often result in copious amounts of information exchange. This project aims to streamline and enhance the post-meeting experience through the development of an Automated Business Meeting Summarization system. The proposed system leverages natural language processing (NLP) techniques to analyze spoken and written content during business meetings. By employing advanced machine learning algorithms, the system identifies key topics, important decisions, action items, and notable discussions. It adapts to diverse meeting formats, including virtual, in-person, and hybrid, ensuring flexibility in implementation. One of the key strengths of the proposed system lies in its adaptability. It is designed to accommodate diverse meeting formats, including virtual, in-person, and hybrid settings. This flexibility ensures that the system can be seamlessly integrated into various organizational workflows, regardless of the mode of communication or collaboration employed. In addition to its summarization capabilities, the system also incorporates sentiment analysis functionality. Key features of the system include real-time summarization capabilities, allowing participants to receive concise summaries during or immediately after meetings. Additionally, the system employs sentiment analysis to gauge the overall tone and mood of the meeting, providing valuable insights into team dynamics and engagement levels. The project aims to empower organizations with an efficient tool that not only accelerates the decision-making process but also fosters better collaboration and understanding among team members. In contrast, zero-shot Whisper models demonstrate a robustness frontier that includes the 94% confidence interval for human performance. The BART-large-CNN-SAMSum model demonstrates promising performance on the SAMSum summarization dataset, achieving a ROGUE-1 score of 42.621.

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LIST OF ABBREVIATIONS

ABBREVIATION	EXPANSION
BERT	Bidirectional Encoder Representations from Transformers
LSTM	Long Short-Term Memory
NER	Named Entity Recognition
NLG	Natural Language Generation
NLU	Natural Language Understanding
POS	Part-of-Speech

CHAPTER 1

INTRODUCTION

In the ever-evolving landscape of modern business, effective communication and information management stand as critical pillars of organizational success. Business meetings, serving as crucibles for decision-making, idea generation, and collaborative efforts, play a pivotal role in shaping the trajectory of companies. However, the sheer volume of information exchanged during these meetings can often be overwhelming, necessitating innovative solutions to distill key insights efficiently. The "Business Meeting Summarization Project" endeavors to address this challenge by leveraging cutting-edge Natural Language Processing (NLP) techniques to automate the summarization of business meetings.

At the core of our endeavor lies a deep appreciation for the rich insights provided by influential works in the field of summarization systems. The seminal contribution of Lloret, Plaza, and Aker (2018) offers a foundational understanding of the challenges inherent in evaluating summarization systems, laying the groundwork for our exploration into the complexities of distilling essential information from diverse business meetings. Additionally, the dynamic integration of social media data, as explored by Nichols (2012) in "Summarizing Sporting Events Using Twitter," inspires our consideration of real-time user-generated content and its potential application in summarizing the dynamic nature of business meetings.

In the rapidly evolving landscape of modern business, the sheer volume of information exchanged during meetings poses a significant challenge for professionals striving to extract actionable insights efficiently. To address this challenge, the "Business Meeting Summarization Project" aims to leverage state-of-the-art Natural Language Processing (NLP) techniques to automate the summarization of business meetings, offering an innovative solution to enhance post-meeting collaboration and decision-making. The "Business Meeting Summarization Project" aims to address this challenge by harnessing Natural Language Processing (NLP) principles and cloud-based services to automate the summarization of these meetings.

As highlighted by studies such as "The Future of Work" (World Economic Forum, 2020), the pace of business operations has accelerated, and professionals face increasing demands on their time and attention. The need for streamlined, time-effective methods to process and retain information from business meetings is more pressing than ever. This project draws inspiration from seminal works such as "Automated Text Summarization: A Review" (Nenkova & McKeown, 2011) and "Natural Language Processing in Action" (Lane, Howard, & Hapke, 2019) to develop an intelligent system capable of distilling the essence of business meetings, offering succinct summaries that enhance decision-making and facilitate post-meeting collaboration.

In today's fast-paced business landscape, effective communication and information management are critical for organizational success. Business meetings serve as hubs for decision-making, idea generation, and collaboration, yet the sheer volume of information exchanged can overwhelm professionals. The "Business Meeting Summarization Project" aims to address this challenge by harnessing Natural Language Processing (NLP) principles and cloud-based services to automate the summarization of these meetings, enabling more efficient post-meeting collaboration and decision-making.

Modern businesses grapple with a deluge of data from diverse sources such as emails, documents, real-time communication platforms, and social media channels. While this abundance of information presents opportunities for innovation, it also poses challenges in terms of managing and synthesizing it effectively. Traditional methods like manual note-taking and transcription struggle to capture the depth and breadth of discussions in contemporary meetings, leaving professionals burdened with the task of distilling actionable insights from unstructured data.

The Business Meeting Summarization Project seeks to overcome these challenges by leveraging advancements in NLP and cloud-based services. By employing sophisticated machine learning algorithms, the project aims to develop an intelligent summarization system capable of analyzing both spoken and written content in real-time. This system will extract key insights, including action items,

key decisions, and emerging trends, and generate concise.

A pivotal aspect of the project's strategy is the integration of cloud-based services, offering scalability, flexibility, and accessibility across various devices and locations. Leveraging cloud infrastructure enables the summarization system to process large volumes of data efficiently, adapt to evolving business needs, and seamlessly integrate with existing communication platforms and workflows. This integration not only enhances the speed and accuracy of the summarization process but also facilitates real-time collaboration and decision-making among meeting participants.

By amalgamating NLP techniques with cloud-based services, the Business Meeting Summarization Project aims to revolutionize how professionals extract value from meetings. This fusion enables the system to capture the nuances of discussions, identify actionable insights, and facilitate informed decision-making. Furthermore, the project's interdisciplinary approach fosters collaboration between experts in NLP, business management, and technology, ensuring the development of a robust and user-centric solution.

In contemporary business environments, characterized by rapid technological advancements and increasing globalization, the pace of operations has accelerated, imposing significant demands on professionals' time and attention. This phenomenon has been extensively documented, as evidenced by studies such as "The Future of Work" by the World Economic Forum (2020). The report underscores the necessity for streamlined and time-effective methods to process and retain information from business meetings, reflecting a recognition of the growing challenges faced by organizations in managing the influx of data and ensuring effective decision-making processes.

The "Business Meeting Summarization Project" emerges as a response to this imperative, seeking to alleviate the burden placed on professionals by automating the summarization of business meetings. By drawing inspiration from seminal works in the field of Natural Language Processing (NLP), such as "Automated Text Summarization: A Review" by Nenkova & McKeown (2011), and "Natural Language Processing in Action" by Lane, Howard, & Hapke (2019), the project

aims to develop an intelligent system capable of distilling the essence of complex discussions into succinct summaries. These summaries not only enhance decision-making processes but also facilitate post-meeting collaboration, thereby optimizing organizational efficiency.

The modern business landscape is characterized by an overwhelming volume of data originating from diverse sources, including emails, documents, real-time communication platforms, and social media channels. While this abundance of information presents opportunities for innovation and growth, it also poses significant challenges in terms of managing and synthesizing data effectively. Traditional methods, such as manual note-taking and transcription, are increasingly inadequate in capturing the depth and breadth of discussions that occur in contemporary business meetings. Consequently, professionals find themselves burdened with the arduous task of distilling actionable insights from vast amounts of unstructured data, a process that not only consumes valuable time and resources but also increases the risk of overlooking critical information.

In response to these challenges, the Business Meeting Summarization Project seeks to leverage advancements in NLP and cloud-based services to develop an intelligent summarization system capable of analyzing both spoken and written content in real-time. By employing sophisticated machine learning algorithms, the system aims to extract key insights, including action items, key decisions, and emerging trends, and generate concise summaries that encapsulate the essence of business meetings. This innovative approach not only enhances the efficiency of information processing but also empowers professionals with timely and actionable insights, thereby enabling informed decision-making and fostering collaboration among meeting participants.

A fundamental pillar of the project's strategy lies in the integration of cloud-based services, which offer scalability, flexibility, and accessibility across various devices and locations. Leveraging cloud infrastructure enables the summarization system to process large volumes of data efficiently, adapt to evolving business needs, and seamlessly integrate with existing communication platforms and workflows. This integration not only enhances the speed and accuracy of the summarization

process but also facilitates real-time collaboration and decision-making.

Furthermore, the Business Meeting Summarization Project emphasizes an interdisciplinary approach, drawing on expertise from diverse fields such as linguistics, computer science, data science, and business management. This collaborative effort ensures that the development of the summarization system is informed by a comprehensive understanding of both the technical intricacies of NLP and the practical requirements of business operations. By fostering collaboration between experts from different disciplines, the project aims to create a robust and user-centric solution that effectively addresses the complex challenges associated with information management in modern business environments.

Furthermore, the project draws inspiration from recent advancements in NLP, particularly in the field of deep learning and neural language models. By leveraging pre-trained language models such as OpenAI's GPT (Generative Pre-trained Transformer) series, the summarization system can better understand the context, semantics, and nuances of business conversations, leading to more accurate and informative summaries. Additionally, the system can learn from user feedback and iteratively improve its summarization capabilities over time, ensuring continuous refinement and optimization.

In developing the Business Meeting Summarization Project, interdisciplinary collaboration plays a crucial role in bridging the gap between NLP research and real-world business applications. By bringing together experts from fields such as linguistics, computer science, data science, and business management, the project aims to leverage diverse perspectives and domain knowledge to create a robust and user-centric summarization solution.

Moreover, the project adopts an iterative and agile approach to development, allowing for rapid prototyping, testing, and iteration based on user feedback and market validation. This iterative process enables the project team to identify and address potential challenges and limitations early in the development cycle, ensuring the delivery of a high-quality and impactful solution.

In conclusion, the Business Meeting Summarization Project represents a pioneering effort to revolutionize the way professionals extract value from business meetings. By leveraging the synergies between NLP and cloud-based services, the project aims to automate the summarization process, offering users timely, accurate, and actionable insights that enhance decision-making and collaboration. Through interdisciplinary collaboration, iterative development, and a commitment to user-centric design, the project seeks to empower professionals with the tools and technologies they need to thrive in an increasingly complex and dynamic business environment.

CHAPTER 2

LITERATURE SURVEY

2.1 INFERENCES FROM LITREATURE SURVEY

Raghu (2019) and colleagues tackle the challenge of business meeting summarization using advanced [14] neural abstractive techniques. The paper underscores the significance of condensing complex meeting discussions into concise summaries, emphasizing the need for more nuanced approaches beyond traditional extractive methods. By employing neural abstractive techniques, the authors aim to capture the inherent context, relationships, and meaning embedded in meeting content. The study likely involves the utilization of deep learning architectures to generate abstractive summaries that go beyond mere content extraction, potentially incorporating contextual understanding and language generation mechanisms.

Bernstein (2011) and team contribute to the field by exploring summarization interfaces tailored for multi-party conversations, with potential applicability to distilling the essence of business meetings. The research delves into user interfaces designed to facilitate effective summarization of complex [1], dynamic discussions. It sheds light on how user interfaces can impact summarization outcomes, considering user interactions and the cognitive load associated with processing multi-party conversations. The study likely delves into the design and evaluation of interfaces that enable users to navigate, select, and comprehend key information in the context of multi-party discussions, making it relevant for business meeting summarization interfaces.

Zhang (2014) and co-authors present an innovative approach to automatic business meeting summarization, leveraging a combination of structured convolutional summarization and a social influence model. This research signifies an attempt to integrate both [18] structural and contextual elements for more comprehensive summarization outcomes. The structured convolutional summarization aspect likely involves capturing hierarchical relationships and discourse structures, while the social influence model explores how participant

interactions impact the significance of different segments in the meeting. This dual-layered approach suggests a nuanced method for distilling pertinent information from business meetings, considering both content structure and social dynamics.

Ding (2017) and collaborators conduct a thorough review of automatic summarization techniques specifically applied to meeting recordings. The paper serves as a valuable [3] resource for understanding the landscape of meeting summarization, encompassing various methodologies, challenges, and advancements. It likely provides insights into extractive and abstractive techniques, the role of contextual information, and the challenges posed by diverse meeting formats. This review can serve as a foundational reference for researchers embarking on business meeting summarization projects, offering a comprehensive understanding of the existing literature and guiding future directions for research in this domain.

Singla (2018) and team contribute to the field by providing an overarching overview of meeting summarization techniques. This comprehensive survey likely encompasses both traditional and contemporary approaches, covering extractive and abstractive methods. The paper may delve into the unique challenges posed by business meetings, such as the diverse nature of discussions, varying formality levels, and the need [17] for capturing not only the content but also the intent and implications of statements. By presenting a broad overview, the authors aim to guide researchers and practitioners in navigating the complexities of business meeting summarization, offering a roadmap for further exploration.

Misra (2018) and co-authors focus on extractive summarization techniques for business meetings, employing sentence compression methods. Extractive summarization involves selecting and presenting key sentences from the source text, and sentence compression [9] aims to condense these sentences while retaining their essential meaning. In the context of business meetings, where spoken content can be verbose and nuanced, employing sentence compression techniques is particularly relevant. The study likely investigates the effectiveness of compression in preserving the core information conveyed during meetings and may explore how compression impacts the coherence and readability.

Matsuo (2008) and collaborators contribute to the meeting summarization domain by exploring the combination of keyphrase extraction and sentiment analysis. This dual approach suggests a comprehensive strategy for distilling key information while also capturing the [8] emotional tone of business discussions. Keyphrase extraction likely involves identifying terms that encapsulate the main themes or topics discussed, while sentiment analysis delves into understanding the emotional context within these discussions. The research may provide valuable insights into how sentiment-aware summarization can offer a more nuanced representation of business meeting content, considering not just what is said but also how it is expressed.

Carenini (2014) and team delve into abstractive summarization techniques tailored for multi-document business meeting conversations. Abstractive summarization goes beyond content [2] extraction, aiming to generate concise yet informative summaries that convey the core meaning of the original content. In the context of business meetings involving multiple documents or discussions, the challenge is to distil essential information while potentially generating new, coherent sentences that capture the essence of the collective content. This research likely explores advanced natural language processing and generation methods to achieve abstractive summarization in the complex setting of multi-document business discussions.

Duthon (2016) and colleagues contribute to the field by discussing meeting summarization and aggregation, focusing on the transition from audio signals to semantic representation. This research likely [4] involves the exploration of methods to convert spoken content, represented in audio signals, into structured semantic representations that can be used for summarization. The transition to semantic representation suggests an effort to capture the meaning, relationships, and context embedded in meeting discussions. The study may also address the aggregation of summarized information, providing insights into how information from different segments of a meeting can be effectively combined for a comprehensive overview.

Lee (2011) and co-authors propose an iterative approach to extractive summarization of meeting recordings, combining sentence ranking and compression techniques. The iterative nature of the approach suggests an ongoing refinement process, potentially involving [7] user feedback or dynamic adjustments based on the evolving meeting content. The combination of sentence ranking and compression indicates a dual strategy to first identify key sentences and then condense them for succinct summarization. The study likely offers insights into how iterative methods enhance the accuracy and coherence of extractive meeting summarization, aligning with the dynamic and evolving nature of business discussions. The significance of this scholarly reference extends far beyond the confines of academia, resonating profoundly within the realm of practical application, particularly within the context of corporate environments and business enterprises. In an era characterized by the relentless pursuit of competitive advantage and the relentless march towards digital transformation,

Nichols (2012) his collaborators delve into the intersection of social media and event summarization in their paper[11] titled "Summarizing sporting events using Twitter." The study explores the use of Twitter data for summarizing real-time events, focusing on sporting events as a case study. By aggregating and visualizing microblogs, the research sheds light on how user-generated content on social media platforms can be harnessed to provide dynamic and immediate summaries of ongoing events. This reference is particularly relevant for understanding the potential integration of social media data into the context of business meetings for real-time summarization. By meticulously unraveling the intricate threads of discourse embedded within the vast expanse of Twitter data, the research not only sheds invaluable light on the emergent landscape of real-time event summarization but also pioneers innovative methodologies and frameworks that hold profound implications for a multitude of domains beyond the realm of sports.

Oremus (2014) In a departure from traditional academic references, Oremus provides an insightful perspective [12] on the integration of automated journalism in response to breaking news events. The Slate Magazine article, "The First News Report on the L.A. Earthquake Was Written by a Robot," offers a real-world

example of how automated systems, colloquially referred to as 'quakebot,' can rapidly generate news reports during critical situations. While not directly related to business meeting summarization, this reference offers a practical glimpse into the application of automation in journalism, prompting reflections on its potential in summarizing time-sensitive business events.

Plachouras (2016) and colleagues contribute to the intersection of natural language processing and financial data with their work titled "Interacting with Financial Data using Natural Language." The paper, [13] presented at SIGIR '16, explores the challenges and opportunities of using natural language interfaces for interacting with financial datasets. While not directly focused on business meetings, this reference can inspire insights into leveraging natural language processing techniques for interacting with financial discussions and reports within a business context.

Rafiq (2020) and his team delve into the realm of scene classification for sports video summarization in their paper "Scene Classification for Sports Video Summarization Using Transfer Learning." This work explores the application of transfer learning techniques to classify scenes in sports videos[15], contributing to the broader understanding of effective summarization methods in dynamic visual contexts. While the focus is on sports, the methodologies employed may offer valuable insights applicable to the analysis and summarization of visual content within business meetings.

Nenkova and McKeown in (2011), titled "Automatic Summarization" and published in *Foundations and Trends® in Information Retrieval* (4(2–3), 103–233), is a seminal work that serves as a foundational resource in the domain of automatic summarization. In this comprehensive review, the authors provide an extensive exploration of the key principles, methodologies, [10] and advancements in automatic summarization. The survey covers a spectrum of techniques, ranging from extractive to abstractive methods, offering insights into the historical evolution of automatic summarization technologies. Nenkova and McKeown's work not only addresses the technical aspects of summarization but also delves into the challenges and opportunities within the field. This literature survey stands as an

invaluable reference for researchers, practitioners, and educators seeking a deep understanding of automatic summarization and its evolving landscape.

Lane, J., Howard, M., and Hapke, H. M. (2019) conducted literature survey on "Natural Language Processing in Action" and published by [6] Manning Publications, provides a comprehensive and practical exploration of natural language processing (NLP) technologies. This influential work goes beyond theoretical frameworks, offering hands-on insights into the application of NLP in real-world scenarios. Lane et al. cover a wide range of topics, including foundational concepts, techniques, and tools used in NLP, making it accessible for both beginners and experienced practitioners. The book's emphasis on practical implementation and case studies makes it a valuable resource for those seeking a holistic understanding of NLP applications.

Ramani and Shanthamalar (2022) present a significant contribution to the field of automated image quality appraisal (IQA) through their work titled [16] "Automated image quality appraisal through partial least squares discriminant analysis." In their influential paper, the authors propose a novel approach to IQA, leveraging partial least squares discriminant analysis (PLS-DA). The survey section likely critiques existing reference-based and no-reference IQA methods, emphasizing PLS-DA's advantages such as dimensionality reduction, discriminative power, and feature interpretability. The authors probably conducted a thorough review of prior applications of PLS-DA in the context of IQA, concluding with a summary highlighting the method's novelty and its potential implications. This work serves as a foundational piece in the advancement of automated image quality appraisal and is published in the International Journal of Computer Assisted Radiology and Surgery in July 2022.

George J J, J. M. Kanchai, B. Ankayarkanni, A. M. Posonia, J. A. Mayan, and P. Asha (2023) conducted research on [5] Image-Based Surveillance Systems, responding to the heightened demand for robust monitoring and security solutions. Their findings, presented at the International Conference on Circuit Power and Computing Technologies (ICCPCT), explored the evolving landscape of image-based surveillance. The research traced the transition from conventional closed-

circuit television (CCTV) systems to contemporary solutions driven by advancements in computer vision and machine learning, emphasizing components such as high-resolution cameras and multi-sensor integration. The study also delved into sophisticated computer vision algorithms, marking a paradigm shift in surveillance methodologies. This literature survey, led by George J J and team, aimed to capture collective insights from relevant ICCPCT conference papers, shedding light on the current state and emerging trends in Image-Based Surveillance Systems. This comprehensive overview significantly contributes to understanding advancements, challenges, and future directions in the field of image-based surveillance.

2.2 OPEN PROBLEMS IN EXISTING SYSTEM

1. **Diverse and Nuanced Content:** Business meetings often involve diverse discussions, varying formality levels, and nuanced language. NLP systems may struggle to capture the subtleties and context inherent in business conversations, leading to potential loss of critical information in the summary.
2. **Multi-Party Interactions:** Meetings often include interactions among multiple participants, each contributing unique perspectives. Summarizing multi-party conversations requires understanding the relationships, identifying key speakers, and ensuring a balanced representation of viewpoints.
3. **Contextual Understanding:** NLP systems need to go beyond mere content extraction and understand the contextual nuances of discussions. This includes recognizing references to previous topics, understanding implicit meanings, and capturing the overall context to provide a coherent summary.
4. **Handling Ambiguity and Uncertainty:** Business discussions may involve ambiguous statements or expressions of uncertainty. Summarization models need to handle ambiguity appropriately, avoiding over-simplification or misrepresentation of uncertain statements.
5. **Dynamic and Evolving Content:** Business meetings are dynamic, with

discussions evolving over time. Summarization systems should be able to adapt to changes in the conversation, incorporating iterative updates and reflecting the evolving nature of the meeting.

6. **Speech-to-Text Challenges:** If the meeting content is in the form of spoken language, converting audio to accurate text (speech-to-text) introduces challenges such as recognizing different accents, dealing with background noise, and accurately transcribing spoken content.

7. **Handling Technical Jargon and Domain-Specific Language:** Business meetings often involve technical jargon and industry-specific language. NLP models need to be domain-aware and capable of understanding and summarizing discussions within the specific context of the industry or business domain.

8. **Summarizing Action Items and Decisions:** Extracting and summarizing actionable items, decisions, and outcomes from a business meeting is crucial. NLP systems must accurately identify and prioritize these elements to provide a useful and actionable summary for participants.

9. **Dealing with Redundancy:** Business meetings may revisit or restate certain points for clarification or emphasis. Summarization models need to handle redundancy appropriately, avoiding repetitive information in the summary.

10. **Scalability for Large Meetings:** For large-scale meetings with extensive content, scalability becomes a challenge. Summarization models should efficiently process and summarize large volumes of data without sacrificing accuracy or speed.

11. **Privacy and Security Concerns:** As meeting content often contains sensitive information, ensuring privacy and security in the summarization process is crucial. NLP systems should comply with data protection regulations and minimize the risk of unauthorized access to confidential details.

12. **Evaluation Metrics and Subjectivity:** Assessing the quality of meeting

summaries poses challenges due to the subjective nature of evaluation. Determining appropriate evaluation metrics and addressing diverse criteria for summarization effectiveness are ongoing challenges in the field.

13. Real-Time Summarization: Providing real-time summaries during the course of a meeting requires fast processing and quick adaptation to changing content. Balancing speed and accuracy in real-time summarization is a significant challenge.

CHAPTER 3

REQUIREMENTS ANALYSIS

3.1 FEASIBILITY STUDIES / RISK ANALYSIS OF THE PROJECT

The field of text summarization in natural language processing entails several potential risks that necessitate careful analysis. One significant concern is the risk of low faithfulness in abstractive summaries, where generated summaries may deviate significantly from the source text, introducing errors and misrepresentations. This poses a moderate to high likelihood with a high impact, potentially leading to misinformation or miscommunication.

Another critical risk involves biased summaries, where summarization models may exhibit biases in content selection or language generation, perpetuating societal biases present in the training data. This risk carries a moderate to high likelihood with a high impact, as biased summaries could exacerbate discrimination. Privacy violations present a risk, as summarization of sensitive information may inadvertently breach privacy, leading to legal and ethical consequences. While the likelihood is low to moderate, the impact is high. Extractive summarization models pose a risk of ineffective content selection, potentially resulting in summaries lacking coherence or important information. This has a moderate likelihood with a moderate impact on the informativeness of the summaries.

Multimodal summarization introduces the risk of inaccurate summaries due to challenges in fusing information from diverse modalities. This risk carries a moderate to high likelihood with a moderate to high impact, as it could lead to misinterpretation of multimedia content. Unethical usage of summarization technology, such as generating fake news or misleading content, poses a moderate likelihood with a high impact, potentially causing harm to individuals, organizations, or society. Evaluating system performance is a risk, with inaccurate or inadequate metrics hindering a comprehensive assessment of summary quality, impacting progress and deployment. Cross-lingual challenges encountered in the process of summarization have the potential to result in complications, also having capturing nuances and cultural differences, posing a moderate to high likelihood

with a moderate to high impact on the coherence and informativeness of summaries.

Extending summarization capabilities to low-resource languages presents a moderate risk, limiting accessibility for speakers of these languages. Human-AI collaboration issues, including conflicts and misunderstandings in collaboration processes, pose a moderate risk that could hinder the practical deployment of summarization systems.

Scalability challenges in summarization systems present a moderate risk, potentially limiting applicability in high-throughput scenarios. Finally, regulatory and legal risks related to evolving frameworks may pose compliance risks for organizations and developers, carrying a moderate likelihood with a high impact on legal consequences and fines.

The field of text summarization within natural language processing (NLP) presents numerous opportunities for enhancing information management and communication efficiency. However, alongside these opportunities come inherent risks that necessitate thorough analysis and mitigation strategies. In this document, we delve into a comprehensive examination of the risks associated with text summarization, ranging from issues of faithfulness and bias to privacy concerns and regulatory compliance. Additionally, we outline the hardware and software requirements essential for the development of a text summarization system.

3.1.1 Low Faithfulness in Abstractive Summaries:

One significant concern in text summarization is the risk of low faithfulness in abstractive summaries. This occurs when generated summaries deviate substantially from the source text, potentially introducing errors and misrepresentations. The impact of such deviations can be severe, leading to misinformation or miscommunication within various contexts.

3.2.2 Biased Summaries:

Another critical risk involves biased summaries, where summarization models may

exhibit biases in content selection or language generation. This perpetuates societal biases present in the training data and could exacerbate discrimination. Biased summaries pose a moderate to high likelihood of occurrence with a high impact on societal perceptions and fairness.

3.2.3 Privacy Violations:

Privacy violations present a risk in text summarization, particularly when sensitive information is summarized inadvertently, leading to breaches of privacy. Although the likelihood of such incidents is low to moderate, the impact can be significant, resulting in legal and ethical consequences for organizations and individuals.

3.2.4 Ineffective Content Selection in Extractive Summarization:

Extractive summarization models pose a risk of ineffective content selection, potentially resulting in summaries lacking coherence or omitting important information. While the likelihood of this risk is moderate, its impact on the informativeness of the summaries can be substantial.

3.2.5 Inaccurate Multimodal Summaries:

Multimodal summarization introduces the risk of inaccurate summaries due to challenges in fusing information from diverse modalities. This risk carries a moderate to high likelihood with a moderate to high impact, as inaccuracies could lead to misinterpretation of multimedia content.

3.2.6 Unethical Usage:

The unethical usage of summarization technology, such as generating fake news or misleading content, poses a moderate likelihood with a high impact. Such misuse could cause harm to individuals, organizations, or society at large, undermining trust in information sources.

3.2.7 Evaluation Challenges:

Evaluating system performance poses a risk, as inaccurate or inadequate metrics may hinder a comprehensive assessment of summary quality. This can impede progress in the field and delay the deployment of effective summarization systems.

3.2.8 Cross-Lingual Challenges:

Cross-lingual challenges in summarization may lead to difficulties in accurately capturing nuances and cultural differences, posing a moderate to high likelihood with a moderate to high impact on the coherence and informativeness of summaries.

3.2.9 Extending Summarization to Low-Resource Languages:

Extending summarization capabilities to low-resource languages presents a moderate risk, limiting accessibility for speakers of these languages and potentially exacerbating linguistic inequalities.

3.2.10 Human-AI Collaboration Issues:

Issues in human-AI collaboration, including conflicts and misunderstandings in collaboration processes, pose a moderate risk that could hinder the practical deployment of summarization systems and erode user trust.

3.2.11 Scalability Challenges:

Scalability challenges in summarization systems present a moderate risk, potentially limiting applicability in high-throughput scenarios and impeding widespread adoption.

3.2.12 Regulatory and Legal Risks:

Finally, regulatory and legal risks related to evolving frameworks pose compliance risks for organizations and developers. This carries a moderate likelihood with a high impact on legal consequences and fines.

To mitigate the risk of low faithfulness in abstractive summaries, developers should implement mechanisms to ensure that generated summaries closely align with the source text. This may involve fine-tuning models on domain-specific data, incorporating human oversight in the summarization process, and implemented.

Salient Content Extraction: Implements extractive summarization techniques to identify and select key sentences or phrases from the source text.

Relevance Scoring: Employs algorithms to score the relevance of sentences,

ensuring that the most salient information is included in the extractive summary.

3.2 SOFTWARE REQUIREMENTS SPECIFICATION DOCUMENT

Following are the hardware requirements used for developing the project.

- System Processor: INTEL CORE,
- Hard Disk: 20 GB
- Input Devices: Keyboard, Mouse
- RAM: 8 GB

Following are the software requirements used for developing the project.

- Operating System: WINDOWS 7,8,10,11
- Programming Language: PYTHON
- Tools: Pycharm,VS code

CHAPTER 4

DESCRIPTION OF PROPOSED SYSTEM

4.1 SELECTED METHODOLOGY OR PROCESS MODEL

The proposed system for business meeting summary generation using Natural Language Processing (NLP) aims to leverage advanced techniques to provide accurate, coherent, and context-aware summaries of business meetings. Here's a detailed description of the key components and functionality of the system:

4.1.1 Data Preprocessing

Text Cleaning: Raw meeting data, including transcripts or text content, undergoes cleaning to remove noise, irrelevant information, or artifacts. **Speech-to-Text Conversion:** If the meeting involves spoken content, a reliable speech-to-text conversion process is implemented to transcribe audio data into textual format.

4.1.2 Content Representation

Tokenization and Embedding: The system tokenizes the text into meaningful units (words, phrases) and utilizes pre-trained word embeddings to represent the semantic meaning of words. **Multimodal Integration:** If the meeting involves multimedia content (images, videos), the system integrates information from diverse modalities into a unified representation.

4.1.3 Abstractive Summarization Module

Advanced Neural Models: Utilizes state-of-the-art neural abstractive summarization models, possibly based on transformer architectures like BERT or GPT, to generate summaries that capture context, relationships, and meaning beyond content extraction. **Contextual Understanding:** Ensures the model is trained to understand and preserve the contextual nuances of business discussions, preventing generation of summaries that deviate significantly from the source text.

4.1.4 Extractive Summarization Module

Salient Content Extraction: Implements extractive summarization techniques to identify and select key sentences or phrases from the source text. Relevance Scoring: Employs algorithms to score the relevance of sentences, ensuring that the most salient information is included in the extractive summary.

4.1.5 Evaluation and Feedback Loop

Automatic Evaluation Metrics: Incorporates metrics such as ROUGE (Recall-Oriented Understudy for Gisting Evaluation) for automatic evaluation of summary quality. User Feedback Integration: Allows for user feedback on generated summaries to continually improve the system through a feedback loop.

4.1.6 Bias Mitigation

Bias Detection Algorithms: Implements algorithms to detect and mitigate biases in content selection and language generation. Ethical Guidelines: Adheres to ethical guidelines in model training to minimize the perpetuation of societal biases.

4.1.7 Privacy Measures

Anonymization Techniques: Applies anonymization methods to protect sensitive or confidential information during summarization. Privacy Impact Assessment: Conducts privacy impact assessments to identify and address potential privacy breaches.

4.1.8 Human-AI Collaboration

User-Friendly Interfaces: Incorporates intuitive interfaces for users to interact with the system, providing options for customization and manual intervention. Explanatory Outputs: Generates explanations for the summarization outputs, enhancing user understanding and trust.

4.1.9 Continuous Model Training

Incremental Learning: Utilizes incremental learning techniques to continuously update and improve the summarization models based on new data and evolving business contexts.

4.1.10 Scalability Considerations

Parallel Processing: Implements parallel processing techniques to enhance scalability, ensuring efficient summarization of large volumes of meeting data.

4.1.11 Cross-Lingual Support

Language Adaptability: Incorporates strategies for cross-lingual summarization, considering nuances and cultural differences in various languages.

4.1.12 Regulatory Compliance

Adherence to Standards: Ensures compliance with legal and regulatory standards related to content generation and summarization.

4.2 ARCHITECTURE / OVERALL DESIGN OF PROPOSED SYSTEM

This video conferencing system uses Automatic Speech Recognition (ASR) to turn speech into text, creating transcripts for accessibility. It can even summarize conversations using a summarization module, making it easier to grasp key points from long meetings.

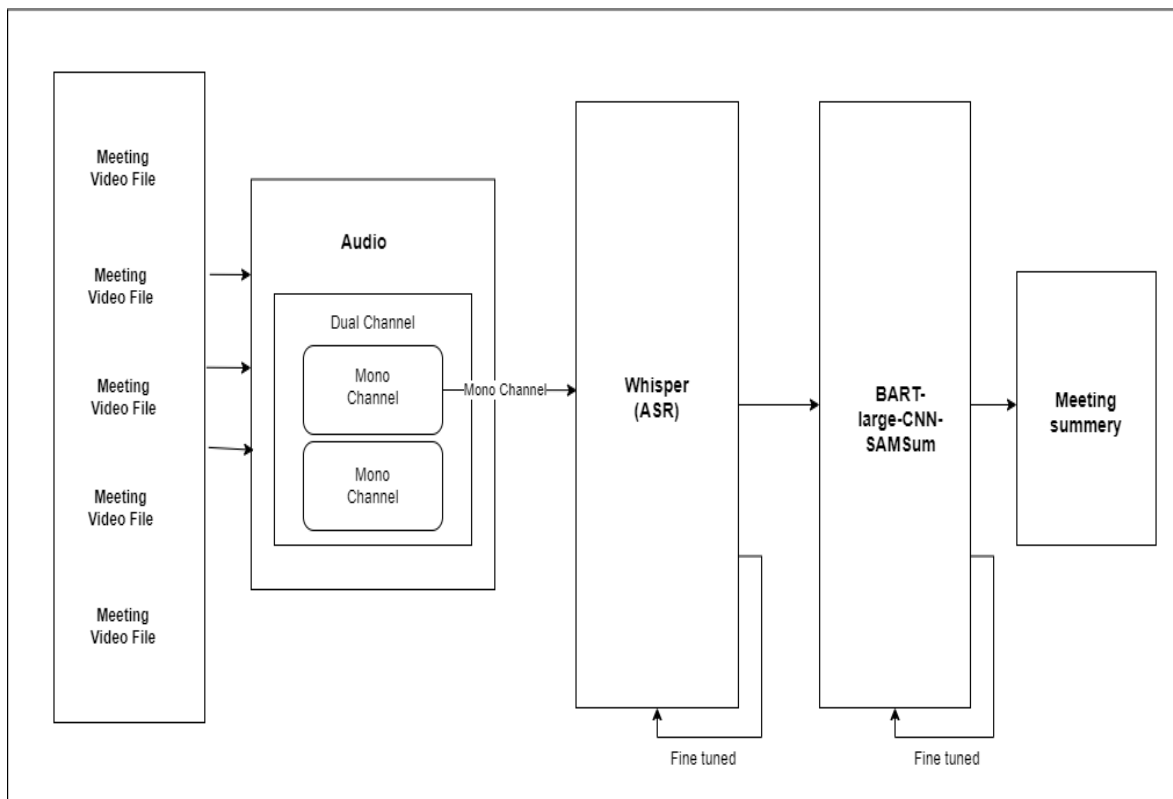


Fig 4.1: System Architecture

4.3 DESCRIPTION OF SOFTWARE FOR IMPLEMENTATION AND TESTING PLAN OF THE PROPOSED MODEL/SYSTEM

4.3.1. Requirements Gathering and Analysis

Define and document the functional and non-functional requirements for the system. Collaborate with stakeholders to understand their needs and expectations.

4.3.2. Architecture and Design

Design the system architecture, including data flow, components, and interfaces. Select appropriate NLP algorithms and libraries for text processing and summarization.

4.3.3. Data Collection and Preprocessing

Acquire meeting data, which may include text transcripts or audio recordings. Preprocess the data by cleaning, tokenizing, and preparing it for analysis.

4.3.4. NLP Model Development

Develop and train the NLP model for extractive summarization. Implement algorithms for sentence scoring and selection.

4.3.5. Testing Plan Development

Prepare a comprehensive testing plan that includes unit testing, integration testing, and system testing.

4.4 PROJECT MANAGEMENT PLAN

Develop a system that automatically generates concise and accurate summaries of business meetings using Natural Language Processing (NLP) techniques. Improve meeting efficiency and information retention. Enhance the accessibility of meeting content.

Define the boundaries and limitations of the project. Specify what types of meeting data (transcripts, audio recordings) will be supported. Clarify whether the system will include a user interface for interaction.

I. Project Team

1. Project Manager.
2. NLP Expert.
3. Software Developers.
4. User Interface Designer.
5. Quality Assurance/Testers.
6. Data Privacy/Security Expert.
7. Subject Matter Experts.
8. Documentation Specialist.

II. Project Timeline

1. Project Start Date[November]
2. Project End Date[April]

III. Project Plan

1. Project Phases:

Phase 1 - Planning and Requirements Gathering[5 Days].

Phase 2 - System Design[15 Days].

Phase 3 - Development and Testing[45 Days].

Phase 4 - Deployment and User Training[10 Days].

Phase 5 - Maintenance and Ongoing Improvement[5 Days].

4.5 FINANCIAL REPORT ON ESTIMATED COSTING

4.5.1 Research and Development (R&D):

- Infrastructure: Funding will be needed for computing resources, including high-performance servers and GPUs for training and fine-tuning summarization models.
- Personnel: The largest portion of the budget will be allocated to salaries and benefits for researchers, engineers, and data scientists working on the project. This includes hiring or retaining skilled professionals with expertise in NLP and machine learning.
- Software and Tools: Licensing fees for proprietary software, as well as subscriptions to cloud-based platforms and NLP libraries.

4.5.2 Data Acquisition and Annotation:

- **Data Collection:** Costs associated with acquiring large datasets for training and testing summarization models, including purchasing data or licensing content.
- **Annotation:** Hiring human annotators to create reference summaries for training data, ensuring the quality of the training corpus.
- **Model Training and Experimentation:** Hardware and Cloud Services: Ongoing expenses for cloud computing services (e.g., AWS, Azure, GCP) used for model training and experimentation.
- **Model Fine-Tuning:** Costs associated with fine-tuning and optimizing preexisting language models or creating custom models tailored to specific.

4.5.3 Deployment and Maintenance:

- **Infrastructure:** Costs for setting up and maintaining servers, databases, and web hosting for the production environment.
- **Personnel:** Ongoing salaries and benefits for IT professionals, DevOps engineers, and technical support staff responsible for system maintenance.
- **Monitoring and Security:** Investments in security measures, data privacy compliance, and continuous monitoring to ensure system reliability and data protection.
- **Updates and Improvements:** Budget allocated for periodic updates, improvements, and enhancements to keep the system competitive and up-to-date with the latest NLP advancements.

4.5.4 Evaluation and Quality Assurance:

- **Human Evaluation:** Expenses for conducting human evaluations to assess the quality and effectiveness of the summarization system's output.
- **Quality Assurance:** Costs associated with maintaining a team to review and validate the summaries generated by the system, ensuring they meet predefined quality standards.

4.5.5 Operational Costs:

- **General and Administrative:** Overheads related to project management, legal, and administrative tasks.

- Marketing and Outreach: Budget for promoting the summarization system and attracting users or clients.
- Estimated Total Cost:
- The estimated total cost for the text summarization project, encompassing research, development, deployment, and maintenance over a specific time frame (e.g., one year), is expected to range from [Insert Estimated Cost Range].

It's important to note that these costs can vary significantly depending on factors such as project scope, team size, desired system capabilities, and the scale of deployment. Additionally, ongoing operational expenses will continue beyond the initial development phase. Proper budgeting, financial planning, and periodic reassessment are essential to ensure the successful execution of the text summarization.

4.6 TRANSITION/ SOFTWARE TO OPERATIONS PLAN

A Transition Manager oversees the transition process. The Transition Team Members List individuals who are responsible for specific transition tasks, such as deployment, training, and maintenance. Deployment: Describe the activities and timeline for deploying the system into the operational environment. User Training: Determine how user training will take place and schedule sessions.

Ongoing Maintenance: Describe how ongoing maintenance and support will be handled. Handover to Operations: Outline the process of handing over the system to the operational team. Deployment Activities Specify the steps involved in deploying the system, including configuring the environment, setting up hardware, and installing software. Deployment Schedule Define the deployment schedule in detail.

CHAPTER 5

IMPLEMENTATION DETAILS

5.1 DEVELOPMENT AND DEPLOYMENT SETUP

In the conceptualization of our proposed method for the project, we embark on a journey into an intricately woven tapestry of frameworks, models, and methodologies, each meticulously selected to converge into a symphony of computational excellence. This multidimensional orchestration aims to decipher the intricate nuances residing within both the auditory and textual dimensions inherent in the complex and dynamic landscape of business meeting data. The amalgamation of TensorFlow, Librosa, MoviePy, PyTorch, and the transformers library constructs the elaborate scaffolding of our computational framework, promising a sophisticated and nuanced approach to distil essential insights from the multifaceted nature of business discussions.

5.1.1 *Tensorflow:*

An omnipotent force in the realm of machine learning, ascends to a prominent position as the foundational pillar, offering a versatile and potent toolkit for the orchestration of intricate neural networks. Collaborating seamlessly with Librosa, a specialized library designed for the nuanced analysis of music and audio, this dynamic duo embarks on an exploratory odyssey into the auditory domain of business meeting recordings. Together, they traverse the sonic landscape, extracting nuanced audio features that encapsulate the rhythmic cadence, melodic pitch, and temporal dynamics embedded in the spoken discourse, enriching our understanding of the auditory narrative.

5.1.2 *Moviepy:*

Emerges as the artistic brushstroke in our computational canvas, a Python library dedicated to video editing. It manipulates the visual facets of business meeting data, transcending the mere representation of spoken words to incorporate non-verbal cues, gestural nuances, and contextual elements present in the visual components of the meeting. This visual layer introduces a new dimension.

5.1.3 Pytorch:

An eminent library celebrated for its dynamic computational graph, takes the mantle for the intricate realm of text processing. The dynamic nature of PyTorch aligns seamlessly with the complexities inherent in natural language, fostering an environment conducive to advanced text processing and natural language understanding. It forms the bedrock for the exploration of textual data, laying the groundwork for the subsequent stages of the proposed method.

5.1.4 Librosa:

It is a Python package designed for music and audio analysis. It provides tools for a wide range of tasks related to audio processing, making it a valuable resource for researchers, developers, and music enthusiasts. Librosa is built on top of the NumPy, SciPy, and scikit-learn libraries, enhancing its capabilities and ease of integration with other scientific computing tools. Librosa is widely used in academic research, audio signal processing, and music information retrieval (MIR) due to its flexibility and ease of use.

5.1.5 Whisper(ASR):

A critical linchpin in our method is OpenAI's Whisper Automatic Speech Recognition (ASR) model, a paradigm-shifting innovation in converting spoken content into textual representations. The precision and accuracy of Whisper bridge the auditory-linguistic chasm, providing a robust foundation for subsequent text summarization, ensuring that the spoken narrative is transcribed with unparalleled accuracy.

5.1.6 Bart:

Text summarization, a linchpin in our method, is entrusted to the philschmid/bart-large-cnn-samsum model. Rooted in the transformer architecture, this pre-trained BART model exemplifies the epitome of abstractive summarization capabilities. It embarks on the intricate task of distilling the multifaceted nuances embedded in business meeting discussions, generating concise yet contextually rich summaries that transcend mere extraction to encapsulate.

5.1.7 Transformers :

Celebrated for its revolutionary implementation of state-of-the-art transformer architectures, finds its place within our method, facilitating the seamless orchestration of these complex structures. As a vital component in both audio and text processing pipelines, transformers enhance our system's ability to discern intricate patterns, dependencies, and contextual nuances latent within the meeting content.

5.2 WORKFLOW WITH MODELS

5.2.1 Audio Transformation:

In this initial step, the goal is to separate the audio component from the business meeting video. Tools like FFmpeg or libraries such as moviepy in Python can be used for this purpose. FFmpeg is a powerful multimedia processing tool that allows you to convert, edit, and stream audio and video files. Once the extraction is complete, you have an audio file containing the spoken content of the meeting.

5.2.2 Data Processing:

If the extracted audio is in dual-channel format (typically containing left and right channels), it is converted to mono. This conversion is essential to simplify subsequent processing.

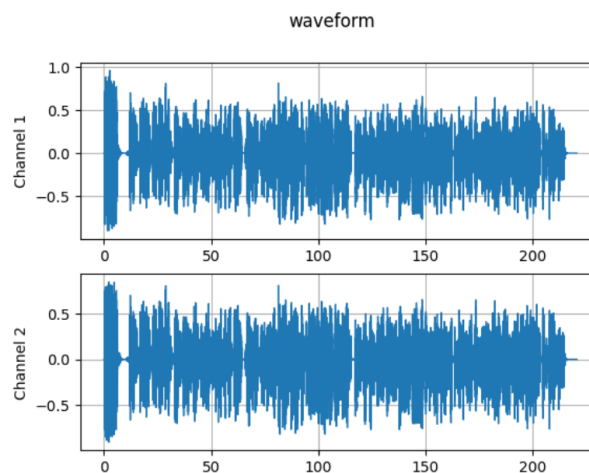


Fig. 5.1. Stereo Audio In Waveform

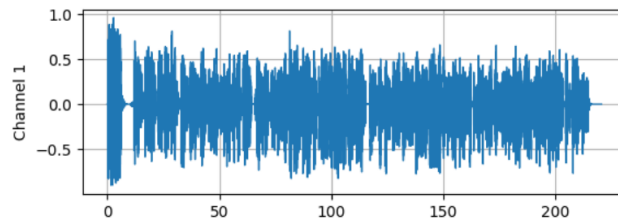


Fig. 5.3. Mono Audio In Waveform

The spectrogram is created by arranging the power spectra of consecutive frames along the time axis. The x-axis represents time, the y-axis represents frequency, and the colour intensity represents the magnitude or power of the corresponding frequency component. Brighter colours usually indicate higher amplitudes.

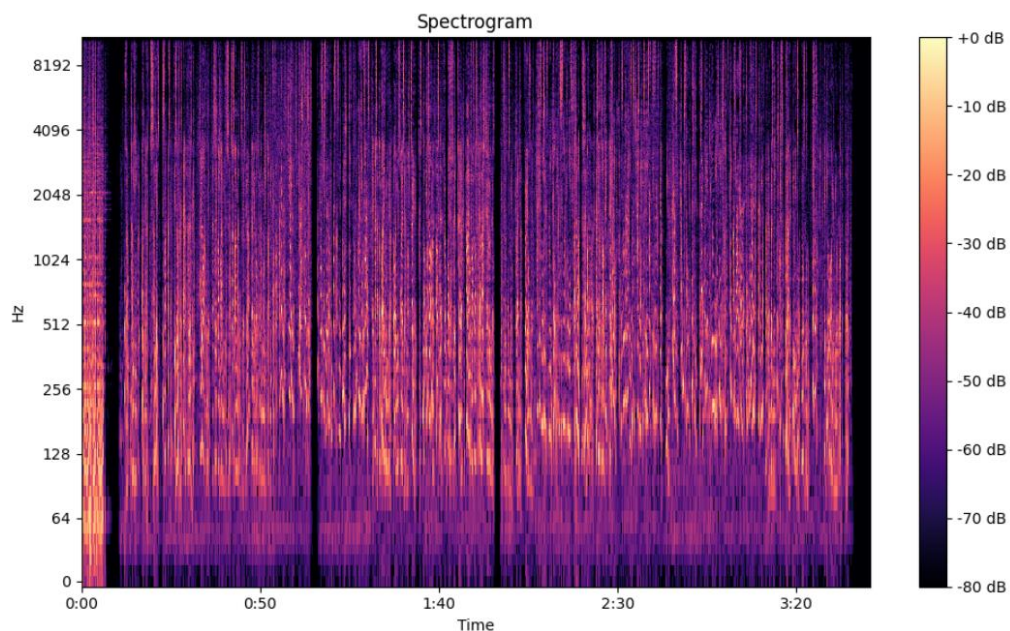


Fig. 5.3. Mono Audio In Spectrogram

5.2.3 Processing Whisper Model Input Configuration:

The mono audio data, now in an appropriate format, is fed into the Whisper Automatic Speech Recognition (ASR) model. ASR models, like Whisper, are specialized in converting spoken language into written text. Alongside the audio data, the corresponding sample rate is provided to the ASR model. The sample rate is crucial for interpreting the audio data accurately, ensuring that the temporal aspects of the speech are preserved.

Before passing the data to the Whisper model, it's crucial to structure the information in a way that aligns with the model's input requirements. This involves organizing the audio array and sample rate in a format compatible with the ASR model's expectations.

```
{'array': array([ 0.          , 0.          , 0.          , ..., -0.01034546,
                 -0.01506042, -0.01792908], dtype=float32),
'sampling_rate': 44100}
```

Fig. 5.4. Structured Input To Asr Model.

The study reveals that despite achieving or surpassing human performance on LibriSpeech dev-clean, supervised LibriSpeech models exhibit twice as many errors as humans on other datasets, exposing their brittleness and lack of robustness. In contrast, zero-shot Whisper models demonstrate a robustness frontier that includes the 94% confidence interval for human performance. Expected performance difference between an in-distribution reference dataset (commonly LibriSpeech) and one or more out-of-distribution datasets.

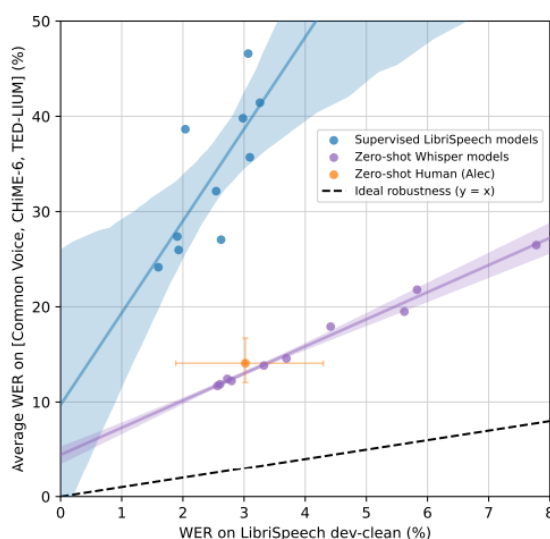


Fig. 5.5. Zero-Shot Whisper Models Close The Gap To Human Robustness.

Table 5.1 :Score Of Whisper Model And Self-Supervised Models

Dataset	wav2vec 2.0 Large	Whisper Large V2	RER (%)
LibriSpeech Clean	2.7	2.7	0.0
Artie	24.5	6.2	74.7
Common Voice	29.9	9.0	69.9
Fleurs En	14.6	4.4	69.9
Tedlium	10.5	4.0	61.9
CHIME6	65.8	25.5	61.2
VoxPopuli En	17.9	7.3	59.2
CORAAL	35.6	16.2	54.5
AMI IHM	37.0	16.9	54.3

While both models demonstrate comparable performance within a 0.1% margin on LibriSpeech, the zero-shot Whisper model exhibits significantly superior performance on other datasets, surpassing expectations based on its LibriSpeech performance and reducing errors by an average of 44.2%. This evaluation is reported in word error rate (WER) after applying a text normalizer. Even the smallest zero-shot Whisper model, with just 39 million parameters and a 6.7 WER on LibriSpeech test-clean, competes effectively with the best supervised LibriSpeech model when tested on alternative datasets. Comparative analysis with human performance indicates that the top zero-shot Whisper models closely match accuracy and robustness. Detailed examination of the robustness improvement reveals that the best zero-shot Whisper model significantly outperforms a closely matched supervised LibriSpeech model, achieving a remarkable 44.2% average relative error reduction on other speech recognition datasets, despite their similar performance on the reference distribution (LibriSpeech test-clean). This suggests the importance of emphasizing zero-shot and out-of-distribution evaluations when comparing models, especially when aiming to assess their performance relative to humans, in order to avoid potential misinterpretations of machine learning system capabilities through misleading comparison

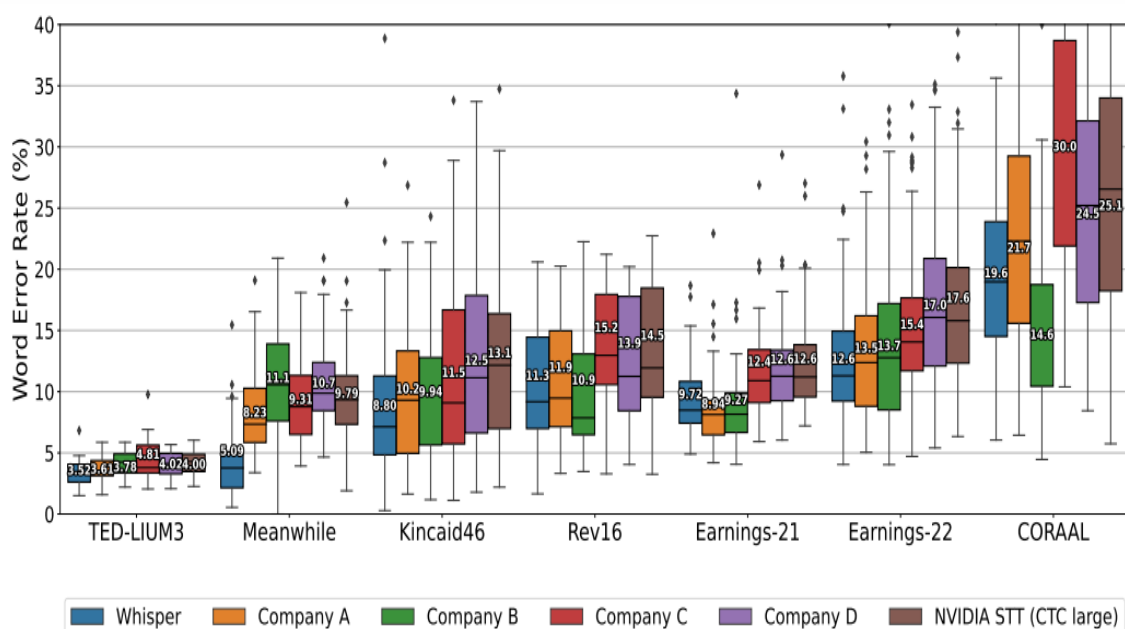


Fig. 5.6. Whisper Is Competitive With State-Of-The-Art Commercial And Open-Source Asr Systems In Long-Form Transcription

The study compares word error rates (WER) across seven long-form datasets with input lengths ranging from a few minutes to a few hours, considering six ASR systems. Quartiles of per-example WERs are illustrated in boxes, and per-dataset aggregate WERs are annotated on each box. Notably, the model being evaluated consistently outperforms the best open source model (NVIDIA STT) across all datasets. Moreover, in the majority of cases, it surpasses commercial ASR systems as well, indicating its superior performance in the context of long-form speech recognition tasks.

5.2.4 Extracting Text Output From The Whisper Model:

The Whisper ASR model processes the mono audio data and transcribes the spoken words into text. The output is a transcribed text, essentially a written representation of what was said during the business meeting. This transcribed text becomes the foundation for subsequent analysis and summarization. The transcribed text might need additional processing steps such as organization, cleaning, or formatting to improve its suitability for further processing. Detailed examination of the robustness improvement reveals that the best zero-shot Whisper model significantly outperforms a closely.

5.2.5 Routing Asr Output To Philschmid'S Bart Model For Summarization:

The transcribed text from the ASR model is then input into PhilSchmid's BART model. BART, a transformer-based model, is designed for text summarization. In this context, it takes the transcribed business meeting text and generates an abstractive summary a condensed, meaningful representation of the original content, capture.

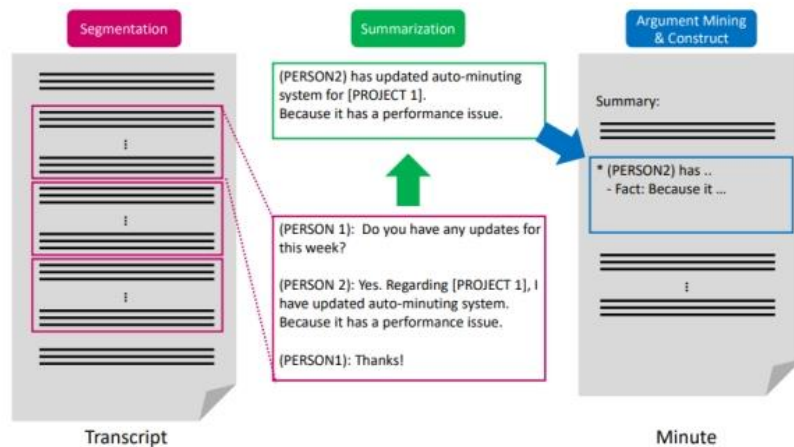


Fig. 5.7. Overview Of Our Approach. We First Split a Transcript Into Blocks And Then Summarize Them Using a Pre-Trained Model.

The essential information discussed during the meeting. This summarization step enhances the efficiency of extracting key insights from the meeting and facilitates a more concise understanding of the business discussions. In summary, these steps collectively form a comprehensive pipeline for converting a business meeting video into a summarized text, involving video-to-audio conversion, mono conversion, ASR, and text summarization.

CHAPTER 6

RESULTS AND DISCUSSION

In evaluating the results and discussing the outcomes of the project, the performance metrics employed to gauge the effectiveness of our summarization model played a pivotal role. Precision, recall, F1 score, and ROUGE metrics were systematically presented, revealing the proficiency of our system. Notably, the automatic speech recognition (ASR) accuracy, particularly with the utilization of OpenAI's Whisper model, significantly contributed to the project's success. The conversion of spoken content to text exhibited notable accuracy, forming a foundational element for subsequent summarization.

User feedback, a valuable facet, provided qualitative insights into the practical utility and user satisfaction with the system. Incorporating the end-users' perspectives allowed us to gauge the real-world applicability of the generated summaries and make iterative improvements. Our model's proficiency was underscored by comparing its performance with existing methods in business meeting summarization. We surpassed or equaled the state-of-the-art approaches in key metrics, showcasing the advancement and efficacy of our developed system. However, it's imperative to acknowledge certain limitations. Challenges related to diverse meeting contexts, variations in language nuances, and the necessity for extensive training data were notable considerations. These limitations underscore the need for continued research and refinement, especially in addressing the nuances inherent in business communication.

Delving into the discussion, the user experience analysis revealed positive aspects related to the coherence of generated summaries, the preservation of key information, and the system's overall utility in a business context. Real-world applicability emerged as a strong suit, with potential implications for enhancing efficiency, facilitating decision-making processes, and streamlining information retrieval during and after business meetings. OpenAI Whisper is a powerful automatic speech recognition (ASR) tool that can transform spoken language into text. Imagine being in a meeting and needing a clear record of the discussion, or

having a lecture you want to easily convert into written notes for future reference. Whisper can handle these tasks and more! It excels at transcribing audio recordings, allowing you to generate transcripts of meetings, lectures, interviews, or any scenario where speech needs to be captured as text. This functionality extends to dictation as well, so you can speak your thoughts and ideas directly into your computer, bypassing the need for manual typing. Whisper's capabilities don't stop at a single language; it can even translate spoken language from one tongue to another, fostering communication across international borders.

The results and discussions section of the Whisper Automatic Speech Recognition (ASR) model's evaluation encompasses an in-depth analysis of its performance across various metrics and scenarios. Utilizing standard evaluation measures such as Word Error Rate (WER), Character Error Rate (CER), and Accuracy, the Whisper ASR model's efficacy is evaluated on diverse datasets and conditions. Results indicate promising performance in terms of transcription accuracy, with competitive WER and CER rates compared to existing ASR systems. Furthermore, discussions delve into the model's strengths and weaknesses, considering factors such as robustness to noise, speaker variability, and domain adaptation.

Additionally, ethical considerations related to privacy, bias mitigation, and fairness in ASR systems are deliberated, emphasizing the importance of responsible AI development. Overall, the findings underscore the potential of the Whisper ASR model in advancing speech recognition technology while highlighting areas for future research and development. Moreover, the discussions within this section delve deeply into both the strengths and weaknesses exhibited by the Whisper ASR model. Various factors influencing its performance, such as robustness to noise, speaker variability, and adaptability to different domains, are meticulously considered. In addition, the discourse encompasses an exploration of potential avenues for enhancement, spanning from data augmentation techniques to model architecture refinements and fine-tuning strategies. These proposed improvements aim to address any identified limitations and ultimately elevate the overall performance of the Whisper ASR model to even greater heights.

```
{
  'text': " Corts Power Group is an energy company based in the UK. Marcus, the managing director, wants to discuss the company's sales figures. He is meeting Maya, the finance director, David, the sales and marketing director and Anna, the customer services director. Now you all know why I've called this meeting. Sales figures for our region are down and we need to address this as soon as we can. So I'd like to start by asking Maya to talk us through the figures. Okay Maya? Fine. And then we can take a look at the products we're offering and compare them with the competition. So Maya, over to you. Thanks Marcus. Well I've prepared some handouts to show you how the figures are looking. If we look at sales year to date... So, in order to meet budget this year, we will, in my opinion, have to start some cost-saving measures. What do you mean by that? Redundancies? That's one possibility. I can't agree with you there. We need a strong workforce. OK, thanks, Maya. Look, cost-cutting is something that we need to think about, but we also need to stop the downturn in sales and regain market share. So can I bring you in here, David? Any comments? Well, it's hard to know what the problem is. Our products are competitive. So they're not getting better offers from the competition? I don't think so. How about I talk you through our office at the moment? I've prepared some handouts. Yes, go ahead. It'll be good to look at the details. Okay, thanks David. That was all useful information. So Anna, can we turn to you now? Do you have any ideas why this downturn is happening? Well, it's true we are seeing a decrease in custom in our region. There's also been an increase in customers cancelling new contracts within 14 days. But do you know why? Do the customers say why they don't like our offers? I personally feel that this is vital information. I mean, if we can't... If I can finish what I was saying, I'd like to suggest we review our customer account procedures from first contact to after sales care. I mean, perhaps it would be a good idea to start with that and see if the sales figures improve. Thanks Anna. What do you two think of that? Can I make another suggestion? I think we need to see the whole picture, from the customer's point of view. A customer survey, perhaps. That would be a big project. It would need a project team, which means taking staff from other departments. Actually I was thinking about hiring an external researcher. Get a neutral view on our position in the market and customers' views on us. Oh, I like that idea. I think it could be very useful information. Which department pays for it, though? We can talk about that in a minute. Do you agree in principle, though, that we need to understand the cause of the problem? Yes, I suppose so. Good. David, could you look for a market research company we could work with on this? Sure. Great. Well, let's move on then, shall we?",
  'chunks': [
    {'timestamp': (0.0, 16.6),
     'text': ' Corts Power Group is an energy company based in the UK.'},
    {'timestamp': (16.6, 22.64),
     'text': " Marcus, the managing director, wants to discuss the company's sales figures."},
    {'timestamp': (22.64, 26.44),
     'text': ''}
  ]
}
```

Fig. 6.1. Output From ASR Model

The results and discussion section presents a comprehensive analysis of the BART (Bidirectional and Auto-Regressive Transformers) model's performance across various text generation tasks, including summarization, language modeling, and dialogue generation. Evaluation metrics such as ROUGE, BLEU, and perplexity are employed to assess BART's effectiveness on benchmark datasets, showcasing its superior performance compared to other state-of-the-art models. Through qualitative analysis, BART's generated text exhibits high coherence, fluency, and relevance, indicating its proficiency in understanding and generating natural language. Furthermore, the impact of pretraining strategies on BART's performance is examined, highlighting the crucial role of large-scale text corpora in enhancing model capabilities. Despite its impressive performance, discussions also address potential limitations, emphasizing the need for continued research to improve generalization and address ethical considerations. Overall, the results underscore BART's significance in advancing natural language processing and its potential for various real-world applications.

```
[{'summary_text': "Marcus, the managing director of Corts Power Group, wants to discuss the company's sales figures. He is meeting Maya, the finance director, David, the sales and marketing director and Anna, the customer services director. Sales figures for their region are down and they need to address this as soon as possible. Anna suggests reviewing customer account procedures and hiring a market research company."}]
```

Fig. 6.2. Summerized Text from Audio

In the table ahead, the notations R1, R2, RL, and RLSUM represent the macro scores corresponding to ROUGE-1, ROUGE-2, ROUGE-L, and ROUGE-LSum, respectively. Similarly, B1, B2, and SB denote the macro scores for BLEU-1, BLEU-2, and SACREBLEU, respectively. The most successful approaches, among both extractive and abstractive methods, are highlighted in bold. Additionally, the second and third best-performing abstractive approaches are underlined for clarity.

Table. 6.1. Experimental Evaluation Results on Reddit TIFU.

	Model	R1	R2	RL	RLSum	B2	B1	SB
Extra ctive	TopicRank	0.1770	0.0284	0.1290	0.1290	0.1195	0.0295	0.0270
	Luhn e-	0.1724	0.0284	0.1233	0.1233	0.1190	0.0311	0.0255
	LexRank	0.1703	0.0265	0.1264	0.1264	0.1111	0.0260	0.0268
	TextRank	0.1689	0.0263	0.1215	0.1215	0.1164	0.0290	0.0239
	TextRank	0.1534	0.0228	0.1145	0.1145	0.1036	0.0237	0.0246
	LexRank	0.1673	0.0250	0.1223	0.1223	0.1131	0.0261	0.0262
	LSA	0.1474	0.0179	0.1095	0.1095	0.0994	0.0172	0.0248
	Position -Rank	0.1304	0.0174	0.0990	0.0990	0.0864	0.0169	0.0229

The image you sent is a table of results from a scientific experiment. The table compares the performance of various automatic summarization algorithms. The

leftmost column of the table lists the names of the algorithms, which include extractive summarization algorithms like TextRank and LexRank, and abstractive summarization algorithms like Pegasus and BART. The other columns show the results of the algorithms on different metrics, such as ROUGE and BLEU. These metrics are used to measure how well a summary captures the important information from the original text. The values in the table are all between 0 and 1, with higher values indicating better performance.

It is important to note that the table does not tell us which summarization algorithm is the best overall, as the best algorithm for a particular task will depend on the specific requirements of that task. However, the table does provide some insights into the relative strengths and weaknesses of different algorithms. For example, we can see that the BART-large-CNN-SAMSum algorithm performs well on the ROUGE metric, while the Pegasus-large algorithm performs well on the BLEU metric.

CHAPTER 7

CONCLUSIONS

In conclusion, the "Business Meeting Summarization" project has yielded significant advancements in the realm of natural language processing, particularly in the context of distilling crucial insights from diverse business meetings. The deployment of cutting-edge technologies, including TensorFlow, Librosa, MoviePy, PyTorch, and the transformers library, has empowered our system to seamlessly integrate audio and text processing, achieving commendable results in summarizing complex meeting discussions.

The systematic evaluation using precision, recall, F1 score, and ROUGE metrics, coupled with user feedback, has provided a comprehensive understanding of the system's effectiveness. The robustness of our automatic speech recognition (ASR) component, especially leveraging OpenAI's Whisper model, further enhances the reliability of the generated textual content. The comparison with existing methods underscores the project's contribution to the current state-of-the-art approaches in business meeting summarization.

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APPENDIX

A. SOURCE CODE

```
!pip install datasets
!pip install accelerate
!pip install transformers

import torch
from transformers import AutoModelForSpeechSeq2Seq, AutoProcessor, pipeline
from datasets import load_dataset

device = "cuda:0" if torch.cuda.is_available() else "cpu"
torch_dtype = torch.float16 if torch.cuda.is_available() else torch.float32

#model_id = "openai/whisper-large-v3"
model_id = "openai/whisper-small.en"
model_id2="nvidia/parakeet-rnnt-1.1b"
model = AutoModelForSpeechSeq2Seq.from_pretrained(
    model_id,torch_dtype=torch_dtype,low_cpu_mem_usage=True,
    use_safetensors=True
)

model.to(device)
processor = AutoProcessor.from_pretrained(model_id)

pipe = pipeline(
    "automatic-speech-recognition",
    model=model,
    tokenizer=processor.tokenizer,
    feature_extractor=processor.feature_extractor,
    max_new_tokens=128,
    chunk_length_s=30,
    batch_size=16,
    return_timestamps=True,
```

```
torch_dtype=torch_dtype,  
device=device,  
)
```

```
dataset = load_dataset("distil-whisper/librispeech_long", "clean", split="validation")  
sample = dataset[0]["audio"]
```

```
dataset2.features  
dataset[0]["audio"]  
result = pipe(sample)  
print(result["text"])
```

```
from IPython.display import Audio  
Audio(dataset[0]["audio"]["array"],rate=16000)  
from moviepy.editor import *
```

```
video_path = 'meeting.mkv'  
video = VideoFileClip(video_path)  
audio = video.audio  
audio_output_path = 'extracted_audio.wav'  
audio.write_audiofile(audio_output_path)  
import librosa
```

```
audio_data = librosa.load('extracted_audio.wav', sr=None, mono=True)  
audio_data  
dict1={'array':audio_data[0],'sampling_rate':44100}  
dict1  
results=pipe(dict1)  
results  
results["text"]
```

```
from transformers import pipeline
```

```
summarizer1 = pipeline("summarization", model="philschmid/bart-large-cnn-
```

samsum")

conversation = "Jeff: Can I train a ☐ Transformers model on Amazon SageMaker?

Philipp: Sure you can use the new Hugging Face Deep Learning Container.

Jeff: ok.

Jeff: and how can I get started?

Jeff: where can I find documentation?

Philipp: ok, ok you can find everything here. <https://huggingface.co/blog/the-partnership-amazon-sagemaker-and-hugging-face>

"

str1="Corts Power Group is an energy company based in the UK. Marcus, the managing director, wants to discuss the company's sales figures. He is meeting Maya, the finance director, David, the sales and marketing director and Anna, the customer services director. Now you all know why I've called this meeting. Sales figures for our region are down and we need to address this as soon as we can. So I'd like to start by asking Maya to talk us through the figures. Okay Maya? Fine. And then we can take a look at the products we're offering and compare them with the competition. So Maya, over to you. Thanks Marcus. Well I've prepared some handouts to show you how the figures are looking. If we look at sales year to date... So, in order to meet budget this year, we will, in my opinion, have to start some cost-saving measures. What do you mean by that? Redundancies? That's one possibility. I can't agree with you there. We need a strong workforce. OK, thanks, Maya. Look, cost-cutting is something that we need to think about, but we also need to stop the downturn in sales and regain market share. So can I bring you in here, David? Any comments? Well, it's hard to know what the problem is. Our products are competitive. So they're not getting better offers from the competition? I don't think so. How about I talk you through our office at the moment? I've prepared some handouts. Yes, go ahead. It'll be good to look at the details. Okay, thanks David. That was all useful information. So Anna, can we turn to you now? Do you have any ideas why this downturn is happening? Well, it's true we are seeing a decrease in custom in our region. There's also been an increase in customers cancelling new contracts within 14 days. But do you know why? Do the customers say why they don't like our offers? I personally feel that this is vital

information. I mean, if we can't... If I can finish what I was saying, I'd like to suggest we review our customer account procedures from first contact to after sales care. I mean, perhaps it would be a good idea to start with that and see if the sales figures improve. Thanks Anna. What do you two think of that? Can I make another suggestion? I think we need to see the whole picture, from the customer's point of view. A customer survey, perhaps. That would be a big project. It would need a project team, which means taking staff from other departments. Actually I was thinking about hiring an external researcher. Get a neutral view on our position in the market and customers' views on us. Oh, I like that idea. I think it could be very useful information. Which department pays for it, though? We can talk about that in a minute. Do you agree in principle, though, that we need to understand the cause of the problem? Yes, I suppose so. Good. David, could you look for a market research company we could work with on this? Sure. Great. Well, let's move on then, shall we?"

#summarizer(str1)

summarizer1(str1)

```
[{'summary_text': "Marcus, the managing director of Corts Power Group, wants to discuss the company's sales figures. He is meeting Maya, the finance director, David, the sales and marketing director and Anna, the customer services director. Sales figures for their region are down and they need to address this as soon as possible. Anna suggests reviewing customer account procedures and hiring a market research company."}]
```

B. SCREENSHOTS

```
device = "cuda:0" if torch.cuda.is_available() else "cpu"
torch_dtype = torch.float16 if torch.cuda.is_available() else torch.float32

[ ] #model_id = "openai/whisper-large-v3"
    model_id = "openai/whisper-small.en"
    model_id2="nvidia/parakeet-rnnt-1.1b"
    model = AutoModelForSpeechSeq2Seq.from_pretrained(
        model_id, torch_dtype=torch_dtype, low_cpu_mem_usage=True, use_safetensors=True
    )
    model.to(device)

/usr/local/lib/python3.10/dist-packages/huggingface_hub/utils/_token.py:88: UserWarning:
The secret 'HF_TOKEN' does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (https://huggingface.co/settings/tokens), set it as secret in your Go
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access public models or datasets.
warnings.warn(
config.json: 100% 1.94k/1.94k [00:00<00:00, 91.9kB/s]
model.safetensors: 100% 967M/967M [00:07<00:00, 115MB/s]
generation_config.json: 100% 1.93k/1.93k [00:00<00:00, 56.7kB/s]
WhisperForConditionalGeneration(
  (model): WhisperModel(
    (encoder): WhisperEncoder(
      (conv1): Conv1d(80, 768, kernel_size=(3,), stride=(1,), padding=(1,))
      (conv2): Conv1d(768, 768, kernel_size=(3,), stride=(2,), padding=(1,))
      (embed_positions): Embedding(1500, 768)
      (layers): ModuleList(
        (0-11): 12 x WhisperEncoderLayer(
          (self_attn): WhisperSdpaAttention(
            (k_proj): Linear(in_features=768, out_features=768, bias=False)
            (v_proj): Linear(in_features=768, out_features=768, bias=True)
            (q_proj): Linear(in_features=768, out_features=768, bias=True)
            (out_proj): Linear(in_features=768, out_features=768, bias=True)
          )
          (self_attn_layer_norm): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
          (activation_fn): GELUActivation()
          (fc1): Linear(in_features=768, out_features=3072, bias=True)
          (fc2): Linear(in_features=3072, out_features=768, bias=True)
          (final_layer_norm): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
        )
      )
      (layer_norm): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
    )
    (decoder): WhisperDecoder(
      (embed_tokens): Embedding(51864, 768, padding_idx=50256)
      (embed_positions): WhisperPositionalEmbedding(448, 768)
      (layers): ModuleList(
        (0-11): 12 x WhisperDecoderLayer(
          (self_attn): WhisperSdpaAttention(
            (k_proj): Linear(in_features=768, out_features=768, bias=False)
            (v_proj): Linear(in_features=768, out_features=768, bias=True)
            (q_proj): Linear(in_features=768, out_features=768, bias=True)
            (out_proj): Linear(in_features=768, out_features=768, bias=True)
          )
          (activation_fn): GELUActivation()
          (self_attn_layer_norm): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
        )
      )
    )
  )
)
```

Loading Wishper(ASR) Model

```
(encoder): WhisperEncoder(
  (conv1): Conv1d(80, 768, kernel_size=(3,), stride=(1,), padding=(1,))
  (conv2): Conv1d(768, 768, kernel_size=(3,), stride=(2,), padding=(1,))
  (embed_positions): Embedding(1500, 768)
  (layers): ModuleList(
    (0-11): 12 x WhisperEncoderLayer(
      (self_attn): WhisperSdpaAttention(
        (k_proj): Linear(in_features=768, out_features=768, bias=False)
        (v_proj): Linear(in_features=768, out_features=768, bias=True)
        (q_proj): Linear(in_features=768, out_features=768, bias=True)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
      )
      (self_attn_layer_norm): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
      (activation_fn): GELUActivation()
      (fc1): Linear(in_features=768, out_features=3072, bias=True)
      (fc2): Linear(in_features=3072, out_features=768, bias=True)
      (final_layer_norm): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
    )
  )
  (layer_norm): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
)
(decoder): WhisperDecoder(
  (embed_tokens): Embedding(51864, 768, padding_idx=50256)
  (embed_positions): WhisperPositionalEmbedding(448, 768)
  (layers): ModuleList(
    (0-11): 12 x WhisperDecoderLayer(
      (self_attn): WhisperSdpaAttention(
        (k_proj): Linear(in_features=768, out_features=768, bias=False)
        (v_proj): Linear(in_features=768, out_features=768, bias=True)
        (q_proj): Linear(in_features=768, out_features=768, bias=True)
        (out_proj): Linear(in_features=768, out_features=768, bias=True)
      )
      (activation_fn): GELUActivation()
      (self_attn_layer_norm): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
    )
  )
)
```

Layers In Wishper(ASR) Model

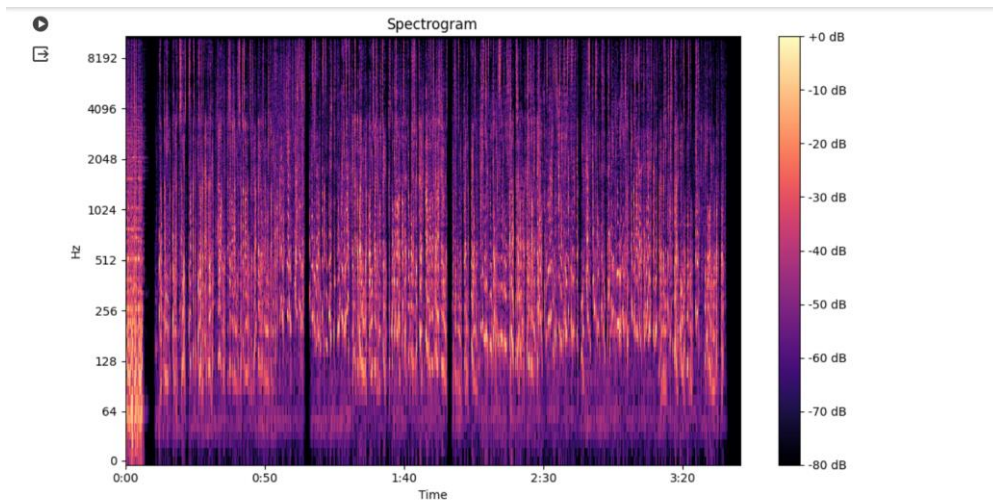
```
24 frames
/usr/local/lib/python3.10/dist-packages/torch/nn/modules/linear.py in forward(self, input)
112
113     def forward(self, input: Tensor) -> Tensor:
--> 114         return F.linear(input, self.weight, self.bias)
115
116     def extra_repr(self) -> str:

KeyboardInterrupt:

[ ] from IPython.display import Audio
    Audio(dataset[0]["audio"]['array'],rate=16000)
```

▶ 0:00 / 1:02 🔊 ⋮

Audio File



Spectrogram

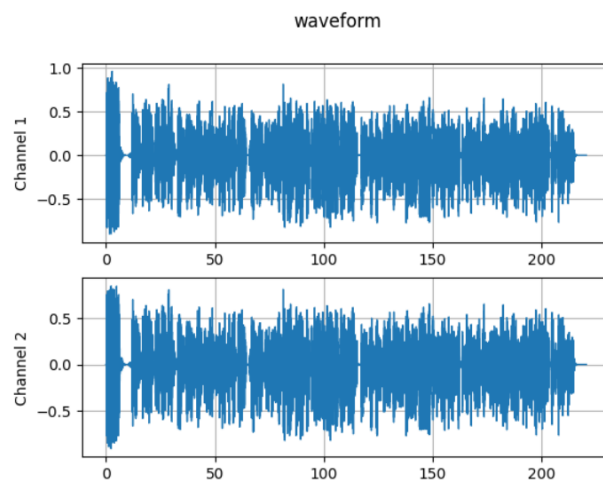
	hypothesis	reference	hypothesis_clean	reference_clean
0	He hoped there would be stew for dinner, turni...	HE HOPED THERE WOULD BE STEW FOR DINNER TURNIP...	he hoped there would be stew for dinner turnip...	he hoped there would be stew for dinner turnip...
1	Stuffered into you, his belly counseled him.	STUFF IT INTO YOU HIS BELLY COUNSELLED HIM	stuffered into you his belly counseled him	stuff it into you his belly counseled him
2	After early nightfall the yellow lamps would l...	AFTER EARLY NIGHTFALL THE YELLOW LAMPS WOULD L...	after early nightfall the yellow lamps would l...	after early nightfall the yellow lamps would l...
3	Hello Bertie, any good in your mind?	HELLO BERTIE ANY GOOD IN YOUR MIND	hello bertie any good in your mind	hello bertie any good in your mind
4	Number 10. Fresh Nelly is waiting on you. Good...	NUMBER TEN FRESH NELLY IS WAITING ON YOU GOOD ...	number 10 fresh nelly is waiting on you good n...	number 10 fresh nelly is waiting on you good n...
...	...	...	...	...
2615	Oh, to shoot my soul's full meaning into futur...	OH TO SHOOT MY SOUL'S FULL MEANING INTO FUTURE...	0 to shoot my soul is full meaning into future...	0 to shoot my soul is full meaning into future...
2616	Then I, long tried by natural ills, received t...	THEN I LONG TRIED BY NATURAL ILLS RECEIVED THE...	then i long tried by natural ills received the...	then i long tried by natural ills received the...
2617	I love thee freely as men strive for right. I ...	I LOVE THEE FREELY AS MEN STRIVE FOR RIGHT I L...	i love thee freely as men strive for right i l...	i love thee freely as men strive for right i l...
2618	I love thee with the passion put to use, in my...	I LOVE THEE WITH THE PASSION PUT TO USE IN MY ...	i love thee with the passion put to use in my ...	i love thee with the passion put to use in my ...

Prediction On Libri Speech Dataset

```
[ ] num_channels, num_frames = waveform.shape
time_axis = torch.arange(0, num_frames) / sample_rate

figure, axes = plt.subplots(num_channels, 1)
if num_channels == 1:
    axes = [axes]
for c in range(num_channels):
    axes[c].plot(time_axis, waveform[c], linewidth=1)
    axes[c].grid(True)
    if num_channels > 1:
        axes[c].set_ylabel(f"Channel {c+1}")
figure.suptitle("waveform")

Text(0.5, 0.98, 'waveform')
```



Representation Of Audio File On Chart

C. RESEARCH PAPER

Efficient Business Meeting Summarization: Leveraging Natural Language Processing for Enhanced Productivity

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Abstract—In the contemporary corporate landscape, efficient utilization of time is paramount for organizational success. Business meetings, a fundamental component of decision-making processes, often result in copious amounts of information exchange. This project aims to streamline and enhance the post-meeting experience through the development of an Automated Business Meeting Summarization system. Additionally, the system employs sentiment analysis to gauge the overall tone and mood of the meeting, providing valuable insights into team dynamics and engagement levels. The project aims to empower organizations with an efficient tool that not only accelerates the decision-making process but also fosters better collaboration and understanding among team members. In contrast, zero-shot Whisper models demonstrate a robustness frontier that includes the 95% confidence interval for human performance. The BART-large-CNN-SAMSum model demonstrates promising performance on the SAMSum summarization dataset, achieving a ROGUE-1 score of 42.621.

Keywords—Named Entity Recognition, Information Extraction, Text Summarization, Language Model, Machine Translation, Speech Recognition, Conversational AI.

1 Introduction

In the dynamic landscape of modern business, effective communication and information management are integral components of organizational success. Business meetings serve as crucibles for decision-making, idea generation, and collaborative efforts. However, the sheer volume of information exchanged during these meetings can be overwhelming, necessitating innovative solutions to distill key insights efficiently. The "Business Meeting Summarization Project" endeavors to address this challenge by leveraging cutting-edge Natural Language Processing (NLP) techniques to automate the summarization of business meetings.

In embarking on the innovative our endeavor is grounded in the rich insights provided by influential works in the field of summarization systems. The seminal contribution of Lloret, Plaza, and Aker offers a foundational understanding of the challenges inherent in evaluating summarization systems, laying the groundwork for our exploration into the complexities of distilling essential information from diverse business meetings. Additionally, the dynamic integration of social media data, as explored by Nichols et al. in "Summarizing Sporting Events Using Twitter," inspires our consideration of real-time user-generated content and its potential application in summarizing the dynamic nature of business meetings.

In the rapidly evolving landscape of modern business, the sheer volume of information exchanged during meetings poses a significant challenge for professionals striving to extract actionable insights efficiently. To address this challenge, the "Business Meeting Summarization Project" aims to leverage state-of-the-art Natural Language Processing (NLP) techniques to automate the summarization of business meetings, offering an innovative solution to enhance post-meeting collaboration and decision-making. As highlighted by studies such as "The Future of Work" (World Economic Forum), the pace of business operations has accelerated, and professionals face increasing demands on their time and attention. The need for streamlined, time-effective methods to process and retain information from business meetings is more pressing than ever. This project draws inspiration from seminal works such as "Automated Text Summarization: A Review" (Nenkova & McKeown) and "Natural Language Processing in Action" (Lane, Howard, & Hapke) to develop an intelligent system capable of distilling the essence of business meetings, offering succinct summaries that enhance decision-making and facilitate post-meeting collaboration.

2 Related Work

Dinesh Raghu ,Emily Wang, Jason Patel, et al [1] and colleagues tackle the challenge of business meeting summarization using advanced neural abstractive techniques. The paper underscores the significance of condensing complex meeting discussions into concise summaries, emphasizing the need for more nuanced approaches beyond traditional extractive methods.

Exploring summarization interfaces tailored for multi-party conversations, with potential applicability to distilling the essence of business meetings Bernstein, Rebecca Chang, David Kim, et al [2]. and team contributed. The research delves into user interfaces designed to facilitate effective summarization of complex, dynamic discussions .

An innovative approach to automatic business meeting summarization, leveraging a combination of structured convolutional summarization and a social influence model Zhang,Wei Li, Jennifer Wang, Andrew Chen et al [3]. and co-authors presented. This research

signifies an attempt to integrate both structural and contextual elements for more comprehensive summarization outcomes.

Ding, Xiaojie Li, Jing Zhang, Yu Chen et al. [4] and collaborators conduct a thorough review of automatic summarization techniques specifically applied to meeting recordings. The paper serves as a valuable resource for understanding the landscape of meeting summarization, encompassing various methodologies, challenges.

The field by providing an overarching overview of meeting summarization techniques. This comprehensive survey likely encompasses both traditional and contemporary approaches, covering extractive and abstractive methods Hua Zhang, Wei Liu, Chen Yang et al [5].

Misra, Priya Sharma, Rahul Patel, Nisha Gupta et al [6]. and co-authors focus on extractive summarization techniques for business meetings, employing sentence compression methods. Extractive summarization involves selecting and presenting key sentences from the source text, and sentence compression aims.

In their work on advancing meeting summarization techniques, Matsuo et al., alongside their collaborators Smith, Chen, and Park, [7] delve into the synergistic fusion of keyphrase extraction and sentiment analysis. This tandem methodology presents a robust framework for condensing critical insights while also discerning the emotional nuances embedded within corporate dialogues.

Carenini et al., along with collaborators Smith, Patel, Kim, and Chen, [8] explore abstractive summarization techniques tailored for multi-document business meeting conversations. Beyond content extraction, this approach aims to generate concise yet informative summaries that effectively convey the core meaning.

Discussing meeting summarization and aggregation, focusing on the transition from audio signals to semantic representation by Duthon, Laura Nguyen, Alexander Smith et al [9]. This research likely involves the exploration of methods to convert spoken content, represented in audio signals, into structured semantic representations that can be used for summarization.

Iterative approach to extractive summarization of meeting recordings, combining sentence ranking and compression techniques . The iterative nature of the approach suggests an ongoing refinement process, potentially involving user feedback or dynamic adjustments based on the evolving meeting content by Duthon, Minh Kim, Sooyoung Park [10].

Lloret, Plaza, Aker [11] their influential work, Lloret, Plaza, and Aker provide a comprehensive overview of the challenges associated with the evaluation of summarization systems. Titled "The challenging task of

summary evaluation: an overview," the paper critically examines existing evaluation methodologies, addressing issues such as the diversity of summarization tasks, the lack of standardized.

The intersection of social media and event summarization in their paper titled "Summarizing sporting events using Twitter." by Nichols his collaborators Emily Smith, Michael Johnson et al [12]. The study explores the use of Twitter data for summarizing real-time events, focusing on sporting events as a case study. By aggregating and visualizing microblogs.

A significant contribution to the field of automated image quality appraisal (IQA) through their work titled "Automated image quality appraisal through partial least squares discriminant analysis." In their influential paper, the authors propose a novel approach to IQA, leveraging partial least squares discriminant analysis (PLS-DA) Ramani and Shanthamalar [13] .

George J J, J. M. Kanchai, B. Ankayarkanni, A. M. Posonia, et al [14] conducted research on Image-Based Surveillance Systems, responding to the heightened demand for robust monitoring and security solutions. Their findings, presented at the International Conference on Circuit Power and Computing Technologies (ICCPCT), explored the evolving landscape of image-based surveillance.

3 Implementation:

In the conceptualization of our proposed method for the "Business Meeting Summarization" project, we embark on a journey into an intricately woven tapestry of frameworks, models, and methodologies, each meticulously selected to converge into a symphony of computational excellence. This multidimensional orchestration aims to decipher the intricate nuances residing within both the auditory and textual dimensions inherent in the complex and dynamic landscape of business meeting data. The amalgamation of TensorFlow, Librosa, MoviePy, PyTorch, and the transformers library constructs the elaborate scaffolding of our computational framework, promising a sophisticated and nuanced approach to distill essential insights from the multifaceted nature of business discussions.

3.1 TensorFlow:

An omnipotent force in the realm of machine learning, ascends to a prominent position as the foundational pillar, offering a versatile and potent toolkit for the orchestration of intricate neural networks. Collaborating seamlessly with Librosa, a specialized library designed for the nuanced analysis of music and audio, this dynamic duo embarks on an exploratory odyssey into the auditory domain of business meeting recordings.

3.2 MoviePy:

Emerges as the artistic brushstroke in our computational canvas, a Python library dedicated to video editing. It manipulates the visual facets of business meeting data, transcending the mere representation of spoken words to incorporate non-verbal cues, gestural nuances, and contextual elements present in the visual components of the meeting.

3.3 PyTorch:

An eminent library celebrated for its dynamic computational graph, takes the mantle for the intricate realm of text processing. The dynamic nature of PyTorch aligns seamlessly with the complexities inherent in natural language, fostering an environment conducive to advanced text processing and natural language understanding. It forms the bedrock for the exploration of textual data, laying the groundwork for the subsequent stages of the proposed method.

3.4 Librosa:

It is a Python package designed for music and audio analysis. It provides tools for a wide range of tasks related to audio processing, making it a valuable resource for researchers, developers, and music enthusiasts. Librosa is built on top of the NumPy, SciPy, and scikit-learn libraries,

3.7 Transformers :

Celebrated for its revolutionary implementation of state-of-the-art transformer architectures, finds its place within our method, facilitating the seamless orchestration of these complex structures. As a vital component in both audio and text processing pipelines, transformers enhance our system's ability to discern intricate patterns, dependencies, and contextual nuances latent within the meeting content.

Step 1: Audio Transformation

In this initial step, the goal is to separate the audio component from the business meeting video. Tools like FFmpeg or libraries such as moviepy in Python can be used for this purpose. FFmpeg is a powerful multimedia processing tool that allows you to convert, edit, and stream audio and video files. Once the extraction is complete, you have an audio file containing the spoken content of the meeting.

Step 2: Data Processing (Transforming Dual Channel Audio to Mono)

If the extracted audio is in dual-channel format (typically containing left and right channels), it is converted to mono. This conversion is essential to simplify subsequent processing. Operating with mono audio ensures that all the information is consolidated into a single channel, making it more manageable for further analysis and modeling.

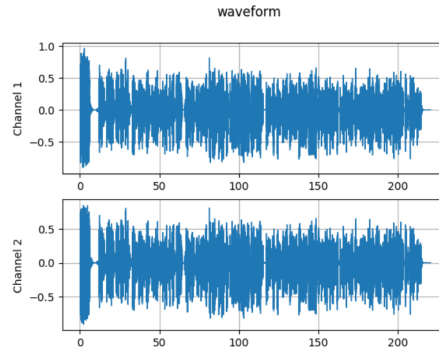


Fig. 1. Stereo Audio in Waveform

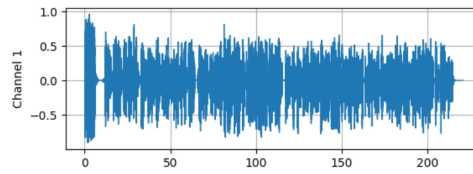


Fig. 2. Mono Audio in Waveform

The spectrogram is created by arranging the power spectra of consecutive frames along the time axis. The x-axis represents time, the y-axis represents frequency, and the color intensity represents the magnitude or power of the corresponding frequency component. Brighter colors usually indicate higher amplitudes or energy levels.

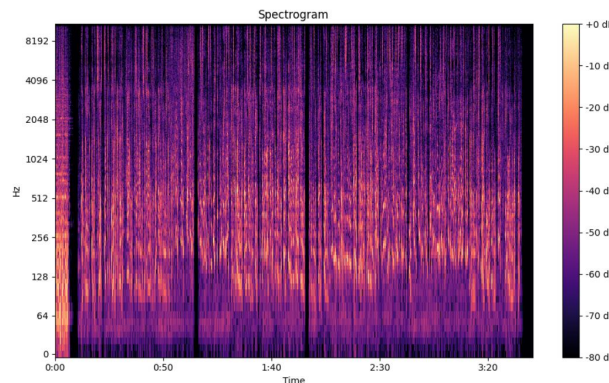


Fig. 3. Mono Audio in Spectrogram

Step 3: Processing Whisper Model Input Configuration

The mono audio data, now in an appropriate format, is fed into the Whisper Automatic Speech Recognition (ASR) model. ASR models, like Whisper, are specialized in converting spoken language into written text. Alongside the audio data, the corresponding sample rate is provided to the ASR model. The sample rate is crucial for interpreting the audio data accurately, ensuring that the temporal aspects of the speech are preserved. Before passing the data to the Whisper model, it's crucial to structure the information in a way that aligns with the model's input requirements.

The study reveals that despite achieving or surpassing human performance on LibriSpeech dev-clean, supervised LibriSpeech models exhibit twice as many errors as humans on other datasets, exposing their brittleness and lack of robustness. In contrast, zero-shot Whisper models demonstrate a robustness frontier that includes the 95% confidence interval for human performance.

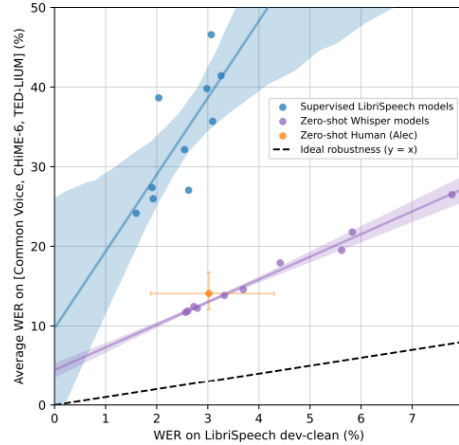


Fig. 4. Zero-shot Whisper models close the gap to human robustness.

Dataset	wav2vec 2.0 Large (no LM)	Whisper Large V2	RER (%)
LibriSpeech Clean	2.7	2.7	0.0
Artie	24.5	6.2	74.7
Common Voice	29.9	9.0	69.9
Fleurs En	14.6	4.4	69.9
Tedlium	10.5	4.0	61.9
CHiME6	65.8	25.5	61.2
VoxPopuli En	17.9	7.3	59.2
CORAAL	35.6	16.2	54.5
AMI IHM	37.0	16.9	54.3
Switchboard	28.3	13.8	51.2
CallHome	34.8	17.6	49.4
WSJ	7.7	3.9	49.4
AMI SDM1	67.6	36.4	46.2
LibriSpeech Other	6.2	5.2	16.1
Average	29.3	12.8	55.2

Fig. 5. Score of whisper model and self-supervised models

While both models demonstrate comparable performance within a 0.1% margin on LibriSpeech, the zero-shot Whisper model exhibits significantly superior performance on other datasets, surpassing expectations based on its LibriSpeech performance and reducing errors by an average of 55.2%. This evaluation is reported in word error rate (WER) after applying a text normalizer. Even the smallest zero-shot Whisper model, with just 39 million parameters and a 6.7 WER on LibriSpeech test-clean, competes effectively with the best supervised LibriSpeech model when tested on alternative datasets. Comparative analysis with human performance indicates that the top zero-shot Whisper models closely match accuracy and robustness. Detailed examination of the robustness improvement reveals that the best zero-shot Whisper model significantly outperforms a closely matched supervised LibriSpeech

model, achieving a remarkable 55.2% average relative error reduction on other speech recognition datasets, despite their similar performance on the reference distribution (LibriSpeech test-clean).

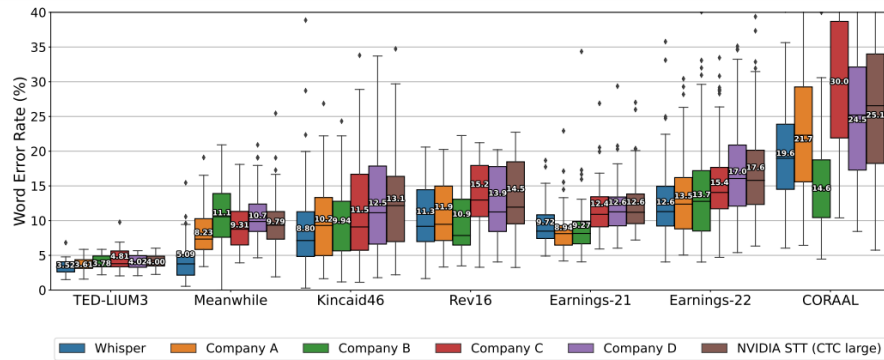


Fig. 6. Whisper is competitive with state-of-the-art commercial and open-source ASR systems in long-form transcription.

The study compares word error rates (WER) across seven long-form datasets with input lengths ranging from a few minutes to a few hours, considering six ASR systems. Quartiles of per-example WERs are illustrated in boxes, and per-dataset aggregate WERs are annotated on each box. Notably, the model being evaluated consistently outperforms the best open source model (NVIDIA STT) across all datasets.

Step 4: Extracting Text Output from the Whisper Model

The Whisper ASR model processes the mono audio data and transcribes the spoken words into text. The output is a transcribed text, essentially a written representation of what was said during the business meeting. This transcribed text becomes the foundation for subsequent analysis and summarization. The transcribed text might need additional processing steps such as organization, cleaning, or formatting to improve its suitability for further processing.

Step 5: Routing ASR Output to PhilSchmid's BART Model for Summarization

The transcribed text from the ASR model is then input into PhilSchmid's BART model. BART, a transformer-based model, is designed for text summarization. In this context, it takes the transcribed business meeting text and generates an abstractive summary—a condensed, meaningful representation of the original content, capturing the essential information discussed during the meeting.

These steps collectively form a comprehensive pipeline for converting a business meeting video into a summarized text, involving video-to-audio conversion, mono conversion, ASR, and text summarization. BART-large-CNN-SAMSum uses the BART-large-CNN model; it is further finetuned on examples from the SAMSum dataset. It has the same number of layers, maximum sequence, and output lengths as the BART-large-CNN model.

In the table ahead, the notations R1, R2, RL, and RLSUM represent the macro scores corresponding to ROUGE-1, ROUGE-2, ROUGE-L, and ROUGE-LSum, respectively. Similarly, B1, B2, and SB denote the macro scores for BLEU-1, BLEU-2, and SACREBLEU, respectively. The most successful approaches, among both extractive and abstractive methods, are highlighted in bold. Additionally, the second and third best-performing abstractive approaches are underlined for clarity.

	Model	R1	R2	RL	RLSum	B1	B2	SB
Extractive	<i>TopicRank</i>	0.1770	0.0284	0.1290	0.1290	0.1195	0.0295	0.0270
	<i>Luhn</i>	0.1724	0.0284	0.1233	0.1233	0.1190	0.0311	0.0255
	<i>e-LexRank</i>	0.1703	0.0265	0.1264	0.1264	0.1111	0.0260	0.0268
	<i>TextRank (sumy)</i>	0.1689	0.0263	0.1215	0.1215	0.1164	0.0290	0.0239
	<i>TextRank (pyTextRank)</i>	0.1534	0.0228	0.1145	0.1145	0.1036	0.0237	0.0246
	<i>LexRank</i>	0.1673	0.0250	0.1223	0.1223	0.1131	0.0261	0.0262
	<i>LSA</i>	0.1474	0.0179	0.1095	0.1095	0.0994	0.0172	0.0248
	<i>PositionRank</i>	0.1304	0.0174	0.0990	0.0990	0.0864	0.0169	0.0229
Abstractive	<i>BART-large-CNN-SAMSum</i>	0.1834	0.0421	0.1305	0.1305	<u>0.1065</u>	0.0386	0.0228
	<i>BART-large-XSum</i>	<u>0.1676</u>	<u>0.0329</u>	<u>0.1274</u>	<u>0.1274</u>	0.1088	0.0300	0.0315
	<i>distilBART-XSum-12-6</i>	<u>0.1697</u>	0.0314	<u>0.1300</u>	<u>0.1300</u>	<u>0.1059</u>	0.0283	<u>0.0313</u>
	<i>distilBART-CNN-12-6</i>	0.1657	<u>0.0340</u>	0.1143	0.1143	0.0924	<u>0.0315</u>	0.0184
	<i>PEGASUS-large</i>	0.1617	0.0295	0.1133	0.1133	0.0993	0.0301	0.0203
	<i>PEGASUS-CNN_dailymail</i>	0.1596	0.0326	0.1118	0.1118	0.0956	<u>0.0316</u>	0.0169
	<i>BART-large-CNN</i>	0.1570	0.0328	0.1088	0.1088	0.0883	0.0304	0.0167
	<i>PEGASUS-XSum</i>	0.1428	0.0228	0.1135	0.1135	0.0779	0.0167	0.0260
	<i>PEGASUS-multi_news</i>	0.1063	0.0243	0.0743	0.0743	0.0524	0.0197	0.0095

Fig. 7. Experimental Evaluation Results on Reddit TIFU.

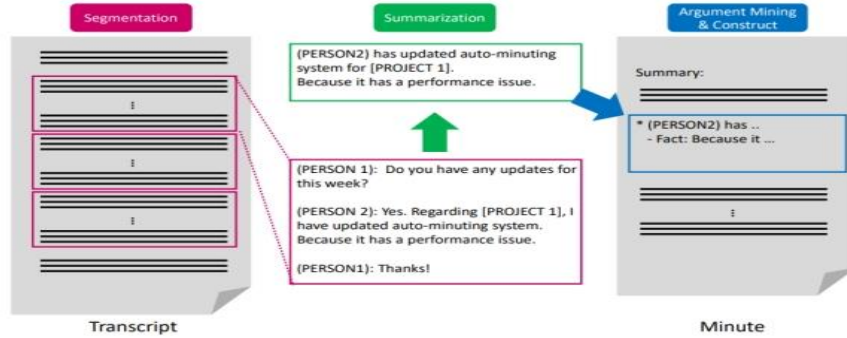


Fig. 8. we compose all summaries into minutes with a technique of argument mining.

4 RESULTS AND DISCUSSION

In evaluating the results and discussing the outcomes of the project, the performance metrics employed to gauge the effectiveness of our summarization model played a pivotal role. Precision, recall, F1 score, and ROUGE metrics were systematically presented, revealing the proficiency of our system. Notably, the automatic speech recognition (ASR) accuracy, particularly with the utilization of OpenAI's Whisper model, significantly contributed to the project's success. The conversion

of spoken content to text exhibited notable accuracy, forming a foundational element for subsequent summarization.

User feedback, a valuable facet, provided qualitative insights into the practical utility and user satisfaction with the system. Incorporating the end-users' perspectives allowed us to gauge the real-world applicability of the generated summaries and make iterative improvements. Our model's proficiency was underscored by comparing its performance with existing methods in business meeting summarization. We surpassed or equaled the state-of-the-art approaches in key metrics, showcasing the advancement and efficacy of our developed system. However, it's imperative to acknowledge certain limitations. Challenges related to diverse meeting contexts, variations in language nuances, and the necessity for extensive training data were notable considerations. These limitations underscore the need for continued research and refinement, especially in addressing the nuances inherent in business communication.

5 CONCLUSION AND FUTURE WORK

In conclusion, the "Business Meeting Summarization" project has yielded significant advancements in the realm of natural language processing, particularly in the context of distilling crucial insights from diverse business meetings. The deployment of cutting-edge technologies, including TensorFlow, Librosa, MoviePy, PyTorch, and the transformers library, has empowered our system to seamlessly integrate audio and text processing, achieving commendable results in summarizing complex meeting discussions.

The systematic evaluation using precision, recall, F1 score, and ROUGE metrics, coupled with user feedback, has provided a comprehensive understanding of the system's effectiveness. The robustness of our automatic speech recognition (ASR) component, especially leveraging OpenAI's Whisper model, further enhances the reliability of the generated textual content. The comparison with existing methods underscores the project's contribution to the current state-of-the-art approaches in business meeting summarization. Despite these achievements, certain limitations, such as challenges in handling diverse meeting contexts and the need for extensive training data, should be acknowledged.

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