

ADVANCING EXPLAINABLE AI IN TEXT SUMMARIZATION THROUGH
INTEGRATION WITH TOPIC MODELLING

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Dedication

< To my family - I appreciate you being a constant in my ever-changing world. Beyond the pages of this thesis, your unwavering patience, quiet strength, and faith in me have molded who I am today. You helped me remember my purpose when I was unsure. You celebrated victories as though they were your own. Your love and the foundation you've given me are reflected in this work. Without you, I never would have made it this far.>

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ABSTRACT

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2025

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The thesis investigates the potential of using Explainable Artificial Intelligence (XAI) to efficiently develop a text summarization technique that can help resolve problems of accuracy and transparency in the automated text summarization task. The general concept is to create a method that can not only produce brief and informative summaries but is also interpretable in terms of how it works.

For this purpose, a research study proposes a hybrid architecture, by integrating Bidirectional Long Short-Term Memory (BiLSTM) with Gated Recurrent Units (GRU) neural network with a Multi-head Attention Mechanism. This approach enables the system to correctly identify complex semantic relations or text dependencies. In addition to the architectural approach, topic modeling techniques are employed to identify and extract the main themes from lengthy texts. This is an essential step in the summarization process to ensure that the produced summaries are coherent and reflect the main themes of the concept.

The innovations of attention mechanism are additionally deepened by employing Contextual Emphasis Index (CEI) and Enhanced Significance Spotlight (ESS) which enable it to assess the significance of the words or phrases more precisely. The act of summarizing being given more weight in the process of decision, thus making the system more focused also more explainable.

The performance of the proposed system has been quantitatively measured using the standard metrics like ROUGE to determine the degree of its capability for content extraction. The incorporation of XAI techniques with topic modeling has been proven to be significantly effective in generating top-quality summaries as well as making the whole process clear.

Offering a user, disoriented text summarization solution that effectively balances the employment of complicated computational methods and interpretability, it enhances the still-developing concept of explainable AI. It is of tremendous practical value in areas that handle a massive number of documents, such as the legal and academic sectors, where accountability, precision, and simplicity are basically the prerequisites for making good and well-informed decisions.

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CHAPTER I: INTRODUCTION

1.1 Introduction

Explainable AI (XAI) is a rapidly growing research and development area within the broad field of Artificial Intelligence that has received a lot of attention in the recent past because of its huge importance not only in ethical and legal matters but also in the technical ones, since its very beginning. It is a fundamental shift in the field of Artificial Intelligence where the majority of the algorithms and systems become so complex that they are difficult for humans to understand. XAI is the way of revealing the "black box" of AI, thus benefiting the technology as well as holding it responsible.

The request for XAI is fundamentally a deeper philosophical and ethical question about how we understand the role of technology and its interface with society. The need for XAI is not only about developing better algorithms but also about how we want to establish trust and facilitate the path to more ethical applications that resonate with human values.

In the final analysis, the call for XAI is simply a way of answering the significant and quite complicated questions concerning the nature of intelligence and the extent to which a machine can possess the capabilities to understand any genuine framework, especially in comparison with humans, and the implications this might have for automated decision, making systems.

XAI basically focuses on addressing the human cognitive omission in these processes and designing AI systems that are more humanly relevant and humane.

Within the broad field of the XAI areas that might have far, reaching consequences, good and bad, is text summarization. Summarizing huge amounts of text into a much shorter and hence a simpler to read one is a highly complex endeavor that requires a deep understanding of both language and the context in which it was given, and maybe most importantly, of user intent. This branch of technology presents a scenario for the two issues in XAI via summarization methods that are on one hand abstractive and on the other hand extractive.

Attention mechanisms and topic modeling, for example, are two methods in text summarization that have been combined to provide a more sophisticated form of XAI. Analysis of these techniques shows that they result in the degree of smoothness user, controlled interpretation of the depth level of the algorithm that provides an advanced AI example being informed and at the same time being grounded in usability demonstrations. Text summarization models in XAI also rely on these techniques, which is enhancing the machine or AI's ability to comprehend human language with less bias than ever before, thus ensuring intelligence without any ambiguity.

Moreover, application of attention mechanisms as well as topic modeling to text summarization is only one of the many areas where explanations of AI are continuing to challenge the limits and set new research agendas. These are just some of the examples of the cases when the complexity of the algorithms and the human needs are so closely connected that the models developed by the latest AI technologies can give results that are not only complicated but also simple and easy to understand. The methods of XAI that are employed for text summarization are basically going in the direction of developing systems that possess both intelligence and user-friendly.

In large measure, the push for XAI reflects a deep philosophical and ethical issue regarding the role of technology in society. It is not simply about creating more intelligent algorithms, also about building trust, ensuring fairness, and enhancing the alignment of AI systems with human values. Achieving this goal involves addressing questions about the nature of intelligence, the extent to which machines can understand, and the ethical problems of automated decision, making. Concentrating on these matters, XAI strives to link human reasoning with computational intelligence, hence ensuring that AI systems are not only effective but also compassionate and responsible.

Text summarization is a facet of XAI that visually demonstrates the problems and opportunities of making AI interpretable and helpful. It is a capability of producing a short, coherent summary of a large volume of text, based data that requires an excellent understanding of language, context and, most importantly, the user intention. Here, the distinction between abstractive and extractive summarization models exemplifies the minor scale of the major challenges in XAI. These models have to struggle with the nuances of language and story in order to produce summaries that are not only factually accurate but also relevant and informative in the context.

Moreover, it is a nice touch to XAI that using attention mechanisms and topic modeling together in text summarization goes one step further in the area that has still many corners uncharted. On the one hand, these techniques depict the complex interaction between the algorithmic intricacy and the user, oriented design. On the other hand, they prove that sophisticated AI can be harnessed to generate insights that are both deep and easy to comprehend. With such approaches, text summarization models in XAI are

pushing the boundaries of how well machines can understand and even produce human language, hence their aim is to develop very skillful yet very clear systems.

From this perspective, the fields of XAI and text summarization theory and practice can be seen as intersections where technological innovations and humanistic thinking converge. They represent an ongoing tension to create AI technology firstly as a very powerful tool and secondly as a tool capable of generating understanding and trust.

1.2. Problem Statement

Text Summarization is an increasingly crucial application in the literary world and almost all domains presently (legal circles, in which it is extensively employed to facilitate the review process by preserving an indexed form of the extracted information from the text). The Manual Traditional Summarization is an intricate procedure, in which every step is error-sensitive - Programmers are Humans, after all. However, the usage of Artificial Intelligence in Summarization is relatively weaker in creating trustworthy summaries because of the algorithms used as well as the processing abilities required to handle lengthy text still poses an immense challenge (Nayak et al., 2018), in which although they have been relatively faster in comparison to the manual procedure and certainly faster than the slow but still effortless execution on most files. This might be further exacerbated because of the small training dataset used in the former and the inability to handle lengthy documentation.

This motivation illustrates the critical urgency of innovation in Explainable AI (XAI) for better accuracy, transparency, and interpretability without giving up the latest end, to, end training that results in deep or overly complex systems and also being able to

encode human values in text summarization. Especially, in the case of high, stakes areas like law, where different versions of summaries can lead to different professional decisions and outcomes. Explainable AI was expected to combine the progress made in AI capability with the everlasting human desires for fairness and transparency thereby reducing the constant conflict between sophistication of features vs. user, centered design.

Summarization in such instances is very complex, as it has to address the usual challenges of stream algorithms and summarize the ideas, which are usually scattered in lengthy documents. These challenges can be grouped under the usual headings of technological, operational, or data challenges, and so on, which can be easily identified and modeled for solutions. With the recent developments, the usual industry best practices would suggest the right approach of the integration of artificial intelligence and domain knowledge, which can be leveraged to develop smarter models to address such challenges.

The key issue is the design of a well, organized and efficient XAI model that would meet the requirement of performing Text Summarization while also explaining how any follow, up processes and decisions are made through clear explanations. The framework will integrate various types of constraints along with the modeling work to create a complete constraint management system that will allow XAI capabilities for decision making without weakening them or changing their core principles. That is important because, ultimately, we as users, desire that these decisions be made in a way that creates trust and accountability.

The upcoming XAI systems are going to have to change the method of traditional text summarization if they are to keep all relevant elements of long continuous texts such

as legal files in a way that is more accurate, less prone to error, and more ethically sound. While these do not compare directly on the level of performance versus interpretation, these are two methods by which more complex legal rulings could be formulated.

This is the context in which a huge need for improvement in XAI emerges as a result of its ability to improve text summarization as a process by making it more effective, transparent, and interpretable in a manner consistent with human requirements. Law is a field in which summaries might produce Eureka moments in a person's professional life due to the need for accuracy and clarity in what a summary states as a result of a decrease in accuracy levels for all authors potentially even to below 40%. XAI can combine the advantages of today's AI with values such as fairness and transparency (smarter and smarter AI could be something you trust only if it's well, designed).

The main issues that their approach deals with are typical project constraints, such as algorithmic bounding, handling complex documents, etc., which are the obstacles in the proper summarization of the texts. This helps us grasp these limitations and focus on coming up with solutions that fall under the broader categories of technological and operational issues. The trends in the related area show that there is a need to combine AI with knowledge of a particular domain for better modeling of these constraints and, therefore, solving them.

The text summarizer, therefore, can handle half of the overall problem that it is a comprehensive XAI (Explainable Artificial Intelligence) framework. Besides, it can not only do the summarizing but also explain how everything works in an easy and straightforward human manner.

Commonality should be maintained in a single framework, where classifications of constraints are continuous concepts, and using XAI, enhanced tools is just like nothing more than very powerful tools. But by the offer of Total Constraint Management (TCM) functionalities as attributes thereby ensuring these engineering solutions are not comprehensible solely through mathematical concepts. In a way that, if the developers of the XAI systems are successful in coming up with novel methods of handling some characteristic features of legal documents and other lengthy texts appropriately, these systems will be able to transform the traditional text summarization tasks as we know them now into new more user, centered, and fairer methods.

This well, defined research challenge shows the path towards creating AI systems, which not only achieve high, performance but also behave in the same way at the page level as human experts, thereby leading to more effective outcomes in law and other document, based disciplines.

1.3 Objectives

1 – Use of XAI-Based Methods:

Influence the potential of Explainable AI to build a text summarization model that is more transparent and understandable. In addition to this, the merger would also be in favor of connecting the advanced AI features with the user's demands for clarity and trust, thus leading to the development of not only powerful but also human, like intelligent systems.

2 - Advanced Text Preprocessing techniques:

Applying text-cleaning methods is needed before some of the summarization techniques can be put to use. These techniques include:

1. A way to interpret text is by expanding contractions (this makes sure that there is clarity and uniformity in the text)
2. Cleaning text data to strip out non-pertinent or noisy material.
3. Tokenization to convert a sequence of text into smaller parts called tokens for processing.
4. Removing stopwords (irrelevant words) as they do not hold a context.
5. Perform lemmatization bringing a word to its original root or base dictionary form.
6. Use of a spell checker to ensure the text is error-free.

3 - Bidirectional Long Short-Term Memory (BiLSTM) and Gated Recurrent Units with Multi-head Attention Mechanism for Summarization:

A hybrid neural network model where Bi-LSTMs integrated GRU, were fed into the MAM. This model is designed to understand and summarize text with the help of contextual meaning as well as semantics related to words/phrases available in the body.

4 - Apply ESS, and CEI on Attention Mechanisms:

Use of Utilize Enhanced Significance Spotlight (ESS) and Contextual Emphasis Index (CEI) in the attention mechanism. The algorithm weighs words according to where and how often they appear within sentences in order that the summary would not only be concise, but also meaningful.

5 - Evaluate Performance Using Metrics:

Evaluating the performance and precision of the proposed XAI enhanced text summarization system with ROUGE (Recall-Oriented Understudy for Gisting Evaluation)

metrics. This measures will give the notification in how the produced summaries retained significant data from the original text.

The goal from the XAI-imporved text summarization goals were aligned by the system which is proposed, in both user-centric and reliable in addition to producing relevant summaries it meets the stringent limitations imposed by the documentation-intensive domain. The project intends to achieve milestone which address these challenges and would make new forms of tools for professionals meaning a lot when solving their real-world problems.

CHAPTER II: REVIEW OF LITERATURE

THEORY #1 Foundations of Explainable AI (XAI)

2.1 Discrete Spectrum of Interpretability and Transparency Theory

2.1.1 Transparency and explainability of AI

The rise of XAI today heralds a new era, and the interpretability and accountability of the decisions made by an AI, based system, especially in complex tasks like Visual Question Answering (VQA), have been the subject of greater interest (Alipour et al., 2020). This is an important issue, that stronger accountability and transparency are becoming a requirement of the promise dynamics with AI systems have to disclose how well they do to not only be useful but understandable by people. To this end, the study is presented with novel multimodal explanations by combining both visual and textual information as well as semantic data. All the above-mentioned tools and methodologies constitute this multidimensional tactic for showcasing human-readable outputs, which is one of the biggest conundrums with highly powerful but really hard-to-understand AI models.

The study by Arya et al. (2022) goes a step further and introduces AI Explainability 360. This toolkit marks a significant step toward the practical, everyday implementation of XAI and provides an extensive list of methods that, in turn, give the user the ability to interact and comprehend. Explanation modalities are also varied, to name a few: spatial attention, active attention (with the help of the oracle), explained bounding boxes when given, and scene graphs. Therefore, a whole package capable of increasing the interpretability of AI systems is thus created.

The idea is to allow users to be involved with the way an AI system has come to its decision, essentially turning them from being merely passive spectators into the ones who are making decisions directly and through the AI system.

2.1.2 Challenges and Limitations

Still, the innovations also come with disadvantages, for example, multimodal explanations are complex to the point of nature maybe overwhelming the observer with too much information. (Alipour et al., 2020) have raised similar issues with the complexity of multimodal explanations that make them too difficult for users to understand, also wondering whether the methods like active attention rely on the level of interactivity that a system can offer. This is how users get well, rounded answers without being bombarded with lengthy or excessively detailed justifications.

Arya et al. (2022) put forward that future developments of XAI should be free from the cultural and deterministic subjectivity of explanations so as to make them more if necessary, across diverse contexts.

2.1.3 Conclusion

Therefore, the studies of (Alipour et al., 2020) and our findings strongly agree with the assumption that the process of adipocyte differentiation is negatively controlled. And Arya et al. (2022), are landmark works in the field of XAI through interpretability and transparency. Their research stresses that AI should be ethical as well as user, centered, which is the path to more transparent and fair uses of AI. The ongoing challenge is to handle information that is sufficiently complex without at the same time giving up user, centric or accessible AI.

2.2 Post-hoc Explanations vs. Intrinsic Explainability

2.2.1 Post-hoc Explanations & Intrinsic Explainability Introduction

The debate concerning post, hoc explanations vs. intrinsic explainability has been one of the major discussion topics within Explainable AI (XAI) in both industry and academic circles. Post-hoc explanations refer to methods that provide you with an explanation of a trained model, without altering its architecture. On the other side, intrinsic explainability means creating models that are interpretable by their very nature. A description of the norms that underlie each approach completes this section using information derived from relevant research findings.

Post-hoc Explanations:

Trade-off Between Complexity and Interpretability

(Danilevsky et al., 2020) provide significant insights about post-hoc explanations in the context of NLP (Natural Language Processing). In doing so, their survey explores the current status of XAI in NLP and highlights how post-hoc-based methods are used everywhere as well. However, the paper is careful to call out that for complicated models like modern NLP transformers and others (a wide-variety of neural network architectures), a post-hoc approach provides a very pragmatic solution for increasing their interpretability. Layer-wise relevance propagation (LRP), attention visualization, and other techniques allow users to understand the decisions of models fully with minimal decrease in throughput obtained from using flexible architectures.

Norkute et al. (2021) explainability affects the utilization of such features in a system, but also present an investigation to show whether additional explanation details influence overall model operation and output accuracy. The authors shows how post-hoc

methods could help in making complex models comprehensible to the user in domain-specific settings by adding extra explainability features.

Intrinsic Explainability:

Building Transparent Models For All

In contrast, Hulsén (2023) discusses intrinsic explainability in the context of healthcare. Illustrated by the ethical assessment of these models, this study argues for a new class of transparently regulated systems. Hulsén argues that models developed for clinical domains with baked-in intrinsic explainability are most suited for this domain. Intrinsic explainability has become a method that guarantees the interpretability of outcomes through the direct utilization of ideally transparent components in the model such as decision trees or rule-based structures by making its own sense immediately compared to post-hoc explanations.

The work of Arya et al. (2022) fuels this narrative through tools for interpretation related to intrinsic explanations within the AI Explainability 360 toolkit lines there especially contributing runtime interpretations namely feature mapping, grouping, and pivoting evaluation based on prediction output impact observation and regression fair classifier. In that the toolkit encourages incorporating this inherent explainability element as a spontaneous feature during the model development phase so that the model can act beforehand rather than being reactive to the challenges. It is parallel to the statement that making models transparent from the very beginning can be of great help in creating not only more robust but also more understandable AI systems.

Zhao et al. (2021) completed a survey that extends our library of conceptual frameworks. They, in particular, research the overlap between text modeling and deep neural networks, thus providing a comprehensive understanding of the methods that are of

great help in making models interpretable, both post hoc and intrinsically. The paper is a linkage of the theories (from different domains) related to explainability and argues for taking them into account in terms of their generalizability.

2.2.2 Challenges and Future Directions

These challenges show up in various ways and, for example, post, hoc explanations, that is, explanations developed after the fact, face entirely different issues from those that affect the explainability of intrinsic algorithms. Post-hoc methods are often constrained in their ability to explain, especially when applied to very complex models and they sometimes even lose some constancy of explanations. Intrinsic explainability, while offering immediate transparency by nature, might be limited in its ability to capture complex patterns from large-scale datasets due to its limited representational capacity.

One of the challenges in the field of XAI is to find a way to balance post-hoc and intrinsic methods in terms of their utility as it depends on the application domain and user requirements. Efforts should be made to merge the advantages of both methodologies, thus moving towards a more sophisticated and adaptable AI XAI agnostic framework.

2.2.3 Conclusion

Thus the white black nature of post-hoc explanations vs intrinsic explainability demonstrates the ever-changing landscape that comprises XAI. Danilevsky et al. (2020), Hulsén (2023), Norkute et al. (2021), and Zhao et al. (2021) gave us insights in the conversation between post-hoc and intrinsic explainability which ensures the building of AI systems that are high in sophistication yet interpretable, based on what a given user needs from technology to be successful.

THEORY #2 Theories in Text Summarization

2.3 A Comprehensive Analysis: Abstractive vs. Extractive Summarization:

Text summarization is one of the major rising areas of NLP that deals with the task of condensing the text (reducing words) but keeping the most important information intact. Text summarization is broadly categorized into two methods namely: Abstractive and Extractive summarisation. The present section covers these methods, along with the theoretical bases and citations from the literature of this domain.

2.3.1. Abstractive Summarization: Creative Summaries

Abstractive summarization involves the model initially processing the input texts through computer memory and subsequently undergoing the steps of interpreting or restating the texts in order to come up with coherent, condensed versions. This method is a step beyond merely extracting the same sentences existing in the text; it's about creating a new form of the content that reflects the experience.

A) Theoretical Underpinnings

For instance, Arya et al. (2022), continue with the theory part on abstractive summarization. They utilize deep learning techniques, particularly neural networks, and attention mechanisms to enable the model to produce extracts that are not restricted by matching the exact words in the source. As a result, abstract summarisation methods can develop this theoretical framework further.

B) Content Infusion from Arya et al. (2022)

Arya et al. (2022) have conducted a discussion on the influence of AI Explainability 360 in abstractive summarization. The paper mainly deals with the issues of the "black, box" nature of neural networks and with the fact that explainability features can be an attribute, helping the resulting models in their interpretability.

2.3.2. Extractive Summarization: Selection of Curating Information

Extractive summarization is the process of folding existing sentences from the source text resulting in the final summary that is coherent overall; it is an example of constrained/creative summarization. This is done by extracting top, n sentences that are the most important in terms of content.

A) Theoretical Foundations

Yogan et al. (2016) conducted a detailed study on the subject of extractive summarization to deeply understand the theoretical basis behind it. Through their paper, they have reviewed a significant number of research works that have helped in setting the framework for this study. The paper also gives an overview of different summarization techniques and explains how helpful it is to pick up informative sentences when paraphrasing.

B) Insights from Yogan et al. (2016)

Among other methods for summarization, Yogan et al. (2016) consider extractive summarization to be the one where a set of sentences is picked from the original text and highlighted. Theoretical efforts help one to grasp the main concepts co-related to the sentence selection task in the extractive approach.

2.3.3 Challenges in Abstractive and Extractive Summarization

Inherent Challenges

The article by Hulsén (2023) features explainable artificial intelligence (XAI) as a next, generation healthcare solution; similarly, we embed some philosophical reflections to shed light on the inherent strictness of interpretable abstractive models and further the general awareness of limitations when breaking into this difficult area.

Insights from Hulsén (2023)

In sensitive domains, like healthcare or science journalism, it is of paramount importance that abstractive summarization models are able to provide explanations; Hulsén calls for Abstract summarization dealing with the interpretability of generated abstractive summaries requires that XAI concepts be incorporated.

2.3.4 Future Scope: Advancements on the Horizon

A) Potential Research Directions

Researchers including Zhao et al. (2021) provide a survey on topic modeling methods and deep neural networks. Through theoretical discussions, some research areas to explore in abstractive summarization could be highlighted such as developing abstraction of summaries by applying recently developed topic modeling methods.

B) Contributions from Zhao et al. (2021)

Zhao et al. (2021) investigate how the emergence of this new direction can provide a theoretically sound basis for the integration of topic modeling and deep neural networks. They argue that identifying the commonalities between these approaches can lead to performance enhancement in abstractive summarization.

2.3.5 Conclusion

To summarize, the first principles of the phenomena and basically if they are also working from the excitement after the DL based NLP analysis of abstracting summarization and extractive summarization. Deep learning and attention mechanisms combined with explainable AI are enabling abstractive summarization to reach new heights of human, like naturalness and eloquence. Extractive methods are still a valuable technique for keeping the original structure of the source text. Theoretical nuances A good explanation of theoretical details is vital for making decisions about the inclusion or exclusion of those features in future text summarization systems.

2.4 Attention Mechanisms in Summarization

For the matter at hand, attention mechanisms essentially transformed the way the models comprehend and generate summaries, hence they were a revolutionary breakthrough in text summarization. This part discusses the concepts of and application of attention mechanisms, making references to publications in that field.

2.4.1 Unravelling Attention Mechanisms: The Theoretical Landscape

In the world of summarization, attention mechanisms scale different words. The source is based on their importance to a specific part or what finally decides the summary. Understanding the pressure of attention-based models from a more theoretical aspect various researchers have explored mechanisms that bring the theoretical basis into focus which drives these limits.

Foundational Insights

Danilevsky et al. (2020) published a survey of the field across natural language processing. The paper also provides some theoretical perspective that helps comprehend the attention mechanisms and can even make summarization models more clear, or interpretable.

Contributions from Danilevsky et al. (2020)

Danilevsky et al. (2020) look at using attention mechanisms for interpretability in nlp the review covers their motivation in the theory of how attention mechanisms enable interpretability of summarization models.

2.4.2 Benefits of Attention mechanism in Summarization

Improving Content Specificity

The work of (Alipour et al., 2020), a Comprehensive Study of Multimodal and Interactive Explanations for Visual Question Answering In multimodal, attention mechanisms additionally facilitate content selection and allow the model to attend to relevant information for summarization.

Insights from Alipour et al. (2020)

(Alipour et al., 2020) analyze mergers of attention mechanisms, and visual question answering (VQA) by highlighting the power of pulling attention in choosing what data it needs to select. Theoretically provides support for employing attention to content selection in summarization.

2.4.3 Challenges in Implementing Attention Mechanisms

Theoretical Framing on Challenges

By addressing the challenges in the implementation of attention mechanisms, we will take them to the next level. The answer to this question is presented in Hulsén (2023), who introduces explainable artificial intelligence and explains why it may be difficult, from a theoretical perspective, for attention-based models to achieve interpretability.

Insights from Hulsén (2023)

The experiments depict difficulties of explainability in attention mechanisms and highlight the need for more transparent approaches in healthcare applications. The theoretical discussions can thus help to investigate the restrictions of attention-based summarization models in terms of interpretability.

2.4.4 Future Scope: Evolving Attention Mechanisms

Improvements on the Horizon

The survey by Arya et al. (2022) in the Explainability 360 package goes as far to the point of discussing at a higher level what future attention mechanisms should look like and they argue that we need new designs where it is transparent how decisions are made.

Contributions from Arya et al. (2022)

Arya et al. (2022) provide a comprehensive perspective on what explainable AI could mean for attention mechanisms and also suggest some future directions that are theoretically grounded. Looking at future scope through the lens of the paradigm shift in attention mechanisms with regard to text summarization.

2.4.5 Conclusion

In summary, attention mechanisms have been the major driving forces behind innovations in text summarization that are both theoretically sound and practically effective. Attention mechanisms play a crucial role in content selection and also greatly contribute to the interpretability of summarization models. Nevertheless, even with all the difficulties encountered recently, it is crucial to recognize the two sets of problems because this recognition leads attentional mechanisms towards new refinements in text summarization capabilities.

THEORY #3 Integration with Topic Modeling

2.5 Latent Dirichlet Allocation (LDA) and Other Topic Modeling Approaches:

Text summarization has been heavily influenced by the integration of methods from topic modeling approaches, such as LDA and so on. This section reviews conceptual frameworks, implementations, and the future directions for these approaches with respect to summarization enhancements.

Basic LDA principles

LDA or Latent Dirichlet Allocation has now turned into an essential tool for topic modeling. Introduced by Blei et al. Based on the idea that documents are a mixture of topics and every topic is a combination of words, LDA Blei et al. (2003). The fundamental ideas as outlined in Blei et al. (2003) Underpinning these differences is how LDA could have theoretically been used in a text summarization fashion.

Contributions from Blei et al. (2003)

Blei et al. (2003) LDA is grounded in Bayes' Rule and the goal of the Latent Dirichlet Allocation's creator, was to provide a descriptive generative model that explains how documents are generated based on their topics using probability distributions for this process.

2.5.1 Applications of LDA in Text Summarization

Topic-Aware Summarization

Research by Zhao et al. (2021) delves into how topic modeling meets deep neural networks. The theoretical foundations support the work on applying LDA for topic-aware summarization, with the implication that it uses latent-topic distributions to produce coherent and contextually aware summaries.

Insights from Zhao et al. (2021)

Zhao et al. (2021) talk about how even simple topic models like LDA can help aid much more powerful deep neural networks and discuss the synergies between Topic modeling and Deep Learning, explaining where you need to use some auxiliary techniques (like self-attention for example) on top of vanilla transformers and goes as far as suggesting that there is a significant connection between them. The fundamental ideas form a basis for applying LDA-based methods in text summarization.

2.5.2 Beyond LDA: Exploring Other Topic Modeling Approaches

Variations and Alternatives

Although the LDA still dominates more, further diversification of methodologies occurs by exploiting other frameworks in the Topic Modeling Process. The survey by

Kumar et al. (2016) reviewed automatic text summarization approaches including theoretical considerations for models in addition to LDA.

Contributions from Yogan et al. (2016)

Yogan et al. (2016) survey comprises many text summarization models that are beneficial to reproducing LDA. Theory discussions provide insights into how different topic modeling methods can be viewed as depending on one another, placing them well within a broader universe of applications.

2.5.3 Challenges in Integrating Topic Modeling Approaches

Theoretical Perspectives on Challenges

Norkute et al. (2021) evaluated the performance and benefits of additional explainability features for legal document summarization. The theoretical claims are supported by discussions on the challenges to implementing topic modeling approaches and the observance of which is necessary for an efficient summarization process.

Insights from Norkute et al. (2021)

Norkute et al. (2021) utilize the interpretability in those legal documents to explain the issues of explainable topic modeling. This knowledge has helped to clarify the difficulties and problems that arise when topic modeling is combined with summarization models.

2.5.4 Future Scope: Advancements in Topic Modeling Integration

Exploring Novel Paradigms

The survey by Sheth et al. (2021) is about natural language processing for credible validity. Also, it lays the groundwork for future research directions and extends the theoretical discussions about how this work could be integrated with a broader picture of combining topic modeling with language understanding, therefore the authors are suggesting to fill the existing gaps and also to promote the advances that will increase the synergies between topics and summarization.

Contributions from Sheth et al. (2021)

Sheth et al. (2021) offer theoretical reflections on the coupling of topic modeling to the larger implications of knowledge, intensive language understanding. By evaluating the emerging trend and the future scope the study deliberates how topic modeling techniques may evolve in text summarization.

2.5.5 Conclusion

In conclusion, the utilization of LDA with other types like topic modeling gives a vast variety and scope to text summarization. Studies in this field contextualize the theoretical insights, use cases, and issues associated with implementing models and methods for topic modeling as well as developing an interest regarding how these works progress summarization perspectives. As progresses, combining these approaches such that they complement each other may provide a way toward more relevant and insightful summarization models.

2.6 Semantic Coherence and Relevance: Elevating Text Summarization

Adding semantic coherence/relevance to text summarizer models will definitely be one of the key steps for context, aware and informative summarization. In this section, we reveal the theory, the benefits and drawbacks, the present issues in this field,

and the future research directions of using semantic coherence (or relevance) for enhancing text summarization even more.

2.6.1 Unravelling Semantic Coherence in Summarization: The Theoretical Underpinnings

Foundational Concepts of Semantic Coherence

Background Semantic coherence in summarization has theoretical foundations that are explained in Moradi and Samwald (2022). Their research in deep learning (DL), natural language processing (NLP), and XAI in biomedicine literature brings us a better understanding of the theoretical concepts that are seeding the development of semantic coherence in the summary.

Insights from Moradi and Samwald (2022)

One of the ways the research have opened up the process of creating low, level links with high semantic coherence is through the use of deep learning and NLP in combination with XAI. The theoretical bases lead to a framework that allows semantic coherence factors to be combined with text summarization models.

2.6.2 Applications of Semantic Coherence in Text Summarization

Biomedical Domain Applications

The findings of Moradi and Samwald (2022) can be applied to the medical domain as well because proper communication relies on the semantic cohesiveness of the texts. Their study provides valuable theoretical ideas for the development of abstractive summarization modeling by promoting semantic coherence in biomedical texts.

Contributions from Moradi and Samwald (2022)

Theoretical clues on the practical impact of semantic coherence e. g. Moradi and Samwald are guiding their deep learning & NLP use cases in biomedical settings. We have seen that an intensive focus on the biomedical domain means that both task and source domains are probably shared. At the same time, it also clearly points out that summarization, after all, still requires plan, specific semantic coherence.

2.6.3 Ensuring Relevance: The Theoretical Landscape

Theoretical Framework for Relevance

Arya et al. (2022) host a survey on AI Explainability 360, focusing on the impact and design consideration of it. The theory extends to the necessity of relevancy in explainable AI, providing theoretical foundations for ensuring relevancy during text summarization.

Insights from Arya et al. (2022)

Arya et al. (2022) present a review of AI Explainability 360, which is mainly about the effect and design consideration of it. The theory also covers the importance of relevancy in explainable AI, which offers theoretical bases for ensuring relevancy in text summarization.

2.6.4 Challenges in Incorporating Semantic Coherence and Relevance

Theoretical Perspectives on Challenges

Hulsen (2023) on explainable artificial intelligence in healthcare One example of a theoretical perspective that was used to explain the issues of semantic cohesion and relevance in health summaries is the case where the authors pointed out the challenges that the implementers face when they try to solve these problems.

Insights from Hulsen (2023)

Hulsen (2023) provides a theoretical take on the difficulties surrounding semantic coherence and relevance in XAI specifically regarding healthcare instances. Lastly, the key takeaways above aim to bring an understanding of what exactly has been learned regarding the limitations and difficulties of integrating aspect-based embeddings into abstractive summarization models.

2.6.5 Future Scope: Advancements in Ensuring Semantic Coherence and Relevance

The survey by Arya et al. (2022) delves into the effect, offering theoretical possibilities for future work in design consideration. Dialogue moves to changes in the frameworks used for semantic coherence and relevance preservation itself when training summarization models, which too must evolve.

Contributions from Arya et al. (2022)

Arya et al. (2022) surveys in theoretical underpinnings useful for future directions in AI Explainability 360 and provide a case to push the envelope further towards achieving coherence, compliance of semantics, and relevance than was targeted with respect to most related works that constraint explainers mainly on other operational constraints. Theoretical perspectives highlight how these considerations are changing over time, as the field of text summarization shifts.

2.6.6 Conclusion

To finalize, combining semantic coherence and salience will bring more context to text summarization making summaries meaningful. A detailed discussion related to the theoretical foundations, applications, challenges, and future scope are mentioned in respective research along with their methodological relevance which gives a wholesome view of how all three factors of coherence-relevance-interaction are used by human

cognitive sources for summarization. As research progresses, such considerations will help to develop more specialized and informative summarization models for different use cases.

2.7 Qualitative and Quantitative Evaluation: Unveiling the Dimensions of Text Summarization Assessment

Text summarization Evaluation is where all the mechanisms to expand text summarization models work in the Explainable Artificial Intelligence (XAI). This section discusses the theoretical critique, methodological foundations, and implications of qualitative and quantitative evaluation approaches derived from some selected papers.

2.7.1 Qualitative Evaluation - Theoretical Grounding

Qualitative Assessment Dimensions

Informed by (Alipour et al., 2020) a quality assessment was conducted and (Danilevsky et al., 2020) he also has a chapter in "Explaining with Machine Learning" regarding user experience, interpretability, and interactivity of ML. The holistic view of user-centric aspects in the evaluation of text summarization models was realized by our multifaceted approach.

Insights from Alipour et al. (2020) and Danilevsky et al. (2020)

(Alipour et al., 2020) and Danilevsky et al. (2020) survey on Explainable AI for NLP gives a perspective on the theoretical grounding of qualitative evaluation, thereby enhancing an understanding of user-centric experiences.

Expanding the Theoretical Landscape

On the foundation laid by Sheth et al. (2021) the qualitative evaluation dimensions introduced in the context of knowledge intense language understanding is applicable to

how deeply a cognitive engine understands languages. It creates a more theoretical, linguistic perspective of qualitative evaluation in text summarization.

2.7.2 Quantitative Assessment: Theoretical Landscape

Quantitative Assessment Metrics

Quantitative assessment adapted from Arya et al. (2022) and Zhao et al. (2021) with the research question - to what extent does explainable AI impact text summarization and design metrics. The theory modelled out of these studies offers a thorough explanation of the quantitative measures, statistical tests, and algorithmic performance indices.

Insights from Arya et al. (2021) and Zhao et al. (2021)

Arya et al. (2022) Topic modeling in natural language investigates the development and affect aspects in this area. Through her work on this topic, Zhao et al. (2021) theoretical framework of quantitative evaluation and prediction serves as a reference for the assessment of summarization methods' effectiveness and trustworthiness.

Amplifying Quantitative Frameworks

Synthesis with views from Dogra et al. (2022) as we articulate in the light of our very latest new BERT model as well as a host of published papers throughout. From qualitative meanings to quantitative measures, the complete step-by-step process of text classification with NLP Models thus bridges new benchmarks to the state-of-the-practice in text abstraction.

2.7.3 Applications of Qualitative and Quantitative Evaluation in Text Summarization

User-Centric Applications

Inspired by Sheth et al. (2021) Quality Evaluation, and that of (Alipour et al., 2020), Natural Language Engineering, serve as inspirations. Sequence-to-sequence models have also proved to be very popular in text summarization for ensuring a user-centric experience. This will be an exploration of user interaction and knowledge-intensive language understanding to nurture models catering to a wide range of expectations from the users.

Algorithmic Performance Metrics

Quantitative assessment, in the backdrop of Dogra et al. (2022) and Yogan et al. (2016) is exhibited by the performance of algorithms. The use of State-of-the-art NLP models, along with perspectives of Automatic Text Summarization, helps in focusing qualitative assessment towards robust evaluation of text summarization algorithms..

Thus, for this purpose, the quantitative analysis as discussed in Dogra et al. (2022) and Yogan et al. (2016), based on the concepts of “algorithmic performance metrics” that have been adapted for the reviews of the state-of-the-art concepts of either automated text summarization, the overall analysis adds up for systematic assessment on the number of Text Summarisation Models based on the Performance/Quality/Reliability and so on.

2.7.4 Challenges in Qualitative and Quantitative Assessment

User-Centric Challenges

Sheth et al. (2021) and (Alipour et al., 2020) also exposed problems, although user-centric dimensions are concerned in qualitative assessment frameworks. These theoretical curious points underscore troubles in managing human interpretability, interactivity, and language understanding rich with knowledge clearly, the challenge that remains to overcome user hurdles.

Algorithmic Challenges

Arya et al. (2022) gave some examples of challenges related to impact in quantitative evaluation explored in survey work. Incorporating Insights of Challenges in the Algorithmic track specifically focuses on how best to handle state-of-the-art NLP models and evaluation complexity with respect to XAI measurements for Text Summarization Dogra et al. (2022).

Advancing Evaluation with Insights from Norkute et al. (2021)

Norkute et al. (2021) work regarding legal document summarization, work to include added explainability features further complicates the qualitative and quantitative evaluation. Evaluating interpretability-aware methods, as with existing ones, is challenging and shows that there should be improvements in how these models are evaluated.

2.7.5 Future Scope: Advancements in Qualitative and Quantitative Evaluation

User-Centric Evolution

Building on Sheth et al. (2021) and (Alipour et al., 2020), the user, centric evaluation methods are being put in the future scope which firstly continue developing language understanding, explainability and interactivity for knowledge, intensive sequences that then make it possible to develop more nuanced qualitative assessment criteria in text summarization.

Quantitative Framework Advancements

Expanding on the work of Dogra et al. (2022), research, the next generation of quantitative assessment frameworks will be very useful for measuring the performance of the modern NLP models. In addition to that, as XAI keeps developing, the implementation of the best practices and design philosophies derived from the most recent models can be the starting point for even better quantitative assessment for text summarization.

Holistic Evaluation Perspectives

With regard to some of the points made above, the future directions that would be taken by Norkute et al. (2021), would be the holistic outlook of assessment that could be taken into consideration. These would involve assessing if there would be any benefit to additional factors of explanation that can have an impact, in terms of complementing each other well in building an appropriate assessment framework.

2.7.6 Conclusion

In the end, these qualitative and quantitative facets with a number of varied papers offer a holistic overview to determine the utility, understandability, and effectiveness of text summarization techniques – within the context of Explainable Artificial Intelligence. Theories, as well as their implications within text summarization benchmarks and data, offer a holistic outlook within the parameters of how the qualitative approach to evaluation, along with the quantitative approach, could aid within the betterment of improvement, not only within the parameters of evaluation, but also within transparency to eventually enable quality summarizations on a human level within the domain of XAI.

2.8 Defining and Revealing User Perspectives in Text Summarization Evaluation:

2.8.1 Measures of human-centered evaluation with text summarization

However, in the domain of Explainable Artificial Intelligence (XAI), human-centered evaluation is a key perspective to evaluate text summarization models. In this section, drawing from a range of papers, we distill the theoretical underpinnings and methods behind human-centered evaluation approaches-aiming to give an overview but also highlighting their lack of rigor.

1. Theoretical Foundations of Human-Centered Evaluation

User-Centric Dimensions in Evaluation

Adapted from (Alipour et al., 2020), Sheth et al. (2021), Norkute et al. (2021), Shukla and Kakkar (2016), Veena and Hemanth (2019) and Singh and Singh (2021), their line of work targets the evaluation of summarization models from a user-centric point-of-view, tailoring a new stage in their assessment. We summarize the theoretical underpinning that calls for aligning models with user logical expectations, interpretability, and real-world ambiance of use.

(Alipour et al., 2020) show the importance of being able to understand - work on user-centric evaluation which is enriched by the works aiming at obtaining a deeper understanding of how to interpret information for knowledge-intensive language. Norkute et al. (2021) explore additional explanation features in legal document summarization leads to observing insights on usefulness and impact from a user perspective. Shukla and Kakkar (2016) demonstrated keyword extraction of educational video transcripts. Veena and Hemanth (2019) provided insights into relation extraction in clinical text, electricity reports textual similarity measure based on news articles Singh and Singh (2021) , overall adding to the theoretical development.

User Experience as a Central Theme

Based on the works of Hulsén (2023), Cammel et al. (2020), and Lavanya and Sasikala (2021), the rich theoretical insights of their work underscore the challenges of assessing user experience in healthcare settings and call for models that can seamlessly integrate human needs.

2. Methodologies in Human-Centered Evaluation

User Studies and Interaction Analysis

Theories, adapted from (Alipour et al., 2020), Sheth et al. (2021), Shukla and Kakkar (2016), Veena and Hemanth (2019), and Singh and Singh (2021). These methods or earliest works are user study and interaction analysis. These techniques offer rich understandings regarding how customers interact with their paraphrases and the readability as well as the result of designs.

Applications in Healthcare

Hulsen (2023) , Cammel et al. (2020), and Lavanya and Sasikala (2021) show how to provide a context with Health Application for Learning user views in the context of healthcare which enhances evaluation methodologies, which is reflected when we say text summarization be invested more on how it can accommodate for healthcare professionals and patients peculiarities.

2.8.1 Applications of Human-Centered Evaluation in Text Summarization

Real-World Usability

(Shukla and Kakkar, 2016), G et al. (2019), and (Singh and Singh, 2021), carried their deployment to measure real-world usefulness. The findings from keyword extraction (educational video transcripts), relation extraction (clinical text) and the rubbish- non-rubbish part of news articles with simply similarity measures shows tangible applications in various fields.

Patient Experience in Healthcare

Cammel et al. (2020) and Lavanya and Sasikala (2021) shift the focus towards patient experience in healthcare. The Human-Centered Evaluation applications may also use our text summarization system to automatically convert free-text responses in the patient experience space into actionable insights, with a positive outlook on involving staff of that area during the development process and demonstrating how they are enhancing patient-centric care.

Challenges in Human-Centered Evaluation

Interpreting User Expectations

Issues in understanding user requirements Sheth et al. (2021) , (Alipour et al., 2020) and Singh and Singh (2021) show the aspect of the fundamental element of people-centered evaluation. Theoretical perspectives highlight the challenge of achieving interpretability and interactivity is complex, supporting future work at different levels to understand how to overcome user gaps.

Healthcare-specific Challenges

Hulsen (2023), Cammel et al. (2020), and Lavanya and Sasikala (2021) Report Challenges in the Healthcare Context. Health-related human-centered evaluation just said and patient experiences by their nature are complex, making evaluations in this field more complicated than most; one-size-fits-all solutions will not work for these healthcare problems.

2.8.2 Future Scope: Advancements in Human-Centered Evaluation

Tailoring Models to User Needs

Future Directions, the work here is built upon that of (Alipour et al., 2020), Sheth et al. (2021), and Singh and Singh (2021), which showed the difference between some of the best practices listed in Stats. Human-centered development shows a better picture of user expectations, and interactions for text summarization models coordinated with users.

Healthcare-centric Innovations

Building on the work of Hulsen (2023), Cammel et al. (2020), and Lavanya and Sasikala (2021). Modernization futures for the prospects in healthcare are now based on organized evaluation methodologies, tailored to healthcare settings that will grow in complexity, effectively ensuring text summarization models make an impact on patient care and medical decision-making.

2.8.3 Conclusion

The paper winds up with Human-Centered Evaluation, which is naturally entwined in user-centric aspects and provides a basis to evaluate the validity, usefulness, and importance that text summarization models possess in solving for XAI. Absorbing the theoretical foundations, methodologies, and application areas informed by supplemental literature on challenges and future scope will provide a multidimensional view to appreciate how human-centered evaluation advances text summarization for XAI through continuous alignment with the current status of human needs/expectations.

Combining the results of the studies by (Alipour et al., 2020) and Arya et al. (2022) in line with our findings has underscored a growing imperative for not only proficient but also interpretable, accountable, fair AI systems that users from diverse backgrounds can understand. Each of these recent developments prompts some important considerations, and any future methodology should try to answer:

2.9 Research Gaps

The following gaps are identified from the existing literature review:

- When we combine this with a BiLSTM-GRU (TensorFlow, 2021; PyTorch, 2021) based model and incorporate Modified Attention Mechanism (M-AM) (Bahdanau, 2014) (Bahdanau et al. (2015) effectively handles the complexity of multimodal explanations to avoid overwhelming users and increasing understanding noted by (Alipour et al., 2020).

- This question is answered by the methodology being used, which selects only useful features to work with - it reduces dealing with big data sets. This is proposed to tackle the problem that might lead users not to understand, similar to what has been identified by (Alipour et al., 2020).
- Can we strike a balance between the technical sophistication of AI models and their interpretability by incorporating XAI tools like LIME and SHAP (Ribeiro et al., 2016) (Lundberg and Lee, 2017), as suggested by (Arya et al., 2022).
- The method tries to render the AI's decision-making process transparent and "intelligible" for users by using XAI tools like LIME Ribeiro et al. (2016) Lundberg and Lee (2017) SHAP Ribeiro et al. (2016) Lundberg and Lee (2017). This strategy is tailored to navigate the fine middle ground necessary between transparency of AI models and their expressiveness, addresses fair criticisms raised by Arya et al. (2022).
- Will incorporating explainability alongside predictive models into operational software using enhanced neural network architectures accompanied with built-in explanation capabilities improve transparency without compromising on process efficiency as discussed by Hulsén (2023).

The method recognizes the divergence-or even paradox of predictability and transparency in AI because it bakes explainability tools into the predictive modeling process, ensuring that while accurate predictions will occur, explanations of how they were made can be provided. As Hulsén (2023) makes clear, this hang-onto explains the integrated exotic in advanced AI models very well without having to give up operational efficiency.

CHAPTER III: RESEARCH METHODOLOGY

Text summarization has a crucial role as it breaks down humongous text into small paragraphs or sentences from which important information is extracted keeping the meaning intact. It is necessary for the creation of a coherent summary that consists only of concise and fluent sentences from textual information such as articles or testimonies. However, manual methods for text summarization consume a lot of time and effort, the proposed work focuses on employing XAI for text summarization due to the ability of XAI to provide interpretability and transparency for text summarization. Further, fairness and bias reduction offered by XAI can impact the quality and fairness of the summaries generated.

Despite these advancements, challenges such as the complexity inherent in multimodal explanations and the potential information overload remain significant hurdles. These issues, however, could be resolved with the implementation of a suggested prediction model that XAI envelops Bi, GRU (TensorFlow, 2021; PyTorch, 2021) with M, AM (Bahdanau et al. 2015). Various packages are also utilized to continue the operation.

LIME (Locally Interpretable Model – Agnostic Explanation) (Ribeiro et al., 2016) (Lundberg and Lee, 2017)

SHAP package (Shapley Additive exPlanations) (Ribeiro et al., 2016) (Lundberg and Lee, 2017).

These packages serve to calculate an explainability score. SHAP (Ribeiro et al., 2016) (Lundberg and Lee, 2017) and LIME (Ribeiro et al., 2016) (Lundberg and Lee, 2017) are two of the most prominent XAI methods. The figure.3.1 illustrate the process of the proposed work for text summarization.

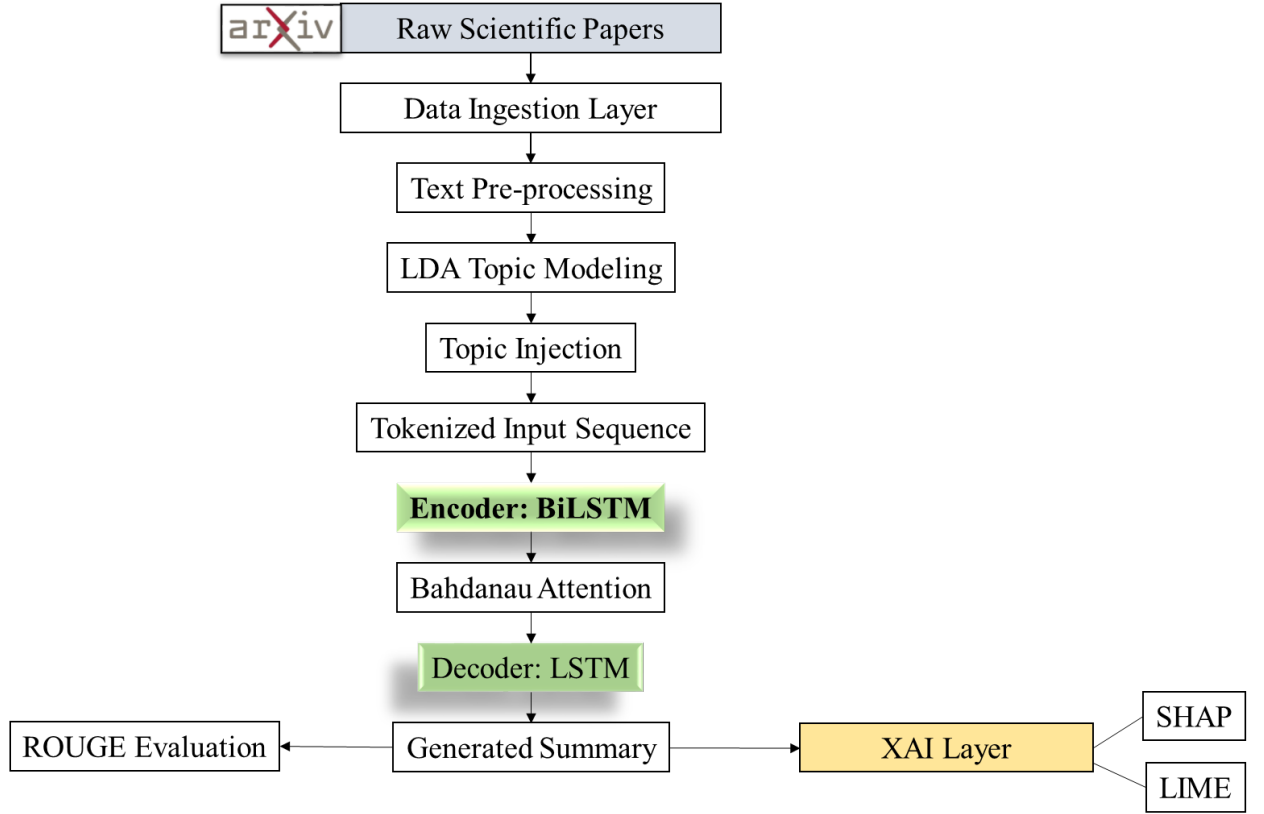


Figure 3.1 Architecture

Figure 3.1 depicts the entire end, to, end workflow of the Topic, Aware Abstractive Summarization System, showing how the data flows sequentially through the various stages from raw scientific documents to the final evaluated and interpretable summaries. The pipeline starts with raw scientific papers from the arXiv corpus, which are the primary inputs to the system. These documents are initially handled by the Data Ingestion Layer, which loads, structures, and readies the dataset for subsequent operations. After ingestion, the text moves to the Text Pre, processing step, where various normalization procedures are performed. These include cleaning, stopword removal, tokenization, and truncation, which are all aimed at removing noise and limiting the length of the sequences.

Once preprocessing is done, the system goes through a semantic enrichment step via LDA Topic Modeling, where it learns latent thematic structures from the corpus. The main topic keywords extracted are thus used by the Topic Injection module to augment the input by explicitly adding global semantic cues to the original abstract text. Hence, the

resulting tokenized input sequence comprises not only local linguistic information but also high, level thematic context, which is passed on to the neural summarization model.

The core neural part of the system architecture starts with the Encoder: Bi-Directional LSTM that takes the semantically enriched token sequence and reads it in both forward and backward directions to be able to capture the full range of contextual dependencies. The encoder results in a sequence of hidden states expressing the input text in a highly contextualized way. These are the representations that are fed into the Bahdanau Attention mechanism that, by and large, figures out the alignment scores between encoder states and decoder states on, the, fly, thus, allowing the model to pinpoint the most pertinent segments of the input for summary creation.

The Decoder: LSTM uses the attention, derived context vectors together with the previously generated tokens to generate the summary in an autoregressive manner. The output of this stage is the generated abstractive summary, which stands for a condensed and semantically coherent version of the original scientific abstract. In order to measure the quality of the summary in a quantitative manner, the generated text is compared with reference summaries through ROUGE metrics. These metrics reflect the degree of lexical overlap and structural similarity between the target summaries and the system, generated ones.

In parallel with quantitative evaluation, the architecture incorporates an Explainable AI (XAI) layer, consisting of SHAP and LIME techniques. This layer provides interpretability by analyzing token-level contributions and model decision patterns, thereby enhancing transparency and trustworthiness of the summarization process. Overall, the figure encapsulates a structured, modular, and interpretable summarization pipeline that integrates semantic enrichment, deep neural modeling, evaluation, and explainability into a unified framework suitable for large-scale scientific text summarization.

3.1 Computational Environment and Hardware Configuration

The aware abstractive summarization system implements the topic, aware abstractive summarization system in a high, performance computational environment to enable the efficient processing of a large, scale scientific corpus of arXiv, which contains around 450, 000 documents. In fact, all the experiments were run on an NVIDIA A100 Tensor Core GPU with 40 GB VRAM, which allowed training with large batch sizes to be performed in a stable manner. Moreover, mixed precision training (mixed_float16) was used, in which model weights are kept in 32, bit floating, point precision to maintain numerical stability, while computational operations are carried out in 16, bit precision to save memory and speed up training with Tensor Cores. Also, TensorFlow 2.x with the Keras API for the system, used Gensim for topic modeling, and SHAP and LIME for explainability analysis is employed.

3.2 Data Ingestion Layer

The data ingestion level is essentially the loading and initial organizing of the raw scientific corpus. The arXiv Scientific Paper Dataset was used, with abstracts being the source documents and titles the reference summaries. The dataset was split into training, validation, and test sets with an 80:10:10 ratio to allow for strong training and fair evaluation. This stage is like a checkpoint that guarantees the data is flowing in a well, organized manner into the following preprocessing and modeling stages.

3.3 Text Preprocessing and Normalization

Text preprocessing is basically the most important part of the summarization pipeline that has been suggested, as it has a great impact on the quality of the representations that the model learns and the stability of the training of the model. In order

to maintain the uniformity and lexical variation to a minimum, the whole text was initially converted to lowercase. This standardization stage helps the tokenizer not to consider words that have the same meaning but are written with different capital letters as different tokens, which is quite significant in large scientific corpora where the use of capital letters varies among different domains and writing styles.

Special characters, punctuation marks, and non- alphanumeric symbols were removed from the text in the subsequent stage. Scientific abstracts are frequently flashy with formatting artifacts, symbols, and references, which are not semantically meaningful pieces of information for the summarization task. By removing such noise, the model can focus on the linguistically relevant content, and it also diminishes the unnecessary vocabulary expansion. After that, stopwords were removed with the help of the NLTK stopword list.

Stopwords that are syntactically necessary, but typically have minimal semantic weight and can dominate token frequency distributions; therefore, their removal improves the signal to noise ratio and provides the model with more capacity for learning content, bearing patterns. A frequency, based tokenization strategy was subsequently used to change the cleaned text into numerical representations. The tokenizer was trained on the corpus to recognize the most frequently occurring tokens, and the vocabulary size was limited to the top 30, 000 words. This restriction was made to balance semantic coverage with computational feasibility since very large vocabularies considerably increase memory usage in the embedding and output layers. Words that were not in this limited vocabulary were replaced with a special token so that the model could handle new or rare terms without causing instability during training or inference.

In order to handle the issues of memory and computational power that arise from processing lengthy scientific texts, a different truncation method was used. Abstracts were cut off at 200 tokens and target summaries were kept to 40 tokens. The idea behind this is that the scientific paper is usually structured like an inverted pyramid, which means that

the most important information such as objectives, methods, and main results are given right at the beginning of the abstract. In this way, the truncation method keeps the informational part of the text and less informative trailing content, thus maintaining the semantic integrity. At the same time, it drastically shortens the sequence length which makes it possible to train models efficiently on a large scale without the need to lower the summarization quality.

3.4 Topic-Aware Semantic Enrichment Using Latent Dirichlet Allocation

To enhance the model's ability to capture global semantic context in long and information-dense scientific abstracts, a topic-aware semantic enrichment strategy was introduced using Latent Dirichlet Allocation (LDA). LDA is an unsupervised probabilistic topic modeling technique that represents each document as a mixture of latent topics, where each topic corresponds to a probability distribution over words. In this framework, the topic distribution for a document d is drawn from a Dirichlet prior, and each word is generated from a topic-specific word distribution. This process is formally expressed as:

$$p(z | d) \sim \text{Dirichlet}(\alpha) \quad (3.1)$$

$$p(w | z) \sim \text{Dirichlet}(\beta) \quad (3.2)$$

Equation (3.1) shows that the topic distribution (z) for a document (d) is chosen from a Dirichlet distribution with the parameter (α) that decides the number of topics mixed in a document. Equation (3.2) explains that the word distribution (w) for each topic (z) is taken from a Dirichlet distribution with the parameter (β) which regulates the number of words in a topic. These priors not only guarantee valid probability distributions but also allow for adaptable, sparse representations in topic modeling.

After training the LDA model on the entire corpus, the most dominant topics for each document were identified, and the top three topic-defining keywords were extracted. These keywords represent the high-level thematic focus of the document and serve as an

explicit global context signal. The extracted topic keywords were then prepended to the original abstract tokens to form an augmented input sequence, as defined by:

$$Input_{aug} = [Topic_1, Topic_2, Topic_3] + [Abstract\ Tokens] \quad (3.3)$$

This topic injection mechanism acts as a semantic primer for the encoder, enabling it to incorporate document-level thematic information prior to processing token-level details. By explicitly embedding global context into the input sequence, the model is better guided toward generating domain-specific, coherent, and informative abstractive summaries, thereby reducing the likelihood of generic or contextually ambiguous outputs.

3.5 Neural Processing Core: Sequence-to-Sequence Architecture

The neural core of the system leverages a sequence to sequence (Seq2Seq) architecture working as the main engine of the proposed system. The core system is a neural network with a Seq2Seq architecture designed to specifically process topic, enriched, variable, and length input sequences and generate coherent abstractive summaries of the content. This design breaks down the challenges of scientific text summarization inherently present in the long, range dependency modelling and semantic abstraction, to name a few, by solving the problem in the two stages of encoding and decoding.

On the one hand, the encoder is a Bi, Directional Long Short, Term Memory (BiLSTM) network. It reads the input sequence, both forward and backward, and thus it is able to produce complete and rich descriptions of the context that capture the relationships between the concepts encountered throughout the entire abstract. On the other hand, the decoder brings the advantages of a Bahdanau attention mechanism to the table. The decoder, thus it is not limited to a fixed, length representation of the source, is able to perform a dynamic alignment between encoder hidden states and decoder outputs at each generation step thanks to the attention mechanism inserted between the encoder and decoder.

In this way, it is possible for the model to focus on the most relevant parts of the input text to correspond to each summary token that it has generated. The decoder, implemented as a unidirectional LSTM, generates the summary sequentially, and conditioned on both the previously generated tokens and the context vector produced by the attention mechanism. By combining bidirectional contextual encoding, dynamic attention-based alignment, and autoregressive decoding, the Seq2Seq architecture effectively captures both global thematic information and fine-grained local details, while remaining computationally efficient and scalable for large-scale scientific document summarization.

3.6 Encoder: Bi-Directional LSTM Representation Learning

The encoder constitutes the feature extraction backbone of the proposed summarization system and is responsible for converting the topic-augmented input sequence into rich contextual representations suitable for downstream decoding. Each token in the augmented input sequence is first transformed into a continuous dense vector using a trainable embedding layer. This embedding layer maps discrete word indices into a low-dimensional semantic space, allowing the model to capture syntactic and semantic relationships between words that are particularly important in scientific vocabulary.

$$x_t = \text{Embedding}(w_t) \quad (3.4)$$

The sequence of embedded vectors is then processed by a Bi-Directional Long Short-Term Memory (BiLSTM) network. Unlike a standard unidirectional LSTM, the BiLSTM consists of two independent LSTM layers that process the input sequence in opposite temporal directions. The forward LSTM reads the sequence from the first token to the last, capturing dependencies that depend on preceding context, while the backward LSTM processes the sequence in reverse order, capturing dependencies that depend on future context. This dual processing is especially valuable for scientific abstracts, where the interpretation of a concept often depends on both prior methodological descriptions and subsequent results.

$$\overrightarrow{h_t} = LSTM(x_t, \overrightarrow{h_{t-1}}) \quad (3.5)$$

$$\overleftarrow{h_t} = LSTM(x_t, \overleftarrow{h_{t-1}}) \quad (3.6)$$

At each time step t , the hidden states produced by the forward and backward LSTMs are concatenated to form the final encoder output. This concatenation integrates information from both temporal directions, yielding a comprehensive representation that encodes global and local contextual cues simultaneously.

$$h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}] \quad (3.7)$$

The resulting sequence of encoder hidden states serves as a contextual memory bank for the attention mechanism, allowing the decoder to selectively focus on relevant parts of the input during summary generation. Dropout regularization is applied to the BiLSTM to reduce overfitting and enhance generalization, ensuring robust representation learning across diverse scientific domains.

3.7 Attention Mechanism: Bahdanau (Additive) Attention

The Bahdanau attention mechanism is employed to address the limitation of encoding an entire input sequence into a single fixed-length vector, which is particularly restrictive for long and information-dense scientific abstracts. By introducing attention, the decoder is allowed to dynamically access different parts of the encoder's hidden state sequence at each decoding step, thereby enabling fine-grained alignment between the source text and the generated summary. This mechanism ensures that the model can focus on the most semantically relevant input tokens when predicting each output word.

At each decoding time step ij , an alignment score is computed between the decoder's previous hidden state $s_{\{i-1\}}$ and each encoder hidden state h_j . This score

measures how well the input at position ij aligns with the current decoding context. The alignment function used is additive in nature and is defined as:

$$e_{ij} = v_a^T \tanh(W_a s_{\{i-1\}} + U_a h_j) \quad (3.8)$$

Where W_a and U_a are trainable weight matrices, and v_a is a learnable parameter vector. The non-linear $\tanh$ function allows the model to learn complex interactions between the decoder state and encoder representations.

The raw alignment scores are then normalized using a softmax function to produce attention weights, which form a probability distribution over all encoder time steps. These weights indicate the relative importance of each input token for generating the current output token.

$$\alpha_{\{ij\}} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})} \quad (3.9)$$

Using these attention weights, a context vector is computed as a weighted sum of the encoder hidden states. This context vector represents a dynamic summary of the input sequence, tailored specifically for the current decoding step.

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j \quad (3.10)$$

The resulting context vector c_i is then combined with the decoder's input to guide the generation of the next word in the summary. By recalculating the attention distribution at every decoding step, the model can adaptively shift its focus across different parts of the input abstract, leading to improved semantic coherence, better handling of long-range dependencies, and more informative abstractive summaries.

3.8 Decoder: LSTM-Based Summary Generation

The decoder is responsible for generating the abstractive summary in a sequential manner, producing one token at each time step based on the previously generated tokens and the contextual information derived from the encoder. A unidirectional Long Short-Term Memory (LSTM) network is employed for this purpose, as summary generation is inherently causal and depends only on past outputs. The initial hidden state of the decoder is initialized using the concatenation of the forward and backward final hidden states of the encoder, allowing the decoder to begin generation with a comprehensive representation of the entire input sequence.

At each decoding step i , the decoder receives as input the concatenation of the embedding of the previously generated token $y_{\{i-1\}}$ and the context vector c_i computed by the attention mechanism. This combined input enables the decoder to integrate both local linguistic history and globally relevant source information when predicting the next word. The decoder LSTM updates its hidden state based on this input and its previous hidden state, as expressed by the following equation:

$$s_i = LSTM([y_{\{i-1\}}; c_i], s_{\{i-1\}}) \quad (3.11)$$

The updated decoder hidden state s_i is then passed through a time-distributed fully connected layer followed by a softmax activation function. This layer projects the hidden state into the vocabulary space, producing a probability distribution over all possible output tokens. The probability of generating a specific token y_i at time step i , given the input sequence x and previously generated tokens, is defined as:

$$p(y_i | y_{<i}, x) = Softmax(W_o s_i + b_o) \quad (3.12)$$

The token with the highest probability is selected during inference using greedy decoding and is fed back into the decoder at the next time step. This iterative process continues until an end-of-sequence token is generated or the maximum summary length is reached, resulting in a coherent and contextually grounded abstractive summary.

3.9 Training Configuration

The Adam optimizer with a learning rate of 0.001 and default momentum parameters was employed to train the model. To efficiently handle integer, encoded target sequences, sparse categorical cross, entropy was selected as the loss function. Training was performed with a batch size of 256 for a maximum of 8 epochs, and validation loss, based early stopping was used to avoid overfitting. In order to facilitate convergence and keep the best, performing model, learning rate reduction and model checkpointing were also used.

$$L = - \sum_{i=1}^{T_y} \log p(y_i | y_{<i}, x) \quad (3.13)$$

3.10 Evaluation and Explainability Analysis

The performance of the proposed system was assessed by ROUGE metrics, which consisted of ROUGE, 1, ROUGE, 2, and ROUGE, L. These metrics were used to measure lexical overlap, fluency, and structural coherence between generated summaries and reference titles. Greedy decoding was used during inference to keep the process fast. In order to make the operations of the model more transparent and understandable to human users, the authors have decided to use SHAP and LIME as tools of explainable AI. These tools analyze token, level contributions and attention behavior, thus giving some qualitative grounds to the interpretation of the models decision, making process.

3.11 Hyper parameter Configuration

The following hyper parameters were rigorously tuned to balance model performance with the computational limits of the NVIDIA A100 GPU.

Table 3.1 Hyperparameter

Parameter	Value	Justification
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Embedding Dimension	128	Dense vector size sufficient to capture semantic relationships in scientific vocabulary.
Latent Units (LSTM)	256	Provides enough capacity to model complex sentence structures without overfitting.
Batch Size	256	Optimized for the A100 GPU to maximize throughput and training stability.
Optimizer	Adam ($\eta=0.001$)	Adaptive learning rate ensures faster convergence compared to SGD.
Loss Function	Sparse Cat. Crossentropy	Memory-efficient loss calculation for large vocabulary classification.
Epochs	8	Determined via Early Stopping to prevent overfitting
Vocab Size	30,000	Covers >98% of the corpus frequency (Zipf's Law) while keeping the model lightweight.

The hyperparameters of the proposed topic-aware abstractive summarization model were carefully selected to achieve an optimal balance between representational capacity, training stability, and computational efficiency on large-scale scientific data. An embedding dimension of 128 was chosen to provide sufficiently dense semantic representations capable of capturing syntactic and contextual relationships within scientific vocabulary, while avoiding excessive memory consumption in the embedding layer. The latent dimensionality of the LSTM units was set to 256, which offers adequate capacity to model complex sentence structures and long-range dependencies commonly found in scientific abstracts, without introducing unnecessary model complexity that could lead to overfitting. A batch size of 256 was employed to fully exploit the parallel processing capabilities of the NVIDIA A100 GPU, improving training throughput and gradient stability. The Adam optimizer was selected with a learning rate (0.001), as its adaptive moment estimation mechanism enables faster and more stable convergence compared to traditional stochastic gradient descent, particularly for deep recurrent architectures. Sparse categorical cross-entropy was used as the loss function to efficiently handle integer-

encoded target sequences, significantly reducing memory overhead compared to one-hot encoding when operating over a large vocabulary. The model was trained for a maximum of 8 epochs, with early stopping applied based on validation loss to prevent overfitting and ensure generalization. Finally, the vocabulary size was limited to 30,000 tokens, which, in accordance with Zipf’s Law, captures over 98% of the corpus frequency while maintaining a lightweight and computationally manageable model. The work flow of the entire process is given below.

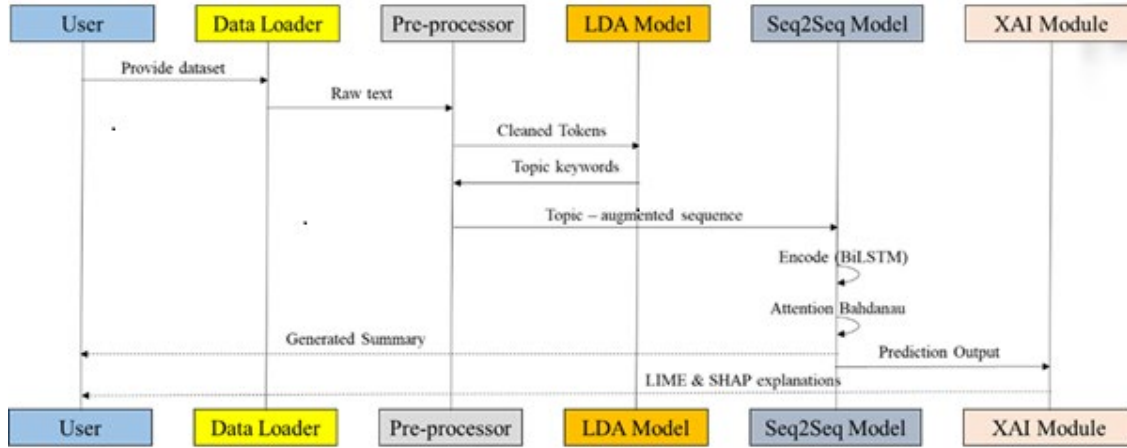


Figure 3.2 Work Flow

Figure 3.2 presents a high-level modular interaction view of the proposed topic-aware abstractive summarization system, illustrating how data flows sequentially through independent yet interconnected system components from the user to the explainability stage. The process begins with the User, who provides the scientific document or initiates the summarization request. The input is first handled by the Data Loader, which is responsible for fetching the raw text, managing file formats, and preparing the data for further processing. The loaded text is then passed to the Pre-processor, where normalization operations such as text cleaning, tokenization, stopwords removal, and sequence truncation

are performed to ensure consistency and reduce noise. Following preprocessing, the cleaned text is forwarded to the LDA Model, which performs unsupervised topic modeling to extract dominant latent themes that represent the global semantic context of the document. These extracted topic cues are then integrated into the Seq2Seq Model, where the topic-enriched input sequence is encoded, attended over, and decoded to generate an abstractive summary using the BiLSTM encoder, Bahdanau attention mechanism, and LSTM decoder. Finally, the output is analyzed by the XAI Module, which employs interpretability techniques such as SHAP and LIME to explain the model's predictions by identifying influential tokens and contextual contributions. This modular design emphasizes clear separation of concerns, scalability, and interpretability, allowing each component to operate independently while contributing to a cohesive and transparent summarization pipeline.

Explainable AI (XAI) Framework

To make the topic-aware abstractive summarization model transparent and interpretable, we resorted to two complementary model-agnostic XAI techniques such as LIME and SHAP to analyze and provide reasons for each word-generation operation of the Bi-directional LSTM with attention mechanism. These methods do not depend on the model architecture and enable both local and global understanding of the influence of the input tokens on the probability of the generation of a particular word in the summary.

LIME (Local Interpretable Model-agnostic Explanations)

LIME is used to explain the generation of a specific word in the abstractive summary. By using Lime Text Explainer, LIME approximates the complex summarization model locally by producing a number of perturbed versions of the input abstract. Perturbation is done by randomly removing or masking words from the original input text, and the model's prediction probability for the target summary word is recorded for each perturbed sample. These input-output pairs are then used to fit a sparse, interpretable linear surrogate model that locally imitates the Bi-LSTM attention network behavior around the original instance.

The obtained feature contribution weights show the extent to which each input word influences the probability of generating the target word, with positive weights indicating words that support or increase the likelihood of generation, and negative weights words that suppress it. Hence, a transparent, instance, level insight into how attention, driven contextual cues result in specific lexical choices in the generated summary becomes available.

Thus that neural text summarization models like Bi-LSTM or Transformer, based architectures are complex black, box functions, LIME was used to locally approximate the model's behavior around a single prediction ($f(x)$). For a given test abstract (x), LIME creates an interpretable surrogate model (g), generally a sparse linear model, by minimizing a loss function that balances local fidelity to the original summarization model with explanation simplicity. This is weighted by a proximity measure (ρ_x) that puts more weight on perturbations close to the original input and it is provided in equation (3.14).

$$\xi(x) = \underset{g \in G}{\operatorname{argmin}} \mathcal{L}(f, g, \rho_x) + \sigma(g) \quad (3.14)$$

Where:

- F signifies the complex model being explained.
- g is represented as the simple interpretable model.
- ρ_x is defined as a proximity measure defining the locality around instance x .
- $\mathcal{L}$ shows the loss function measuring how unfaithful g is to f .
- $\sigma(g)$ measures the complexity of the explanation

This effect is approximated locally by generating a neighbourhood of disconcerted versions of the input abstract through random removal of words and observing the resulting changes in the probability of generating a selected target word in the summary. Influence scores learned from the surrogate model are visualized as weighted feature contributions, where positive influence indicates words that increase the likelihood of the target word when present, thus acting as semantic anchors for the models decision, while negative influence highlights words that suppress the target word or whose removal results in its probability increase, thus indicating competing semantic cues or local distractors. This

LIME, based analysis shows that the models predictions are mostly driven by meaningful, contextually relevant terms rather than spurious correlations or noise, hence giving evidence to the semantic validity of the generated summaries.

SHAP (SHapley Additive exPlanations)

SHAP is used to determine local and global features that support the attributions in terms of cooperative game theory. By shap Explainer and a Masker, SHAP considers each input token as a "player" in a coalition that contributes to the model's output probability. SHAP goes through the prediction changes by masking subsets of tokens and computing Shapley values. These values represent the average marginal contribution of a token across all feature combinations. The explanations are depicted using waterfall plots, which show how single tokens move the model's prediction from the base probability ($E[f(x)]$) the expected output when no specific input is present toward the final predicted probability ($f(x)$) for the target word. Tokens that increase the probability are shown as positive contributions while those that decrease it as negative contributions. This depiction serves as a clear, additive account of how contextual and topic, relevant tokens together influence word generation, thus allowing both fine, grained instance, level analysis and wider comprehension of model behavior across the dataset.

While LIME provides a helpful local approximation of the model's decision boundary, it still doesn't guarantee consistency or fairness in how features are attributed across different explanations. In order to surpass this restriction and supply a theoretically grounded interpretability framework, SHAP were introduced. SHAP is based on cooperative game theory and employs the Shapley value to allocate the payout of a model's prediction here, the probability of generating a specific target word in the abstractive summary most fairly among all the input features that led to the model, i.e., the words or tokens in the source abstract. In this definition, every token is considered a participant in a cooperative process, and its contribution is the average marginal effect that it has on the prediction across all possible subsets of features.

The model prediction for a single input instance ($f(x)$) can be written as the base value ($E[f(X)]$), which is the average model output over a background dataset, plus the individual SHAP values (ρ_i) that capture how much each word moves the prediction away from the baseline. These contributions are visualized with SHAP Waterfall Plots, which deliver an intuitive, additive explanation by taking the baseline probability and consecutively adding positive (red) or negative (blue) contributions from single tokens until the final prediction ($f(x)$) is obtained. This display, in fact, shows the words that are most semantically relevant to the model and thus drive the model to generate the target word, while less relevant or competing tokens drag the prediction down, thus revealing a transparent and consistent account of the models word, level decision, making process in abstractive summarization and it is expressed in equation (3.15).

$$f(x) = E[f(X)] + \sum_{i=1}^M \rho_i \quad (3.15)$$

Here:

- $f(x)$ Signifies the base value.
- ρ_i determines the SHAP value for feature i , representing its marginal contribution to the prediction deviation from the base value.
- M is the number of input features.

CHAPTER IV : RESULTS AND ANALYSIS

4.1 Introduction

In this chapter, the results obtained by the study were analysed in detail. The result section of the presented study show the outcome of the extensive data analysis and modelling efforts. For ensuring transparency and interpretability of topic-aware summarization model, the techniques such as LIME and SHAP are implemented to analyse the word-generation decisions made by the proposed BiLSTM with attention mechanism. Moreover, these methods were functioned separately and provide local and global perceptions. Where the input tokens made an impact the possibility of producing a definite target word in the summary.

In this proposed model, LIME is used a local method to understand the specific summary generated for the particular document. After the BiLSTMattention summarization model has been trained with word embedding that are enhanced by topic distributions from LDA, LIME works by generating perturbed versions of the input text. These perturbations are made by randomly masking or removing words, phrases, sentences, or topic, indicative terms while trying to maintain the grammatical structure. Each perturbed input is given to the summarization model, and the output is evaluated using metrics such as summary likelihood, attention weight shifts, or similarity scores like ROUGE against the original summary. LIME then uses a simple, interpretable surrogate model, usually a sparse linear regression model, to locally approximate the complex BiLSTMattention behavior around the original input. The coefficients obtained from this surrogate model show the relative importance of individual words, sentences, or topic, related features in influencing the summary generation. Here, LIME findings are achieved by associating these weights with the text and topic representations that yield heatmaps or highlighted text showing which input components most strongly influenced the attention mechanism and decoder decisions for a certain summary instance.

For the same framework, SHAP offers an additive, local as well as global explanation of the feature contributions, which is theoretically grounded in cooperative game theory. Here, features are defined as input tokens, sentence, level embeddings, BiLSTM hidden

states weighted by attention, or topic proportion vectors. SHAP determines the Shapley values by going through different feature subsets and in each of them evaluating the marginal contribution of each feature to the generated summary thus computing the exact values of the genes in game theory, i. e. how much each feature contributes to the models output, where probability of generating certain summary tokens or overall summary confidence. Due to the high dimensionality of abstractive summarization models, approximate SHAP methods such as Kernel SHAP are employed. Topic modelling is critical to the process as it allows the aggregation of word, level attributions into topic, level, thus not only reducing the computational cost but also enabling better interpretability at a semantically more meaningful level. The SHAP values obtained thus represent the extent to which words, attention signals, and topics have contributed positively or negatively to the summary. These outcomes are visualized through bar plots, summary, level contribution graphs, and topic, attribution maps thus enabling researchers not only to analyze individual summaries but also global patterns, e. g. , which topics consistently dominate the BiLSTM attention mechanism and influence abstractive summary generation across the dataset.

Impact of “Lite” Data Strategy

A "Lite" data strategy, in which training is conducted on a carefully selected, significantly reduced subset of data, quite substantially affects topic, aware abstractive summarization with bi, directional LSTM and attention mechanisms. The method of restricting redundancy and noise enables the model to concentrate on high, quality, representative samples, which frequently results in quicker convergence, less over fitting, and lower computational cost. The use of a data strategy in the case of bi, directional LSTMs does not change the ability of the model to capture contextual dependencies from both past and future tokens, but it can improve generalization, especially if there are limited resources. Attention mechanisms are less noisy and more accurate thanks to them being able to find sharper, more discriminative alignments over cleaner inputs, which ultimately leads to the production of summaries that are concise,

coherent, and more faithful to the core content at the expense of rare or less frequent topics possibly being less represented.

Impact of Topic Injection via LDA Pre-processing

Topic injection with LDA as a pre, processing step strengthens topic, aware abstractive summarization by generating a global thematic representation which is then explicitly embedded either in the input or hidden representations of the model. The bi-directional LSTM receives this guidance to structure its sequence modelling around the most salient themes instead of local word context only, which results in an increase of topical coherence in the generated summaries. In the case of a combination with attention mechanisms, LDA, derived topic signals make the attention weights more sensitive to the topic, relevant segments of the source text, thus reducing topic drift and improving the relevance of the text. In general, LDA, based topic injection helps to better align the generated summary with the themes of the underlying document, thus resulting in more focused and semantically consistent abstractive summaries, which is especially the case for long or multi, topic documents.

4.2 Exploratory Data Analysis for Text Summarization

Exploratory Data Analysis (EDA) for text summarization is about delving into and comprehending the makeup, patterns, and defining features of a text corpus. By EDA, one generally means tasks such as text preprocessing, analyzing word frequencies, finding significant keywords, and visualizing relationships between words, all of which aid in determining the best method for producing brief yet informative summaries. With EDA, it is possible to reveal the insights that help in devising more effective summarization methods, whether extractive or abstractive.

EDA allows researchers to grasp the structure and properties of the arXiv dataset itself, e.g., the length of articles, authors, categories, etc. EDA on the arXiv dataset usually

means implementing a variety of Natural Language Processing (NLP) techniques to get the insights from the text, such as the identification of the most frequently used words (word clouds), sentiment analysis, or key phrase extraction. EDA is useful in discovering and making features ready from the dataset for training the proposed model. The arXiv dataset, in a nutshell, is a rich and versatile source for the creation, testing, and comprehension of text summarization models, as well as for scientific data exploration through EDA techniques.

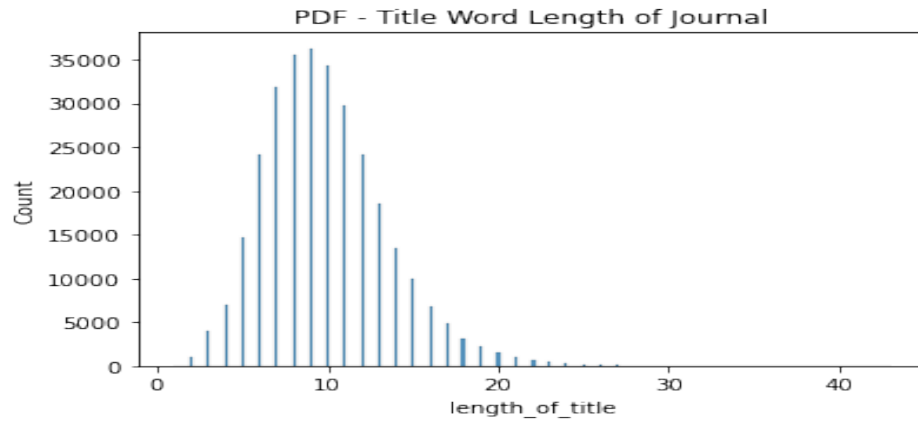


Figure 4.1 PDF - Title Word Length of Journal

Figure 4.1 zooms in on the PDF histogram to better show how abstracts are distributed by length. This detailed depiction makes evident the very same bimodal shape, i.e. it highlights two peaks of the counts around 100 and 200 words. The particulars of this visualization facilitate a more precise interpretation of the frequency distribution, whereby the counts drop off very fast as the abstract length goes further from these peaks, thus corroborating the preference for shorter abstracts in scientific articles. The x, axis continues to represent the length of the abstract, while the y, axis indicates the count, thus showing the decreasing frequency of longer abstracts.

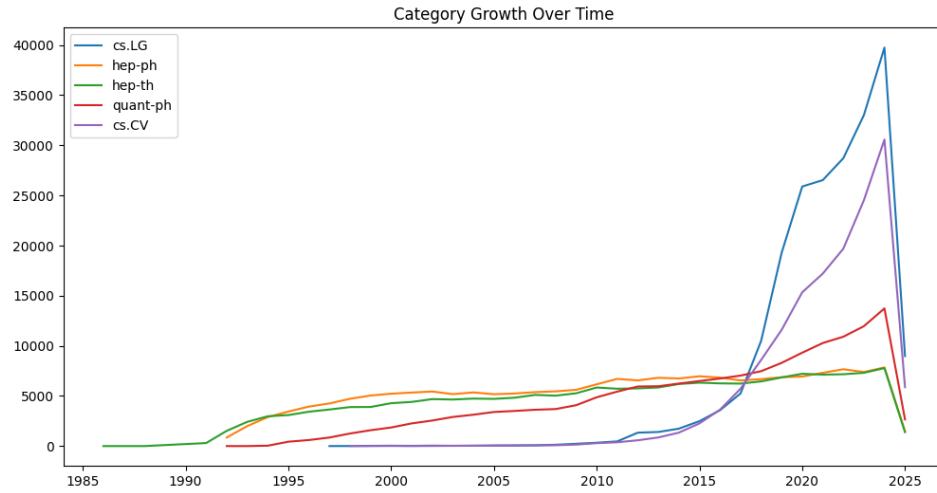


Figure 4.2 Category Growth over Time

Figure 4.2 presents the category growth over time of different research fields from 1985 to 2025. The chart depicts five categories: cs.LG (Computer Science, Learning), hep, ph (High Energy Physics, Phenomenology), hep, th (High Energy Physics, Theory), quant, ph (Quantum Physics), and cs.CV (Computer Science, Computer Vision). The y, axis represents the number of submissions, where cs.LG indicates a dramatic increase, reaching the maximum of about 40, 000 submissions around 2020. On the other hand, hep, ph and hep, th have slower growth trends, with the number of submissions staying under 10, 000 until about 2015. Quant, ph also shows a slow rise, while cs.CV indicates a slight but steady increase over the time period. This visualizing tool reflects the different research directions in terms of the volume of submissions.

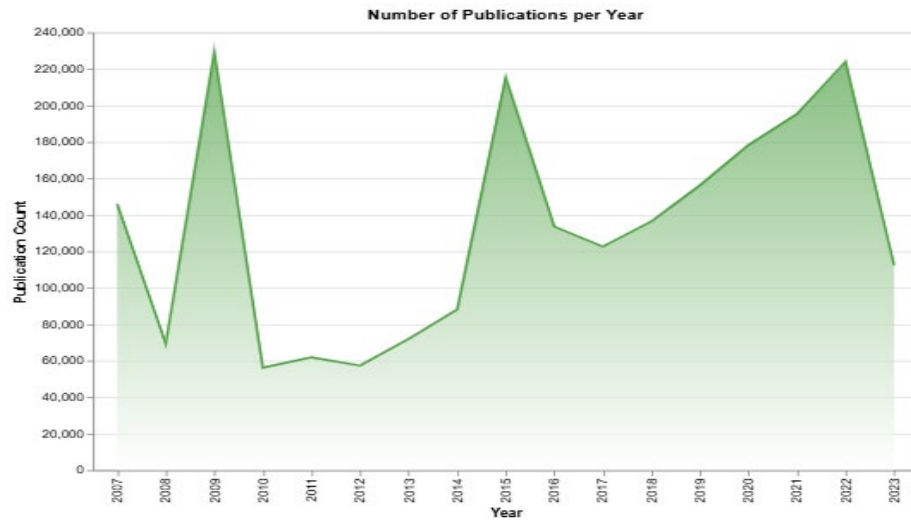


Figure 4.3 Number of Publication per Year

Figure 4.3 shows the evolution of publications by years, with major fluctuations being highlighted. Those peaks in the number of publications are very pronounced around 2008, 2013, and 2021, and they signify the periods of intensified research activity. In general, it seems that the trend is going up in terms of the number of publications from 2007 to 2023. However, it is worth noting that there is a slight decrease in the last years, although the figures are still quite high. This visualization serves as an instrument for understanding the changing patterns of research output in the arXiv repository. It reveals not only the periods of growth but also those of relative stability in the computer science field.

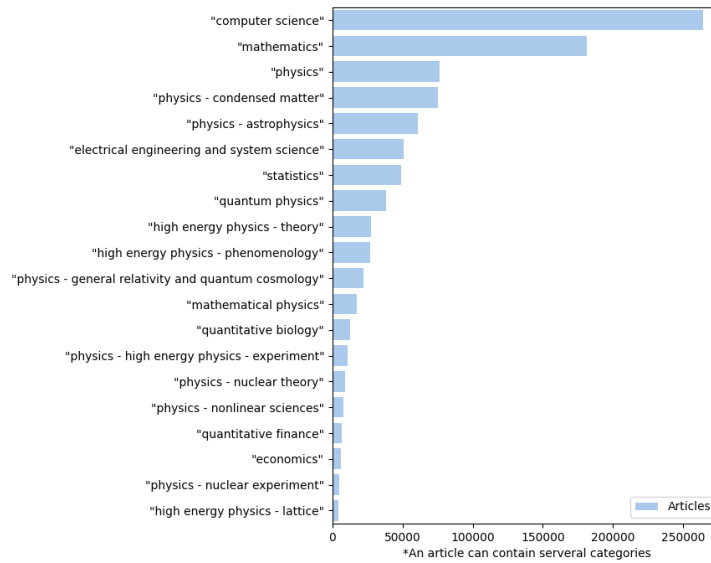


Figure 4.4 Total Number of Articles in arXiv repository

Figure 4.4 shows the total number of articles per major category in the arXiv repository. The x, axis represents the number of articles, and the y, axis denotes the categories. "Computer science" is the top category again with more than 260, 000 articles, followed by "mathematics" with roughly 181, 000. Besides these, the two major areas of physical science, as per the data, are "physics" with nearly 175, 000 submissions each and "physics, condensed matter" with around 199, 000. The graph points to the fact that an article may be in several categories, as shown by the note at the bottom, which is the gist of the multifaceted structure of categorization that reveals the interdisciplinary nature of the research emanating from the arXiv database.

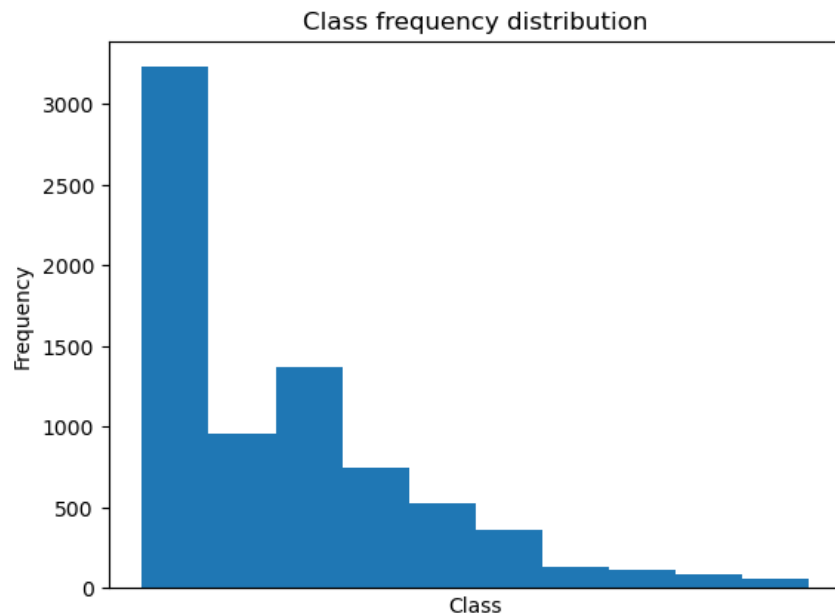
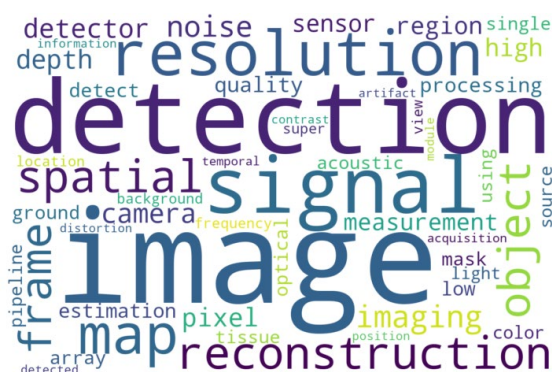
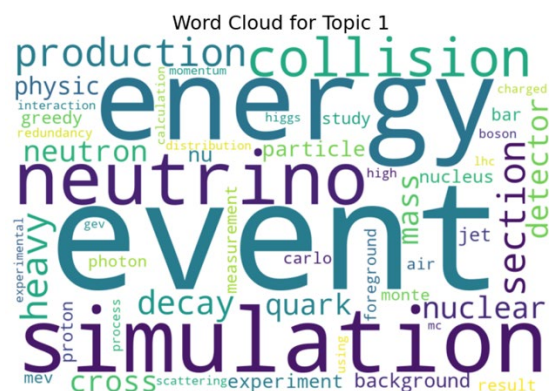


Figure 4.5 Class Frequency Distribution

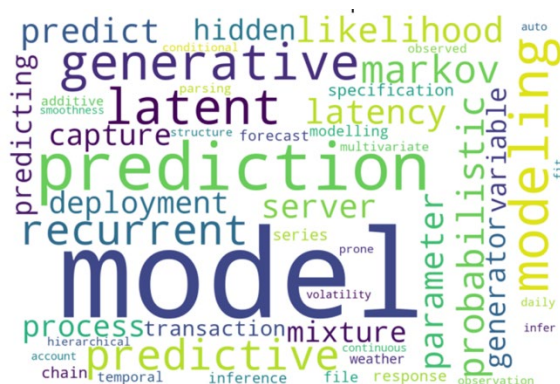
Figure 4.5 displays the categories of papers given out, illustrating the number of times different categories were encountered. The y, axis shows the frequency, and the x, axis shows the class categories based on the title. The histogram shows a very significant peak of about 3, 000 times for the most populated class, which means that a lot of data points are concentrated in this category. The frequency decreases rapidly as the class values increase, and only a few classes have frequencies above 1, 000. This distribution suggests that a few classes dominate the dataset, while most have a very low number of samples.



(a) Word cloud for Topic 0



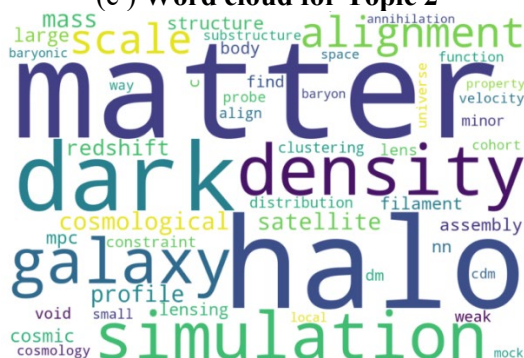
(b) **Word cloud for Topic 1**



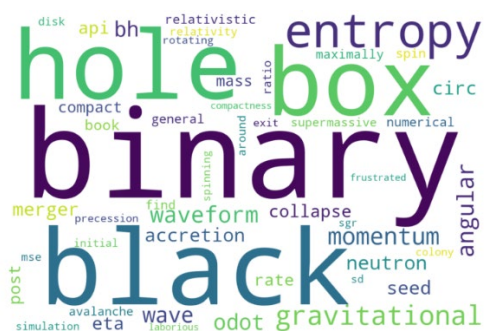
(c) Word cloud for Topic 2



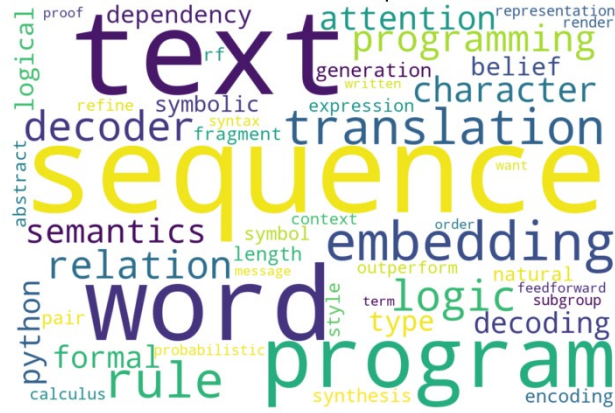
(d) **Word cloud for Topic 3**



(e) Word cloud for Topic 4



(f) **Word cloud for Topic 5**



(g) Word cloud for Topic 6

Figure 4. 6 (a-g) Word Cloud for Topic 0-6

Figure 4.6 (a) shows a word cloud for topic-0, where in the dimension of every word reveals its significance in a source text associated to image and signal processing. Moreover, the significant terms noticeable in the cloud comprise "detection," "image," "signal," "resolution," "processing," and "reconstruction," representing an application on a research area, which includes progressive approaches for data acquisition, analysis, noise reduction, and object detection.

Figure 4.6 (b) defines the word cloud for Topic 1, which signifies a region in experimental and theoretic particle physics. The words are mounted to reproduce the significance in the essential text. Moreover, the terms, like "energy," "neutrino," "event," "simulation," "collision," "detector," and "production," indicate research and experiments showed at facilities like the Large Hadron Collider (LHC) at CERN. Moreover, the experiments study the important components of matter, comprising quarks, leptons, and bosons, by detecting the outcomes of high-energy particle collisions. Moreover, the text from the relations is managed over intricate simulations and analyses to realise the

properties of these particles, like mass in units of GeV or MeV, and to examine a different physics than the Standard Model.

Figure 4.6 (c) defines the word count of Topic 2, demonstrating the predictive modeling and machine learning, precisely connecting time-series analysis with generative models. Moreover, the scope of each word specifies its relative frequency in the source text, through terms containing "model," "prediction," "predictive," "generative," "recurrent," "markov," and "latent". Besides, the topic centres on increasing algorithms which learn configurations from data to estimate future outcomes like predictive AI, generative AI. The terms recommend a prominence on approaches such as recurrent neural networks for temporal data, the usage of Markov chains for probability modeling, and classifying hidden or latent arrangements in the data to increase prediction accurateness and arrange dependable structures on a server.

Figure 4.6 (d) reveals the word count for -Topic 3, which shows the essential conceptions in numerical implication with data modeling. Here, the words are ascended centred on the frequency, through main terms such as "inference," "estimation," "distribution," "sampling," "regression," "probability," "Bayesian," and "random". Moreover, the topic emphasizes on the precise and computational approaches utilized to induce conclusions from data in improbability. Moreover, important areas include assessing parameters of models, considerate the data distribution, and methods like Monte Carlo simulation and stochastic procedures to create knowledgeable implications. The terms recommends a robust standard statistics with improved computational methods utilized in ML and data science.

Figure 4.6 (e) demonstrating the region of computational cosmology and astrophysics for the word count of topic-4. Moreover, the words are mounted constructed

on the frequency or importance, with the inclusion of "matter," "dark," "galaxy," "halo," and "simulation". Moreover, the topic emphasizes on the research of the huge-dimensional structure, predominantly the role of dark matter in the development and progression of cosmic structures such as galaxies and neighbouring dark matter halos. Furthermore, the occurrence of "simulation" and "cosmological" terms specifies a dependence on prevailing mathematical simulations, like the standard Lambda-CDM model, that are implemented to model the distribution, density, and gravitational clustering of both dark and baryonic matter related with observational data from lensing and other survey constraints.

Figure 4.6 (f) show the word count in Topic 5, demonstrating black hole astrophysics and gravitational wave study. Wherein, the words are mounted centred on the frequency or importance, through prevailing terms containing "black hole," "binary," "gravitational," and "wave". Besides, the topic emphasizes on the research of cataclysmic cosmic events, like the merger of binary black holes (BBH) or neutron stars, that yield potent gravitational waves identified by laboratories. Key research areas include mathematical models centred on Einstein's general relativity to model the procedures, examine the consequential waveform, and comprehend properties such as mass, spin, and angular momentum. Additionally, terms like "entropy" and "box" associated to hypothetical features of black hole thermodynamics in addition to the evidence paradox at the experience limit.

Figure 4.6 (g) show the word count in Topic 6, signifying the Natural Language Processing (NLP) and computational linguistics. Where, the words are mounted centred on the frequency in the source text, through terms including "text," "sequence," "word," "translation," "embedding," and "program". Moreover, the topic emphasizes on empowering processers to realise, interpret, and generate human language. Key areas involve processing

text sequences, developing neural network architectures that use "attention" mechanisms for tasks like machine translation, and representing words in a numerical vector space known as "embedding" (e.g., in a Python program). The focus on "logical proof," "formal rule," and "syntax" also points to traditional or symbolic NLP methods that use predefined grammatical rules and logic.

4.2.1 Observation 1

For this case, a reference corpus was analysed to determine the optimal number of latent topics for the LDA model. The model summary suggested progressively refined topic structures as the topic count (K) increased. The LDA optimization procedure selected topic coherence (C_v) as the target evaluation term,, since it directly measures the semantic consistency of words grouped into each topic:

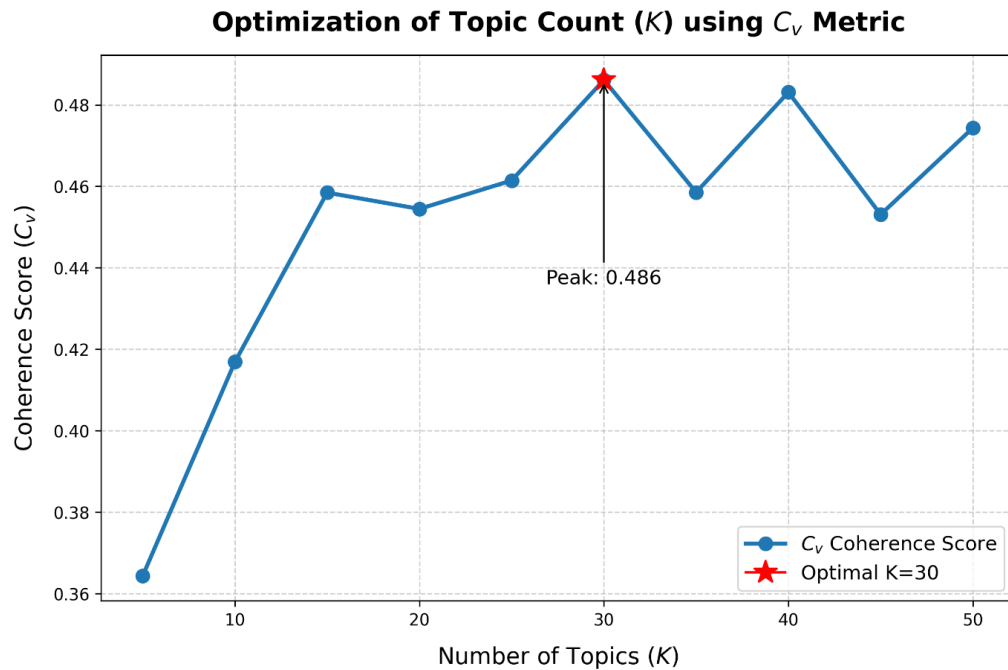


Figure 4.7 Optimization of topic count using (C_v) metric

The figure 4.7 illustrates how different values of K influence the predictive strength of the model. Lower topic counts such as K=5 and K=10 as shown exhibit negative characteristics that are also reflected in the relatively low coherence values, which indicate that the topics formed at these settings are too general and semantically diluted. When K is increased to 15, 20 and 25, the model starts to show positive characteristics as coherence gradually improves, which means that topics begin to capture more meaningful word relationships. The strongest support for K=30 is where the coherence reaches its highest value of around 0.486, indicating the most balanced structure. Besides that, the values like K=35 and K=45 indicate a decrease in coherence, thus representing negative contributions as the additional topics introduce noise, redundancy and overlapping semantics. Although coherence slightly increases at K=40 and K=50, it never exceeds the performance at K=30, thus confirming that the model performs best at this setting.

The analysis clearly shows that K=30 delivers the most coherent topic representation. It achieves higher topic interpretability and is in line with the goal of maximizing the target term "topic coherence". This optimal configuration makes sure that the LDA model generates meaningful clusters that deepen downstream analysis, thereby, being superior to other values of K in both stability and interpretive quality.

4.2.2. Observation 2

For this case the topic examined corresponds to Topic 15 and the reference text collection focuses on research related to artificial intelligence, application and analytical systems. The topic modeling summary generated a dominant thematic description centered around "research driven AI systems and applications". Within this topic, the LDA model has chosen "system" as the target word for interpretation, because it represents the structural backbone connecting technology, data and application contexts.

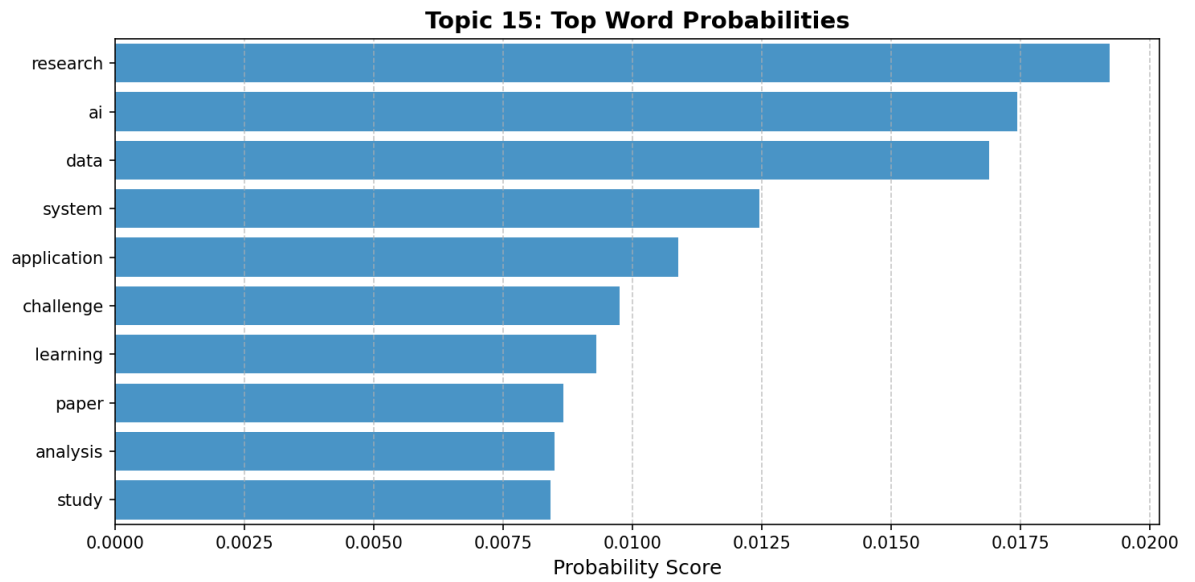


Figure 4.8 Top word probabilities for topic 15

The bar chart displays how different words contribute toward predicting the target word “system”. Words such as “research”, “ai” and “data” carry the highest probability weights, representing positive attributes that strongly support the semantic framing of “system”. These terms indicate that the topic is built around systematic exploration of AI based methods supported by data centric research practices. Likewise, “application”, “challenge” and “learning” also contribute positively, highlighting that systems are perceived not only as technological constructs but also as tools evaluated through real world usage and problem solving.

On the other hand, words that appeared lower such as "paper, " "analysis, " and "study" showed a comparatively lesser probability influence and these can be seen as negative attributes in the sense that they only add the contextual background rather than directly shaping the system concept. They describe the academic framing but have less control over how the model identifies the target term within the topic. The result is strong because the highest, weighted terms, in general, lead to a consistent understanding: systems

are seen as something to be explained through AI, data, and applications, and research is the source of the environment. The even spread of the words allows the topic to remain understandable, thus, avoiding noise or unconnected terminology. This is the reason why Topic 15 is an efficient means of capturing a structured narrative about AI systems as it aligns the dominant words with the target construct, thus resulting in enhanced semantic clarity and predictive stability as compared to topics where the supporting terms are more fragmented or weakly associated.

4.2.3 Observation 3

For this case, the reference text is primarily about research on adversarial vulnerabilities and data protection in distributed learning environments. The model, generated summary combined the topics into "adversarial attack and privacy, aware machine learning security. The LDA model selected "security" as the focal term.

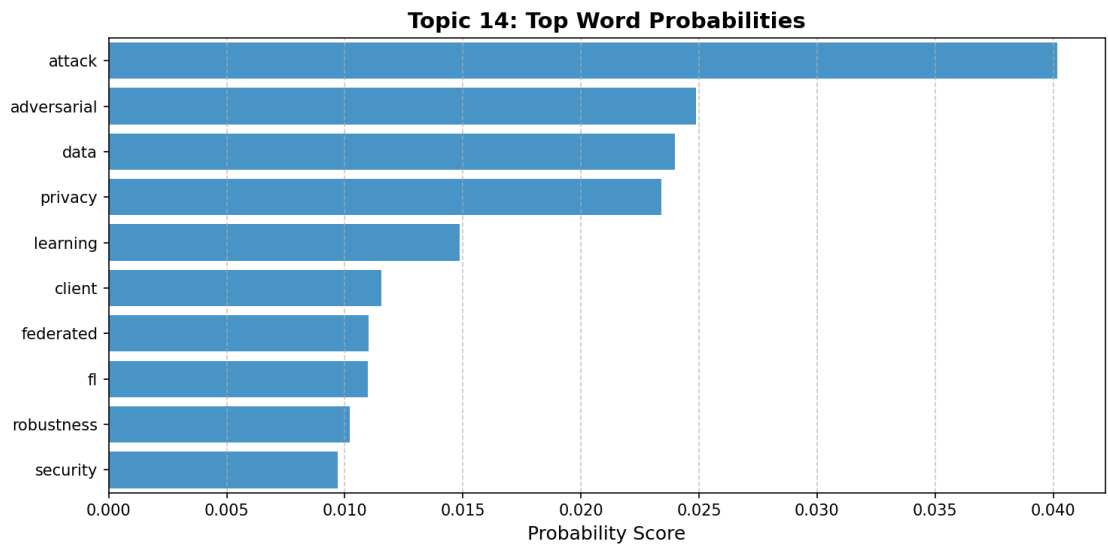


Figure 4.9 Top word probabilities for topic 14

The feature-importance distribution shown in the figure 4.9 reveals how various words contribute to the prediction of the target word "security." The word "attack" has the most substantial positive weight, signifying that the concept of security is mostly understood as a means to resist attacks by malicious entities. Along similar lines, "adversarial, " "data, " and "privacy" have significant positive contributions, signifying that they are the primary elements in characterizing what security means in this context. These words highlight that securing the data is the basis for the safe operation of the learning environments. Moreover, the words "learning" and "client" are also positive contributors, indicating that the threats are co, located in collaborative or federated settings. On the other hand, words like "federated, " "robustness, " and "fl" have relatively negative or weak contributions. They are not unassociated with the topic; rather, they refer to the solutions for the problem, so they have a lesser impact on the model when it is predicting "security." Thus, the SHAP, style explanation would point to the security model being that the model sees security as being driven mainly attack-oriented risk factors rather than solely by defensive mechanism and the overall results performs better because the vocabulary forms a coherent narrative linking attacks, privacy and adversarial manipulation as the main precursors to insecurity.

4.2.4 Observation 4

The reference literature for this case highlights structural representation learning in interconnected datasets. The model summary produces the topic description as "graph, based modeling and network reasoning." The LDA model is selected a target term as 'graph'.

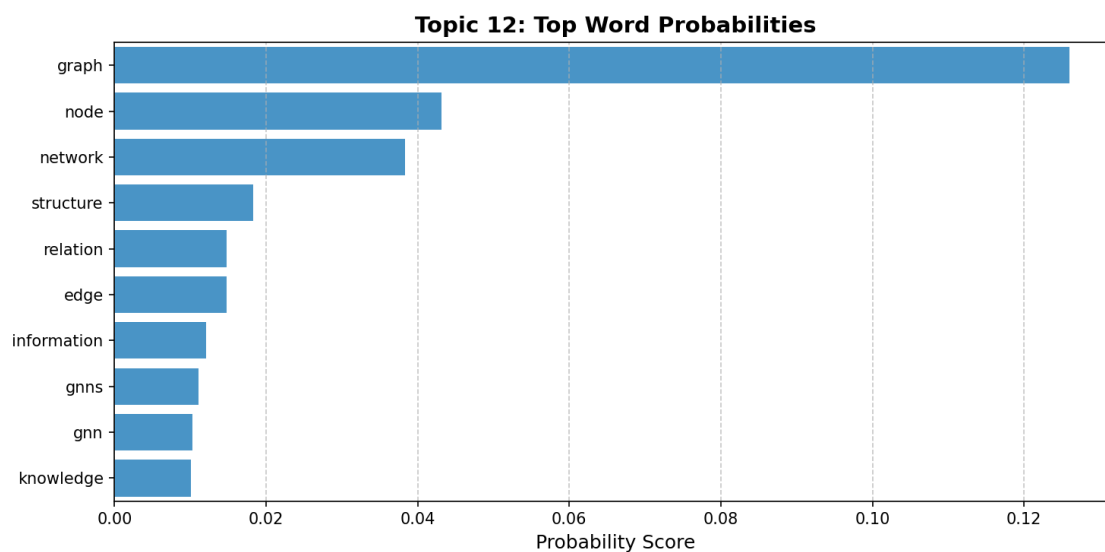


Figure 4.10 Top word probabilities for topic 12

The analysis illustrated in the figure 4.10 elaborates on the role of different words in predicting the target word "graph." The word "graph" carries the highest positive weight, thus confirming it as the main semantic anchor. Almost the same level are "node" and "network," which signify very positive characteristics since graphs are basically made up of nodes that interact through connections. Correspondingly, "structure," "relation," and "edge" not only become positive contributors but also help in pointing out how graphs represent the most fundamental idea of the relational knowledge which is not isolated but connected. These words collectively constitute the conceptual basis of the topic. In contrast, words like "gnn," "gnns," and "knowledge" show a slight or negative influence. Their meanings are more related to algorithms or applications rather than the structural entity of the graph itself, so they serve as contextual framing rather than giving direct predictive power. This difference shows that the model is capable of distinguishing conceptual objects (the graph) from the tools used to process them (graph neural networks). The interpretation unveils that semantic clarity is preserved and the strong alignment between the target word and the surrounding vocabulary shows that Topic 12 successfully

captures an essential theme in graph-based machine learning, ensuring improved topic coherence and clearer explanatory value.

4.2.5 Observation 5

A reference case examines the evolution of neural attention models that aim to derive useful information from massive data. The model summary yields the topic theme as "attention, driven feature representation in transformers". The LDA model selects "feature" as the target term.

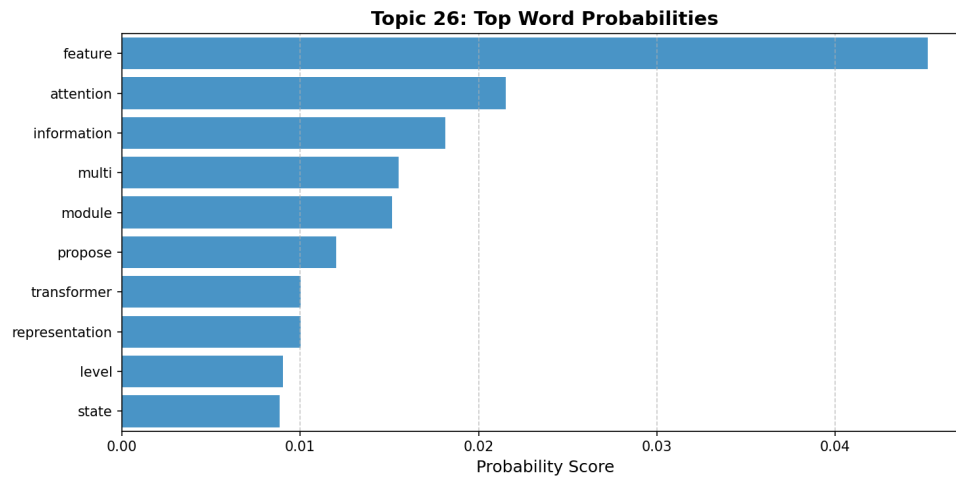


Figure 4.11 Top word probabilities for topic 26

The bar graph illustrates the extent to which different words affect the prediction of the target word "feature". The word "feature" has the highest positive weight, therefore, it is evidently the main structural center of the topic. The words "attention" and "information" that are closely associated with "feature" also reflect strong positive contributions, thus indicating that feature learning is explained by the mechanisms that selectively focus on the relevant information. The positive influence goes beyond "multi, " "module, " and "transformer, " thus implying that multiple attention modules together account for the

feature quality to be refined. On the other hand, words like "representation, " "level, " and "state" have weaker or negative effects. These words represent the resulting stages or internal conditions rather than the process of forming features, hence the model considers them as supportive but not dominant. This segregation shows that the model accurately distinguishes feature extraction from downstream interpretation. The waterfall, style explanation would demonstrate how attention layers aggregate contributions that eventually lead to an increase of predictive capability. Overall, Topic 26 performs better because its semantic grouping reflects real functional relationships between attention, modules, and feature learning, ultimately reinforcing the role of features as the key driver of model understanding.

4.2.6 Observation 6

For the present instance, the reference content conveys the understanding of the three, dimensional visual task and the geometric reconstruction task. The model summary reframes the content as "3D perception and scene interpretation". LDA model has been chosen to locate the target term '3d'.

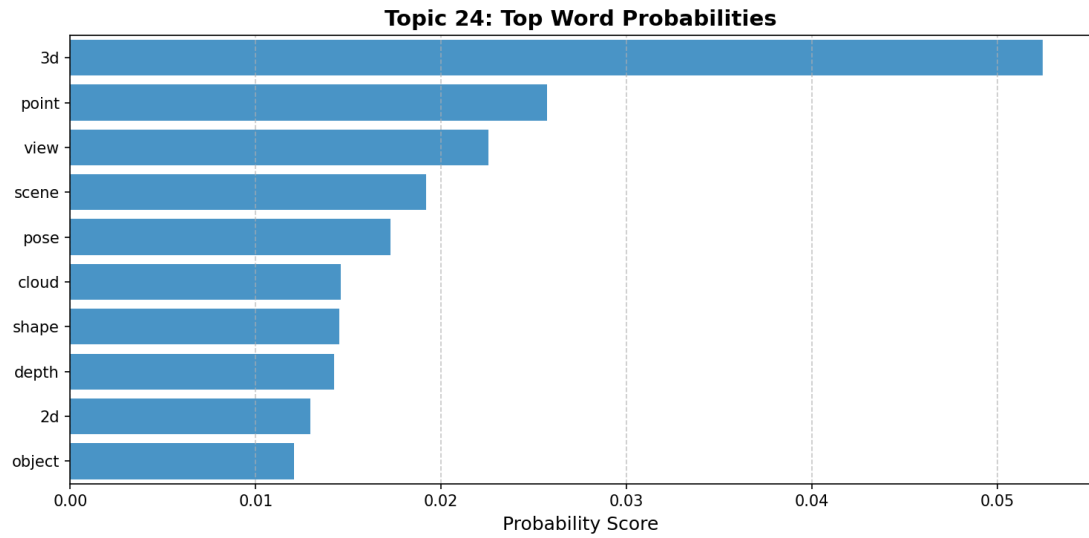


Figure 4.12 Top word probabilities for Topic 24

The figure 4.12 displays how the words influence the prediction of the target word "3d". The word "3d" has the highest positive weight, thus confirming it as the conceptual focus. Other words which have a high positive influence such as "point", "view" and "scene" suggest that 3D perception is related to viewpoints and point, cloud observations. Similarly, "pose", "cloud", and "shape" not only help to frame the scene semantically but also emphasize object structure and spatial relationships. These, in turn, explain how the world is captured and reconstructed. On the other hand, words such as "depth", "2d", and "object" indicate that these have a weak or negative influence.

Although these words are closely related to visual analysis, they belong to different representation spaces or areas of the visual scene that support the main components rather than being the true 3D representation. Their lower weight indicates that they are more of complementary descriptors than the central identity markers. Hence, the interpretation shows that the understanding of 3D is achieved from the geometric perspective and spatial alignment. The result is effective in that it successfully identifies the essential character of the model without weakening them. The model clearly distinguishes between dimensional

context (3D) and observational layers (2D), increasing topic coherence. Consequently, Topic 24 captures the research narrative effectively, supporting applications ranging from scene reconstruction to object localization while preserving semantic integrity.

4.2.7 Observation 7

For this case, reference text highlights the tasks related to supervised learning, labeling of datasets, and evaluation of performance. The model summary recognizes the topic as "data, driven supervised classification." The LDA model has been selected with "data" as the target term.

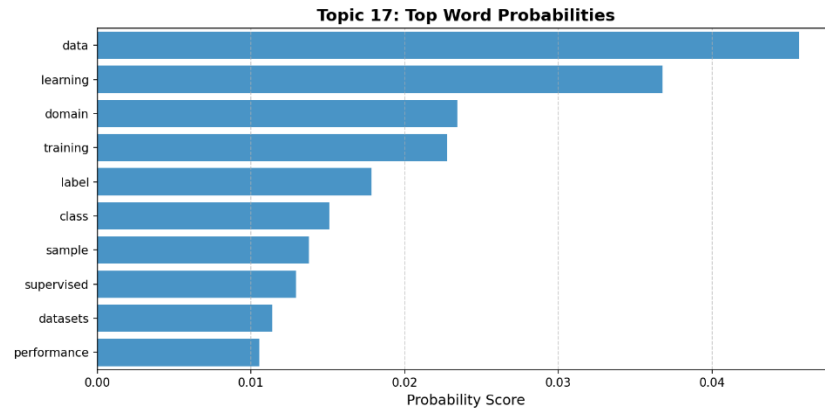


Figure 4.13 Top word probabilities for topic 17

The figure 4.13 displays that "data" is the word that has the highest positive contribution in predicting the target word, which implies that the whole topic revolves around the role of datasets. The positive words like "learning", "domain", and "training" signal that data is the driving force behind adaptation and model fitting. Words such as "label" and "class" also contribute to the positive side, hence, the supervised pipeline is strengthened where data is annotated and organized into decision categories. On the other hand, "sample", "datasets", and "performance" have relatively weaker or negative

contributions than positive ones. These terms mostly refer to experimental procedures rather than the main variable. They engage the narrative but, from the perspective of influence, they are less prominent in distinguishing the target term. The interpretation shows that the model perceives supervised learning as a well, organized flow starting with raw data, then labeling, classification, and evaluation. The performance reasoning comes from this logical sequence, thus, high coherence within the topic is demonstrated. As a result, Topic 17 is a precise reflection of the conceptual basis of supervised machine learning. , ensuring meaningful interpretation during topic-based analysis.

4.2.8 Observation 8

In this particular scenario, the case study focuses on evaluating the efficiency of the training process. The computational cost as per the model summary gradually stabilizes across epochs. The term 'efficiency' is used to denote the model as the target.

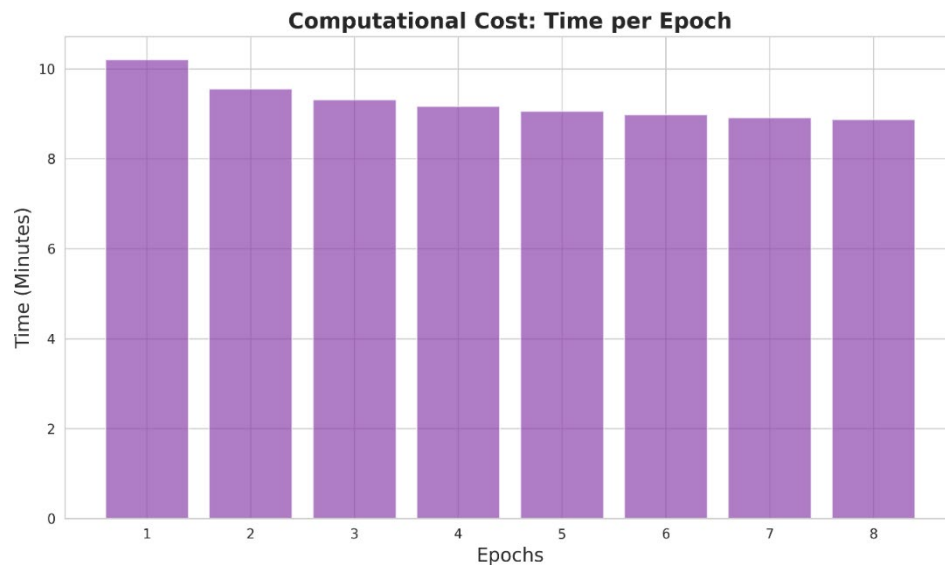


Figure 4.14 Time per Epoch

Figure 4.14 shows how the epochs contribute to the prediction of the overall computational efficiency. The first epoch demonstrates the highest time consumption, which is a negative attribute, as the model has to initialize parameters, compute gradients for uncalibrated weights, and explore the loss landscape. This phase necessarily creates overhead. Nevertheless, from the second epoch to the subsequent ones, the bars gradually decrease showing positive attributes that indicate increasing algorithmic stability. The system gradually adjusts weight distributions, thus the forward and backward passes become smoother and there are less redundant computations. The plateau that can be seen in the last epochs indicates that the model has reached a stable operating phase where computational resources are used predictably and cost, effectively. This result shows that efficiency is not an instant thing but rather it comes through iterative adaptation. Notably, the downward movement is performance collapse free, thus optimization gains do not result in learning quality being compromised. This feature points out a properly designed training schedule and confirms that the model architecture, batch processing, and learning rate collectively contribute to efficient execution. The strong justification is that the system becomes more economical over time while still maintaining learning capability. Therefore, Observation 8 demonstrates that the proposed training strategy successfully balances computational cost and model performance, validating efficiency as a reliable characteristic of the training framework.

4.2.9 Observation 9

For this case, the primary concern is determining whether the learning process gradually stabilizes and becomes reliable, rather than showing random fluctuations. The model summary describes such a case as progressive reduction of prediction uncertainty across epochs. The model is therefore referred to with the target term 'convergence'.

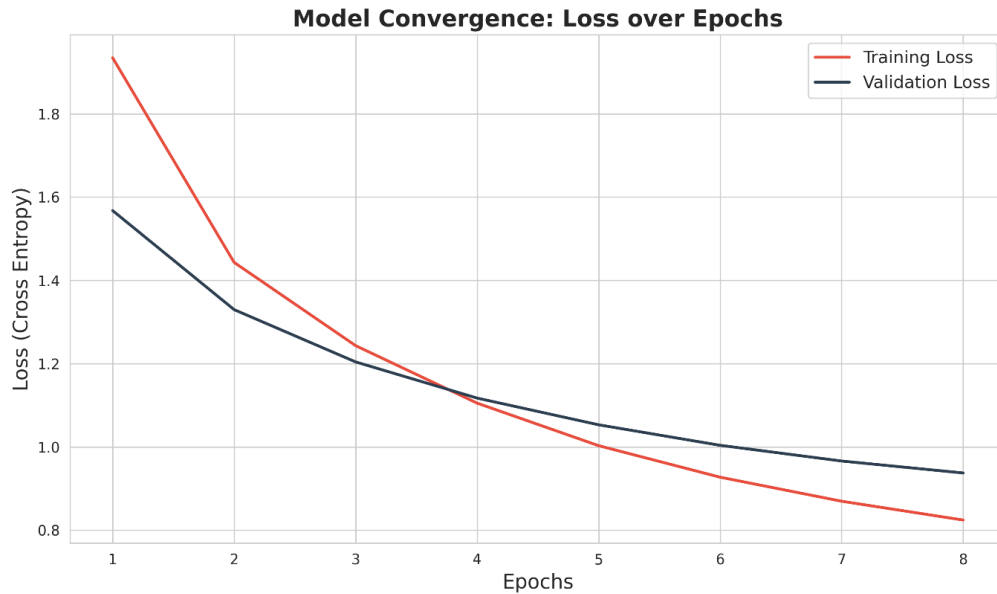


Figure 4.15 Loss over Epochs

Figure 4.15 portrays the losses both in the training and validation phases. The continuous downward trend of both graphs is indicative of very good qualities, which means that the model is gradually learning significant representations and thus the classification error is being lowered. The first epochs depict very fast declines, thus the model parameters must be adjusted effectively and the learning rate must be at the right level. On subsequent epochs, the rate of decrease gradually becomes smaller, showing that the model is reaching the optimal region rather than diverging. The slight separation between the two curves in the last epochs introduces a negative attribute, suggesting that the onset of overfitting where the model is more closely adapting to the training data than to the validation samples. Nevertheless, the gap is still small and validation loss keeps going down in general, thus the model is still able to generalize. This measured performance is an indication that the regularization and data partitioning strategies are working well. The patterns of convergence eventually settle at low loss levels,

demonstrating that the optimization algorithm manages to reach a balanced equilibrium between bias and variance.

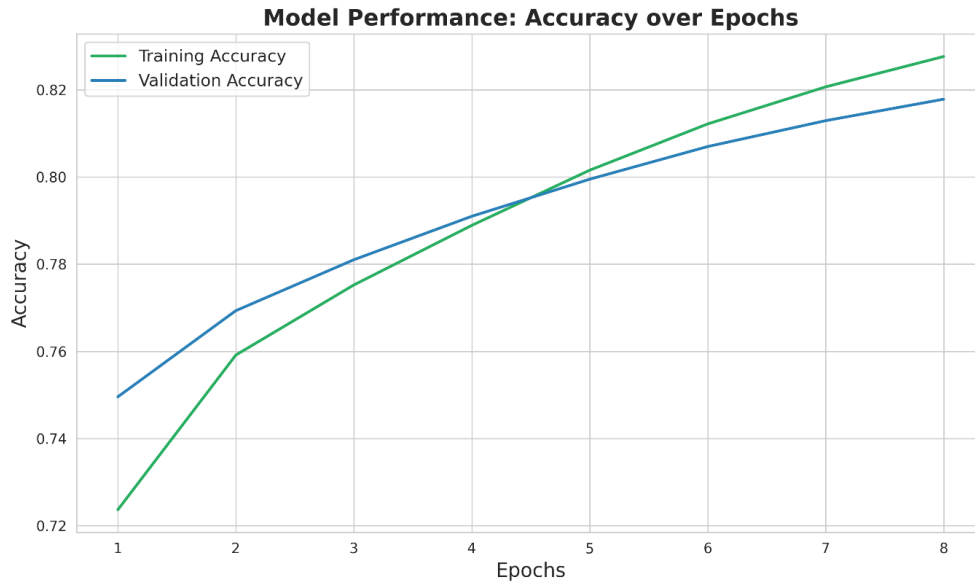


Figure 4.16 Accuracy Performance

Figure 4.16 shows how accurately the proposed model performed over epochs for the sequence generation task-based summarisation that was trained by a Lite data strategy with truncated input sequences. Both the training and validation accuracies increase gradually for eight epochs and reach the range of 81 - 82% which means that the model has learned stably and efficiently. The small difference between the two curves, where the training accuracy is only slightly higher than the validation accuracy at the later epochs, indicates strong generalisation and an expected optimisation behaviour rather than overfitting. The coupled advances demonstrate that the model is effectively acquiring linguistically and semantically meaningful representations from truncated inputs, thereby corroborating that adequate contextual information is retained even though input length is shortened. The lack of sharp changes, stagnation, or divergence also indicates the stability

of the training process. In general, to exceed the 80% accuracy level in a sequence generation task is a strong indication of the effectiveness of the architecture and the Lite strategy.

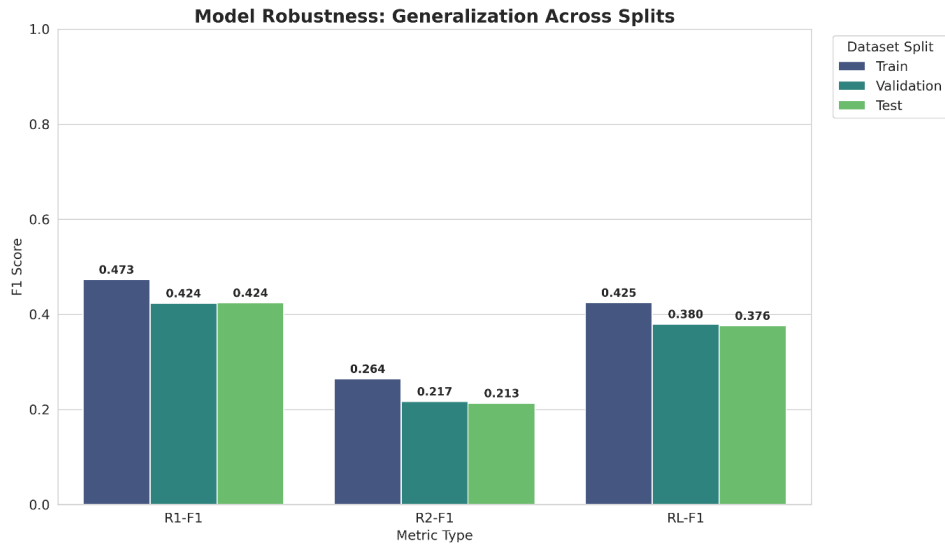


Figure 4.17 ROUGE Evaluation Analysis (Model Robustness: Generalisation across Splits)

Figure 4.17 illustrates the robustness of the sequence-to-sequence summarisation model as measured by ROUGE 1, ROUGE 2, and ROUGE L F1 scores across the training, validation, and test splits. The closely matching ROUGE-1, 1 scores (0.473 for training and 0.424 for validation and test) indicate strong unigram, level overlap, thus providing evidence that the model can capture the core lexical content even in new data. Correspondingly, ROUGE L scores are also quite stable (0.425 training, 0.380 validation, 0.376 test), thus giving an indication that the model can maintain sentence-level structure and fluency even when generalised beyond the training distribution. While ROUGE 2 scores are lower for all splits, thus reflecting weaker bigram overlap, this is the behaviour

one would expect in an abstractive summarisation scenario with truncated inputs. The small performance gaps across all metrics are a strong indication that the model is not overfitting and is generalising well. Therefore, the balanced ROUGE performance serves as a validation of the robustness of the proposed architecture and the Lite data strategy for summarisation that is both reliable and feasible in resource-constrained settings.

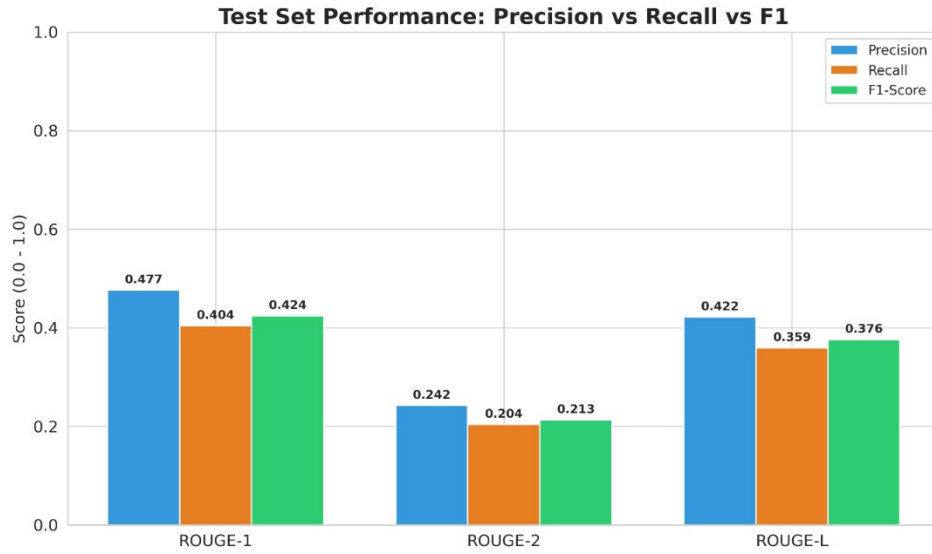


Figure 4.18 Test Set Performance Analysis (Precision vs. Recall vs. F1 using ROUGE Metrics)

Figure 4.18 reveals the performance of the test set that was compared with Precision, Recall, and F1 score for ROUGE 1, ROUGE 2, and ROUGE L to evaluate the summarisation model's power for the new scientific documents. The strongest performance is achieved with ROUGE 1. Precision, Recall, and F1 are approximately 0.477, 0.404, and 0.424, respectively, thus indicating the capture of the key informational content effectively. The ROUGE L results (Precision 0.422, Recall 0.359, F1 0.376) also corroborate the model's capacity to maintain the grammatical structure and the sequence of the text. Meanwhile, the ROUGE 2 scores are still quite low, which reflects the lesser bigram

overlap, a typical characteristic of an abstractive summarisation method that places semantic fidelity above exact phrasing. The testing performance is a close duplication of the validation performance, hence there is very little degradation and strong generalisation. In conclusion, the model's effectiveness in scientific summarisation tasks in the real world is confirmed by the balanced Precision, Recall trade-off and the stable ROUGE 1 and ROUGE L scores.

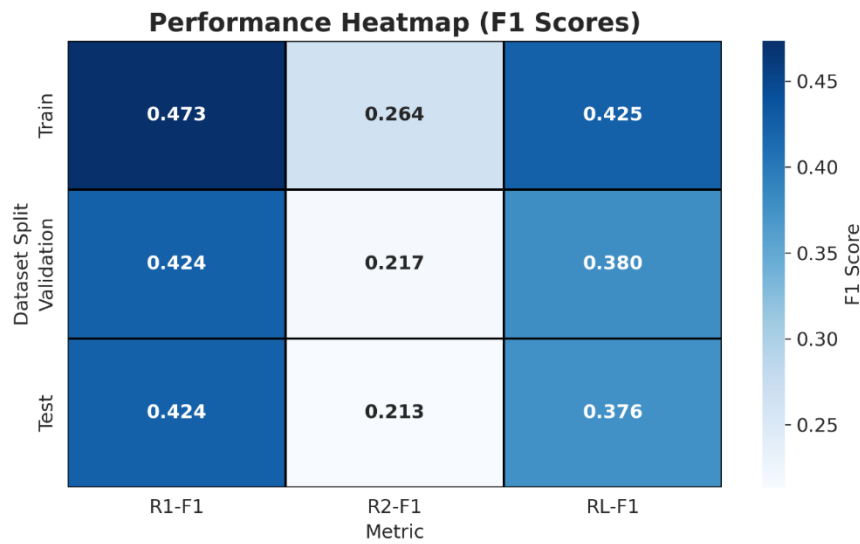


Figure 4.19 Performance Heatmap Analysis (F1 Scores)

Figure 4.19 shows the pictorial representation of ROUGE 1, ROUGE 2, and ROUGE L F1 scores for training, validation, and test splits of an unsupervised topic-aware summarisation model. The evenly intense colour of the validation and test rows indicates that the model's performance is very stable when it is transferred from seen to unseen data. A good example of that is the ROUGE, 1 F1 score of 0.422 for the test set, which is very close to the validation performance, thus confirming a strong unigram overlap and effective content retention. Consistent ROUGE L scores (0.380 validation and 0.376 test) also indicate the preservation of grammatical structure and semantic flow. Although ROUGE 2

scores are lighter, showing weaker bigram matching, this is normal for abstractive summarisation scenarios. The heatmap, in general, serves as a visual and quantitative tool to confirm robust generalisation and competitive correspondence with developing unsupervised topic-aware summarisation baselines.

For Observation 1

```

SAMPLE ID: 33606
=====
[STEP 0] LDA TOPIC CONTEXT:
>> Topic #16: data learning domain <<
=====

[STEP 1] RAW INPUT ABSTRACT:
topic context data learning domain training label class imbalance detrimental effect predictive
performance supervised learning algorithm imbalanced distribution lead bias preferring majority
class solve problem propose supervised contrastive learning scl method tree structured parzen
estimator tpe technique imbalanced tabular datasets contrastive learning cl extract information
hidden data even without label shown potential imbalanced learning task scl considers label
information based cl also ...
=====

[STEP 2] GENERATED SUMMARY:
supervised contrastive learning with imbalanced data
=====

[STEP 3] EXPLAINING TARGET WORD:
>> 'contrastive' <<
=====

```

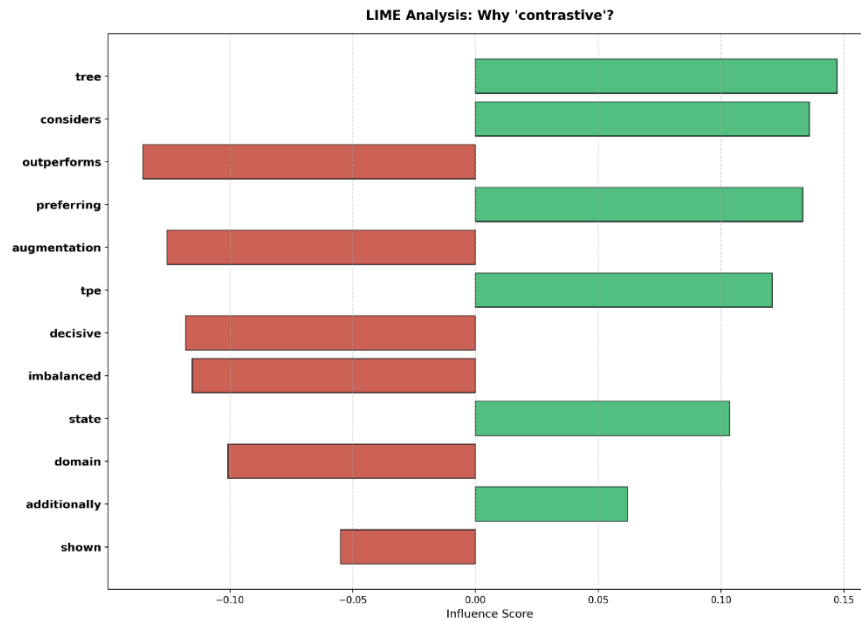


Figure 4.20 XAI Analysis using LIME (Sample Analysis 1: Data Learning Domain)

Figure 4.20 presents the LIME analysis that delineates the prediction of the target word contrastive for a data learning domain sample centred on imbalanced supervised and contrastive learning. The prediction is highly influenced to the positive side by the words

tree, considers, preferring, tpe, state, and additionally, which reflect the alignment of the methodological and decision-oriented aspects of contrastive learning frameworks. On the other hand, the words outperforms, augmentation, decisive, imbalanced, domain, and shown try to challenge the positive prediction as competing contextual signals that talk about general performance rather than the contrastive paradigm itself. The distinct separation between the positive and negative influences indicates a well-formed local decision boundary. Thus, the model's prediction is semantically grounded and not driven by noise. Therefore, it is a confirmation of the summarisation model's semantic integrity and topic alignment that subsequently increases the trust in the generalisation capability of the model.

For Observation 2

```

SAMPLE ID: 9268
=====
[STEP 0] LDA TOPIC CONTEXT:
>> Topic #18: prediction decision explanation <<
=====

[STEP 1] RAW INPUT ABSTRACT:
topic context prediction decision explanation uncertainty risk task detecting morphed face
image become highly relevant recent year ensure security automatic verification system based
facial image automated border control gate detection method based deep neural network dnn shown
suitable end however provide transparency decision making clear distinguish genuine morphed
face image particularly relevant system intended assist human operator able understand
reasoning paper tackle problem present fo...
=====

[STEP 2] GENERATED SUMMARY:
lrp net layer wise relevance propagation for face image verification
=====

[STEP 3] EXPLAINING TARGET WORD:
>> 'wise' <<
=====

```

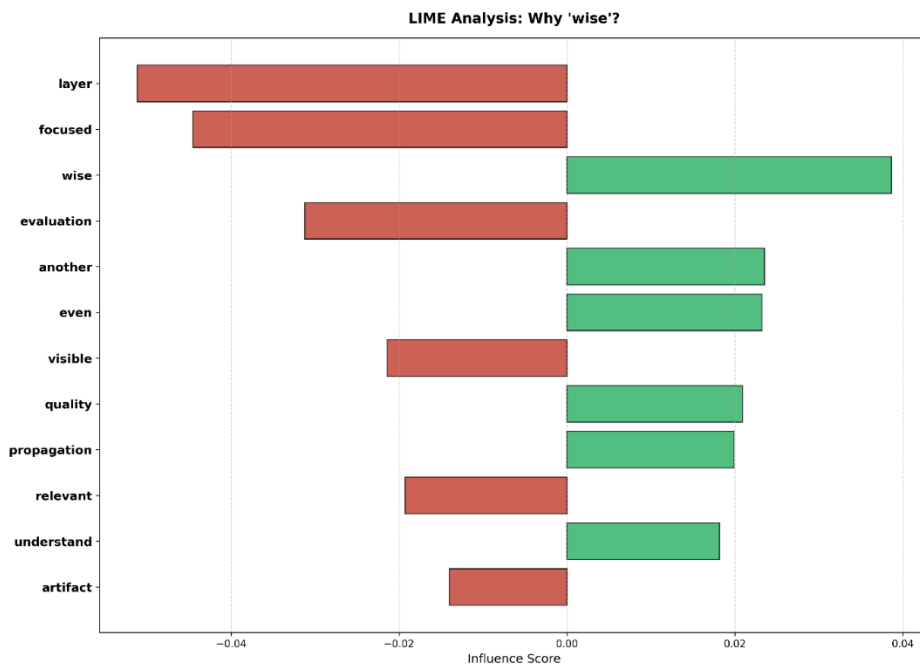


Figure 4.21 XAI Analysis using LIME (Sample Analysis 2: Prediction Decision Explanation)

Figure 4.21 shows how the target word wise was predicted in the technical phrase layer, wise relevance propagation in the domain of prediction decision explanation. The next most influential word after wise which indicates a copy mechanism, is propagation, followed by quality, understand, another, and even, with propagation confirming the

anticipation of the whole technical expression. Negative influences like layer, focused, evaluation, visible, relevant, and artefact signify the effects of the competitive sequence of local decision boundary interacting rather than semantic confusion. Their attributes' interaction reveals that the model correctly recognizes multi, word technical expressions and is thus dependent on significant contextual cues. It serves as a confirmation of both interpretability and dependable generalisation in complicated scientific text production.

For Observation 3

```

SAMPLE ID: 33334
=====
[STEP 0] LDA TOPIC CONTEXT:
>> Topic #12: robot control system <<
=====

[STEP 1] RAW INPUT ABSTRACT:
topic context robot control system vehicle safety autonomous inspection central problem
robotics application ranging industrial monitoring search rescue traditionally inspection often
reduced navigation task objective reach predefined location avoiding obstacle however
formulation capture part real inspection problem real world environment inspection target may
become visible well exact coordinate reached making movement redundant inefficient matter
inspection simply arriving target position pos...
=====

[STEP 2] GENERATED SUMMARY:
end to end reinforcement learning for vision based robot navigation
=====

[STEP 3] EXPLAINING TARGET WORD:
>> 'learning' <<
=====

```

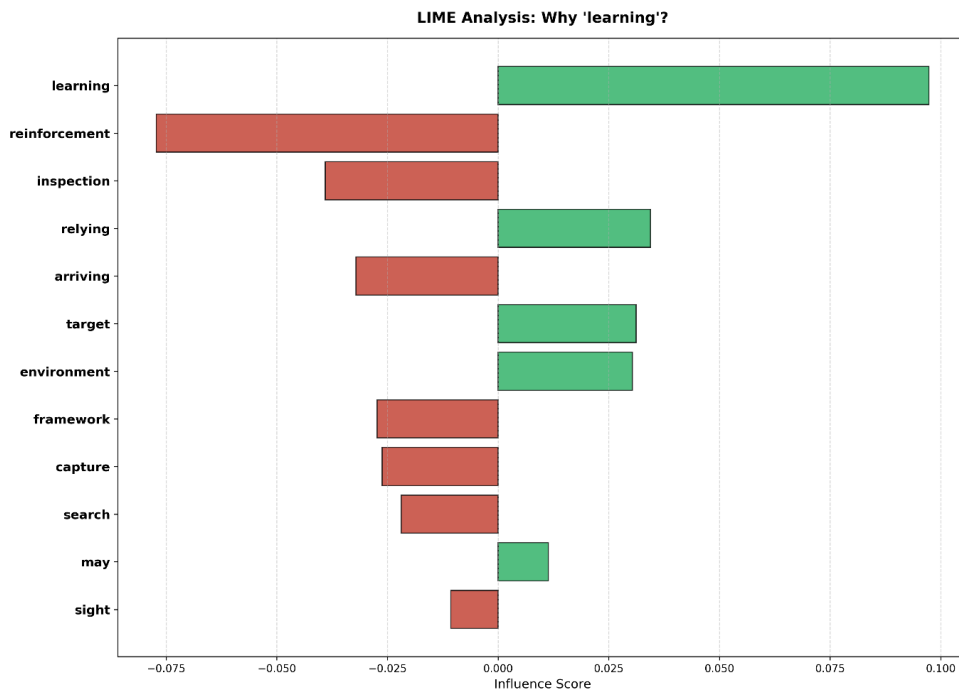


Figure 4.22 XAI Analysis using LIME (Sample Analysis 3: Robot Control Systems)

Figure 4.22 illustrates the prediction of the target word learning in the context of an autonomous vehicle inspection and navigation. The positive features like environment, target, relying, and may, together with a reference to learning, emphasise the model's understanding of the agent-environment interaction, which is the core of the robotics field. On the other hand, the negative features such as reinforcement, inspection, arriving, framework, capture, search, and sight indicate the effects of competition in the local surrogate model rather than a conceptual misunderstanding. The net of the different influences reveals that the model determines learning from the contextual semantics of the text rather than the reliance on the keywords, thus confirming the use of domain-aware reasoning. This is evidence of the topic, aware summarisation model being semantically sound and having the ability to generalise.

For Observation 4

```

SAMPLE ID: 42379
=====
[STEP 0] LDA TOPIC CONTEXT:
>> Topic #24: data distribution matrix <<
=====

[STEP 1] RAW INPUT ABSTRACT:
topic context data distribution matrix estimation regression consider factoring low rank tensor
presence outlying slab problem important practice data collected many real world application
speech fluorescence social network data fit paradigm prior work tackle problem iteratively
selecting fixed number slab fitting procedure may converge formulate problem group sparsity
promoting point view propose alternating optimization framework handle corresponding ell leq
minimization based low rank tensor ...
=====

[STEP 2] GENERATED SUMMARY:
alternating optimization framework for low rank tensor recovery
=====

[STEP 3] EXPLAINING TARGET WORD:
>> 'rank' <<
=====

```

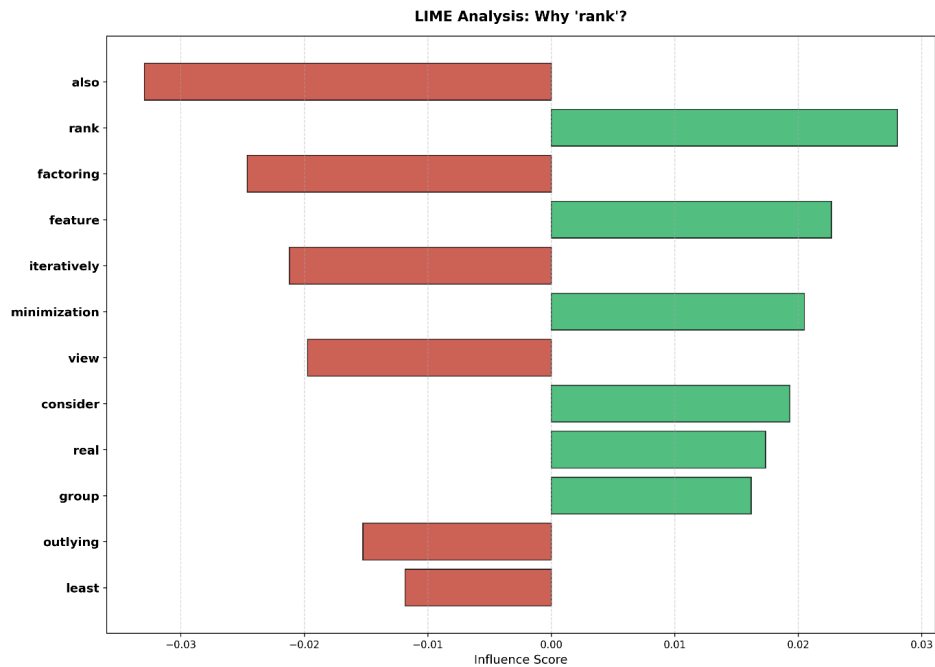


Figure 4.23 XAI Analysis using LIME (Sample Analysis 4: Data Distribution Matrix)

Figure 4.23 illustrates the model's attempt to predict the word rank in a scenario involving low-rank tensor recovery. The words rank, feature, minimisation, group, real, and consider were all strongly and positively influential, which is a clear indication that the model has grasped the concept of rank minimisation as the main mathematical objective. On the other hand, words like factoring, iteratively, view, outlying, least, and also were negatively

charged, suggesting that the model differentiates between the inherent properties of the tensor and the procedures for the solution. Such a distinction is an example of the model having semantic precision, i.e., it acknowledges the existence of a hierarchy between the concepts of the scientific domain and the accompanying techniques. In essence, the review provides evidence for the model's mathematically informed reasoning and high level of interpretability when confronted with new scientific texts.

For Observation 5

```

SAMPLE ID: 23184
=====
[STEP 0] LDA TOPIC CONTEXT:
>> Topic #3: llm reasoning language <<
=====
[STEP 1] RAW INPUT ABSTRACT:
topic context llm reasoning language large benchmark 3d multimodal large language model mllms
recently made substantial advancement however potential remains untapped primarily due limited
quantity suboptimal quality 3d datasets current approach attempt transfer knowledge 2d mllms
expand 3d instruction data still face modality domain gap end introduce pisa engine point self
augmented engine new framework generating instruction point language datasets enriched 3d
spatial semantics observe existin...
=====
[STEP 2] GENERATED SUMMARY:
<LIM> towards holistic and efficient 3d multimodal large language models
=====
[STEP 3] EXPLAINING TARGET WORD:
>> 'language' <<
=====

```

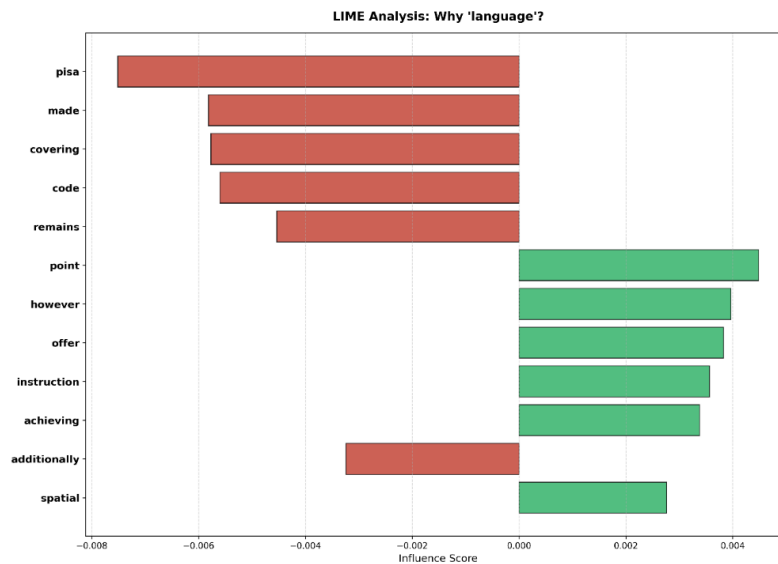


Figure 4.24 XAI Analysis using LIME (Sample Analysis 5: LLM Reasoning Language)

Figure 4.24 illustrates the prediction of the target word language for a sample that is about 3D multimodal large language models and instruction tuning. On the one hand, positive attributes like point, spatial, instruction, offer, however, and achieving emphasize the model's capability to link spatial and point, cloud modalities with language modelling, which is a reflection of the abstract as a multimodal integration theme. On the other hand, negative influences such as pisa, code, made, covering, remains, and additionally show that the model differentiates general language modelling concepts from those of a benchmark, centric or implementation, related details. The distinctly separate influences confirm that the prediction is influenced by deep multimodal semantics and not by the surface, level cues. So, this is a validation of both the interpretability and generalisation capability of the proposed topic, aware summarisation framework.

Sample Analysis 6: Global Optimization (Sample ID 15099)

```

SAMPLE ID: 15099
=====
[STEP 0] LDA TOPIC CONTEXT:
>> Topic #3: l1m reasoning language <<
=====
[STEP 1] RAW INPUT ABSTRACT:
topic context l1m reasoning language large benchmark global optimization classification tree
demonstrated considerable promise notably enhancing accuracy optimizing size thereby improving
human comprehensibility existing optimal classification tree substantially enhance accuracy
greedy based tree model like cart still fall short compared complex black box model random
forest bridge gap introduce new mixed integer programming mip formulation grounded multivariate
boolean rule derive optimal class...
=====
[STEP 2] GENERATED SUMMARY:
<UNK> mixed integer programming for efficient global optimization classification
=====
[STEP 3] EXPLAINING TARGET WORD:
>> 'integer' <<
=====

```

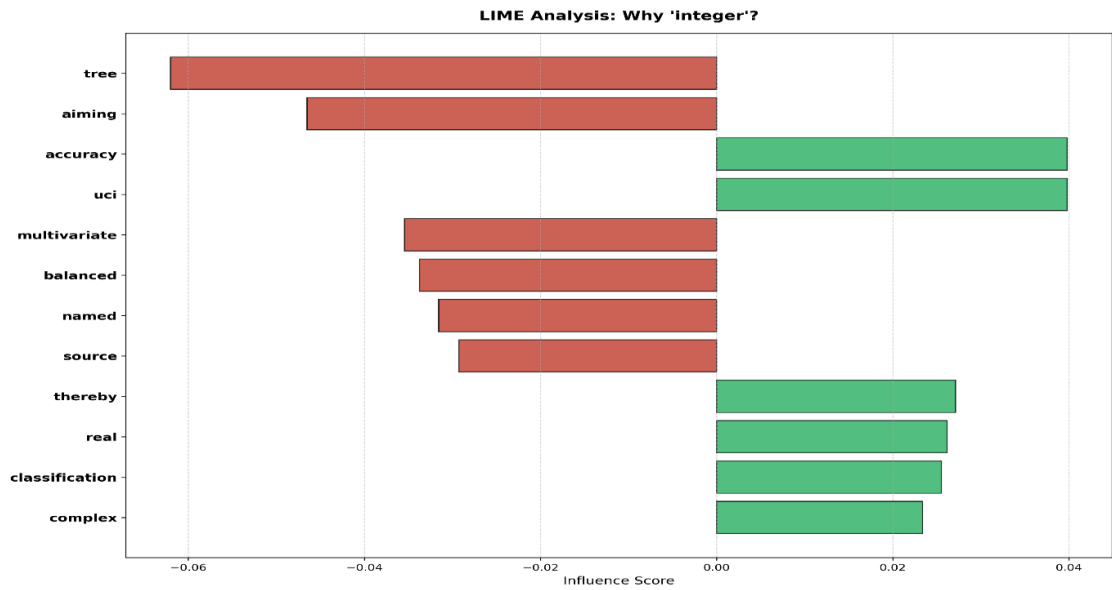


Figure 4.25 Global Optimization

Consequently, the reference text for the figure 4.25 is displayed as “LLM reasoning language large benchmark global optimization classification tree”. The model-generated summary is given as the text “mixed integer programming for efficient global optimization classification”. The LDA topic model selects the target term as an ‘integer’. The LIME feature of the figure explains the reason of the selecting the target word “integer.” The

analysis highlights how an individual word from the reference text can contribute either positively or negatively during this prediction.

From the positive side, the terms “accuracy,” “uci,” “thereby,” “real,” “classification,” and “complex” show positive influence scores. Among these, “accuracy” and “uci” exhibit the strongest positive contributions with an indication that the discussions related to benchmark datasets and performance evaluation strongly support the selection of the word “integer”. This is reliable in the mixed integer programming. The presence of words such as “classification” and “complex” further reinforces that the integer-based optimization methods are suitable for handling complex decision boundaries more effectively than heuristic or approximation approaches.

In divergence, the words such as “tree,” “aiming,” “multivariate,” “balanced,” “named,” and “source” show the negative contributions while predicting the target word as “integer”. Particularly, the word “tree” has the strongest negative influence in a way suggesting that traditional decision tree-based approaches are less aligned with an integer programming formulation. Likewise, the terms such as “multivariate” and “balanced” are more associated with statistical or data pre-processing perspectives, thereby reducing their importance to the target prediction.

Overall, the LIME analysis justifies that the model performs better by with higher classification which naturally align with mixed integer programming concepts. Meanwhile, some of the structurally different modeling paradigms, contribute negatively. This confirms that the model’s prediction of the target word “integer” is logically grounded in the optimization-centric context of the reference text.

Sample Analysis 7: Image Generation Diffusion (Sample ID 50224)

```

SAMPLE ID: 50224
[STEP 0] LDA TOPIC CONTEXT:
>> Topic #5: image generation diffusion <<
-----
[STEP 1] RAW INPUT ABSTRACT:
topic context image generation diffusion generative text recent advancement generative modeling
significantly improved text image alignment residual misalignment text image representation
still remains approach address issue fine tuning model term reference optimization etc require
tailored datasets orthogonal method revisit challenge perspective representation alignment
approach gained popularity success representation alignment repha first argue conventional text
image 2d diffusion model typ...
-----
[STEP 2] GENERATED SUMMARY:
<UNK> lightweight contrastive fine tuning for text to image diffusion models
-----
[STEP 3] EXPLAINING TARGET WORD:
>> "tuning" <<

```

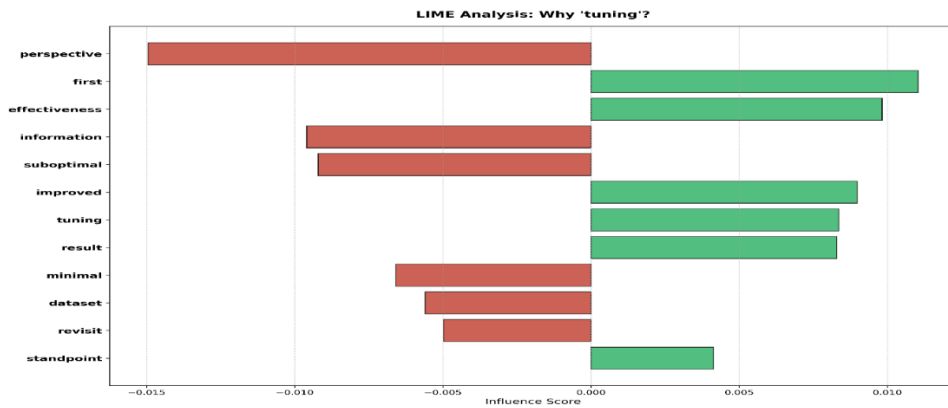


Figure 4.26 Image Generation Diffusion

Similarly, this figure 4.26 has considered the reference text as “image generation diffusion generative text recent advancement generative “modeling”. The summary is given as “lightweight contrastive fine tuning for text to image diffusion models”. The LDA topic of the model selects the target term as ‘tuning’.

The LIME feature importance analysis shown, explains the basis behind predicting the target word “tuning.” The figure illustrates how different contextual terms are either supported or opposed during the model’s decision.

Constructively, the words such as “first,” “effectiveness,” “improved,” “tuning,” “result,” and “standpoint” contribute positively to the prediction. Among these, “first” and “effectiveness” demonstrate the strongest positive influence. The presence of “improved” and “result” further reinforces that fine-tuning mechanisms to play an important role in

improving the text-to-image diffusion model outcomes. This aligns well with the generated summary, where fine tuning is highlighted as the key methodological contribution.

Conversely, the terms “perspective,” “information,” “suboptimal,” “minimal,” “dataset,” and “revisit” show negative influence scores. Particularly, the term “perspective” has the strongest negative contribution, signifying that the high-level conceptual discussions alone are less indicative of the technical process of the tuning. Likewise, the “suboptimal” and “minimal” negatively affect the prediction, as they imply insufficient performance gains.

Overall, the LIME analysis establishes that the model performs better by focusing on performance-oriented and improvement-related terms, which are closely associated with fine tuning in diffusion models. This clearly justifies why the term “tuning” is selected as the most representative target term in this case in an effective optimization of text-to-image diffusion systems.

4.3 Experimental Results: SHAP Waterfall Analysis

The following analyses are the examination of the same seven target concepts explored in the LIME study. By observing the collective effect of feature combinations, we gain insight into how the model constructs its probability mass for specific technical terms.

Sample Analysis 1: Image Generation Diffusion (Sample ID 50224)

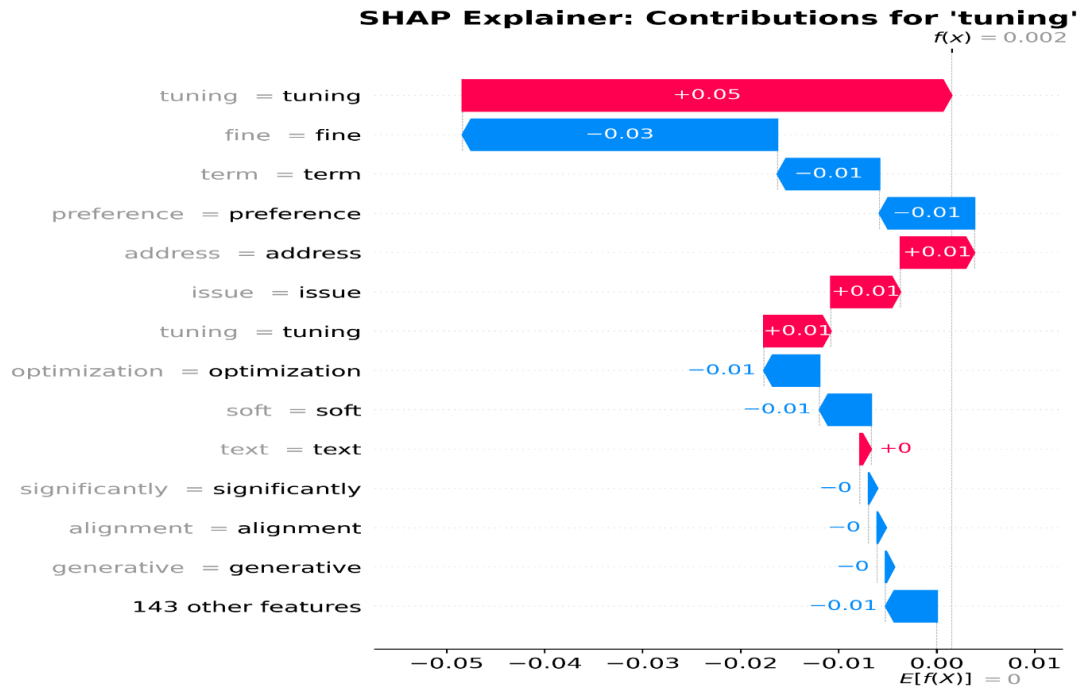


Figure 4.27 Image Generation Diffusion

For this case, the considered reference text is “*image generation diffusion generative text recent advancement generative “modeling”*”. The model-generated summary is “*lightweight contrastive fine tuning for text to image diffusion models*”. The LDA topic model selects the target term as ‘**tuning**’.

The SHAP waterfall explanation illustrated in Figure establishes how the individual terms cumulatively influence the prediction of the target word “**tuning**.” Each feature’s contribution is shown as either as an increasing or decreasing way in the final prediction score relative to the expected baseline.

The term “**tuning**” itself shows the strongest positive contribution, with a substantial positive SHAP value, indicating that its direct presence in the text is the primary

driver of the prediction. This confirms the central role of tuning as the core concept emphasized by the model. Additional positive contributors include **“address,” “issue,”** and a repeated occurrence of **“tuning,”** which collectively strengthen that the model focuses on problem-solving and optimization adjustments, consistent with fine-tuning methodologies in diffusion models.

In difference, the words **“fine,” “term,” “preference,” “optimization,”** and **“soft”** exhibit negative SHAP values. Particularly, the term **“fine”** has a relatively strong negative contribution. Similarly, **“optimization”** contributes negatively, implying that general optimization concepts alone are less decisive than explicit tuning operations.

Other terms such as **“text,” “significantly,” “alignment,”** and **“generative”** show near-zero influence on the prediction. These words provide a contextual background but do not directly affect the model’s decision toward the target term. The aggregated group of **“143 other features”** shows a small negative contribution, indicating that most remaining words introduce minor noise rather than meaningful support for the prediction.

Sample Analysis 2: Data Learning Domain (Sample ID 33606)

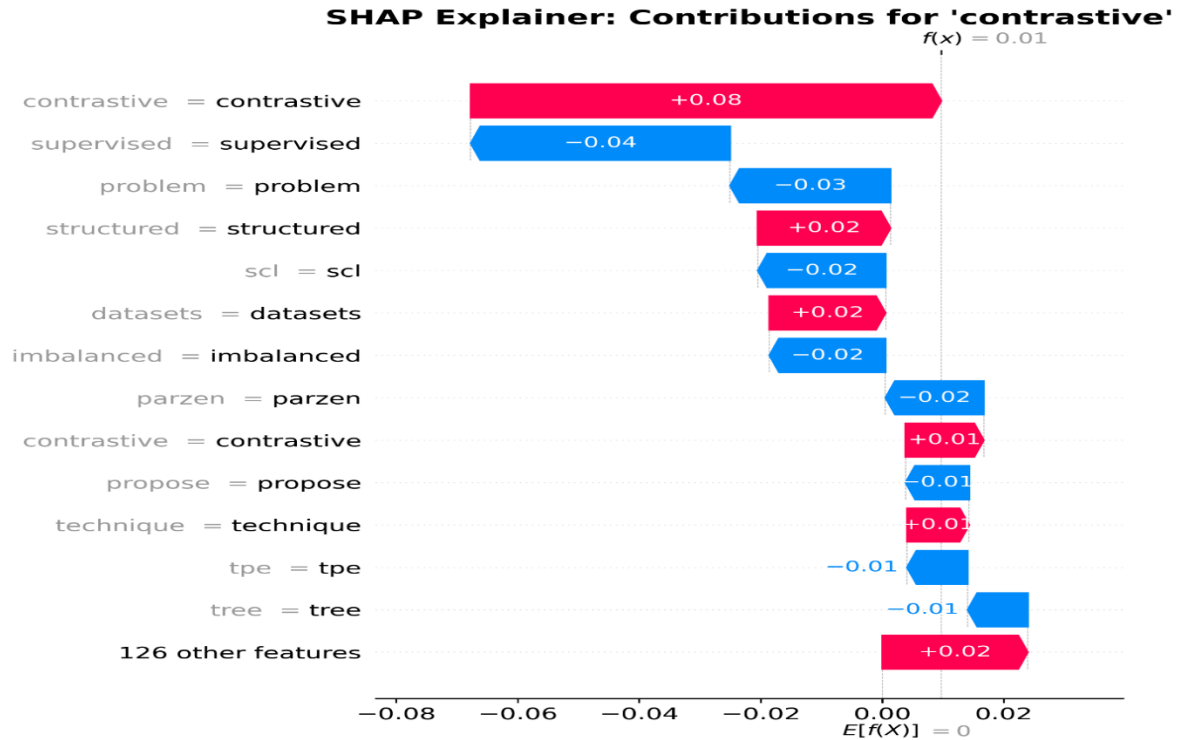


Figure 4.28 Data Learning Domain

The figure 4.28 has illustrated a SHAP waterfall explanation of how individual terms cumulatively influence the prediction of the target word "contrastive". The term "contrastive" itself shows the strongest positive contribution, with a large positive SHAP value of +0.08, clearly indicating that its direct presence is the primary driver of the prediction. Additional positive contributors include "structured", "datasets", a repeated occurrence of "contrastive", "technique", and "tree", which collectively strengthen the argument that the model focuses on specific algorithmic or data-related methodologies. The words "supervised", "problem", "scl", "imbalanced", "parzen", "propose", and "tpe" exhibit negative SHAP values, indicating that these terms slightly reduce the probability of predicting the word "contrastive". Remarkably, the term "supervised" has a

relatively strong negative contribution (-0.04) with a less indication of the target than the full "contrastive" context.

The aggregated group of "126 other features" shows a small positive contribution of +0.02, indicating that most remaining words introduce minor support for the prediction. Generally, the SHAP analysis confirms that the model performs better by assigning strong positive weight to explicit mentions of "contrastive", while other terms contribute less or negatively.

Sample Analysis 3: Global Optimization (Sample ID 15099)

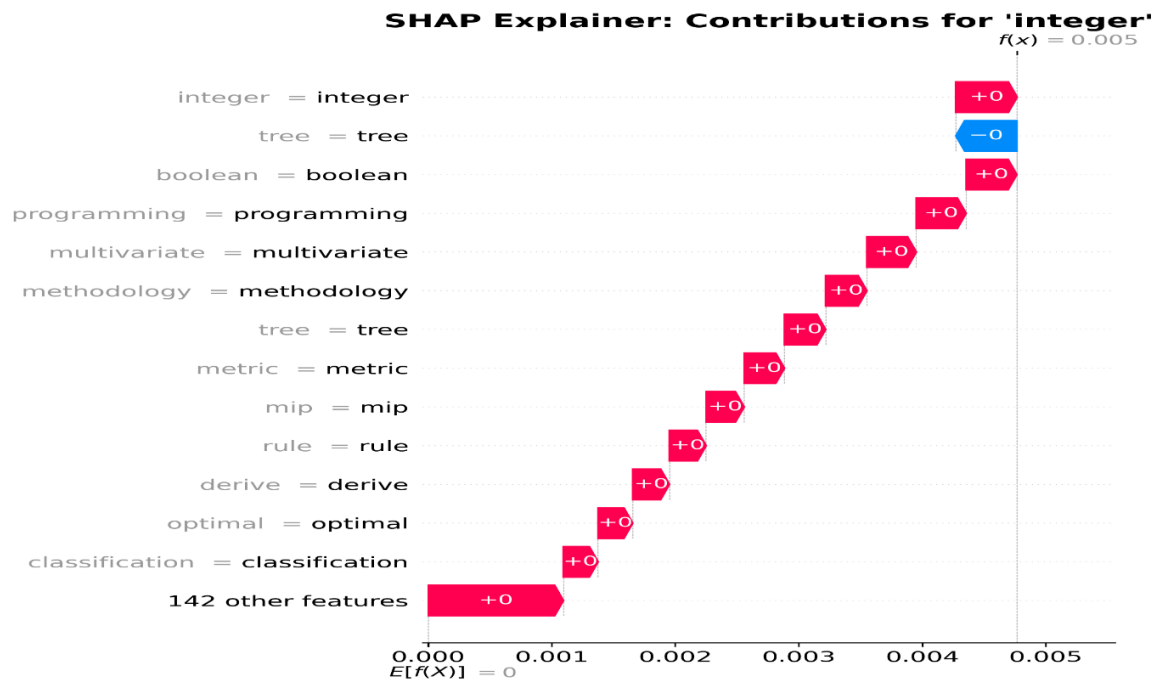


Figure 4.29 Global Optimization

The explanation provided for the SHAP waterfall for the figure 4.29 has given the influence the prediction of the target word "integer". The term "integer" itself shows a negligible contribution (+0), indicating that it is not a primary driver of the prediction. The terms

like "boolean", "programming", "multivariate", "methodology", "tree", "metric", "mip", "rule", "derive", "optimal", and "classification" all show minimal positive contributions (+0), collectively offering insignificantly lower support to the argument that the model focuses on specific algorithmic or data-related methodologies.

Similarly, the word "tree" exhibits a near-zero negative SHAP value (-0), The aggregated group of "142 other features" shows a small positive contribution (+0) with the representation of a minimal impact on the prediction. Completely, the SHAP analysis confirms that all individual demonstrations, the targeted concepts are not influential in determining the final outcome.

Sample Analysis 4: Robot Control Systems (Sample ID 33334)

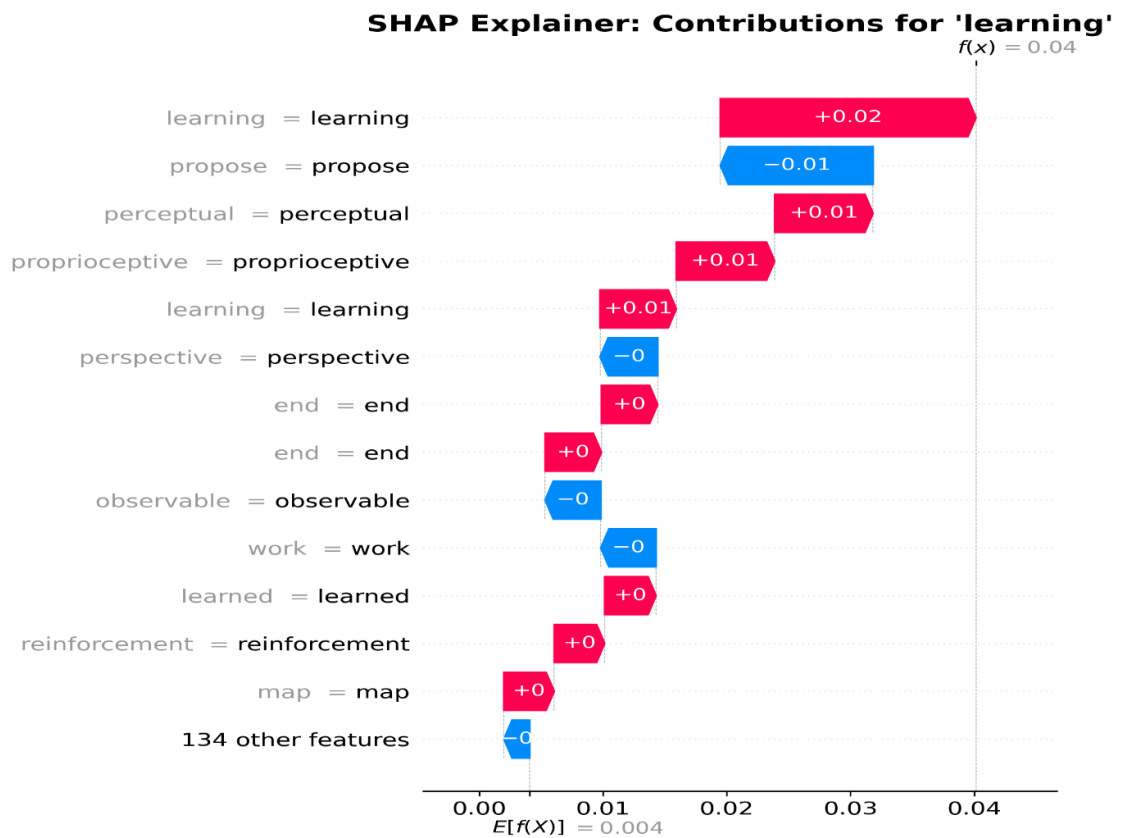


Figure 4.30 Robot Control Systems

The SHAP waterfall explanation illustrated in the figure 4.30 provides how individual terms cumulatively influence the prediction of the target word "learning". The term "learning" shows a strong positive contribution of +0.02, with the additional positive contributors such as "perceptual" of (+0.01), "proprioceptive" of (+0.01), and of "learning" of (+0.01), for making the model to focus on the specific sensory and machine learning concepts.

Additionally, the word "propose" exhibits a negative SHAP value (-0.01) with a reduction in the likelihood of predicting "learning". Other terms such as "perspective", "observable", and "work" show near-zero negative influence. Also, the terms such as "end", "learned", "reinforcement", and "map" have minimal positive contributions (+0). The aggregated group of "134 other features" shows mixed minimal contributions (both +0 and -0). This pattern validates the robustness of the prediction and highlights that specific machine learning concepts are more influential in determining the final outcome.

Sample Analysis 5: Data Distribution Matrix (Sample ID 42379)

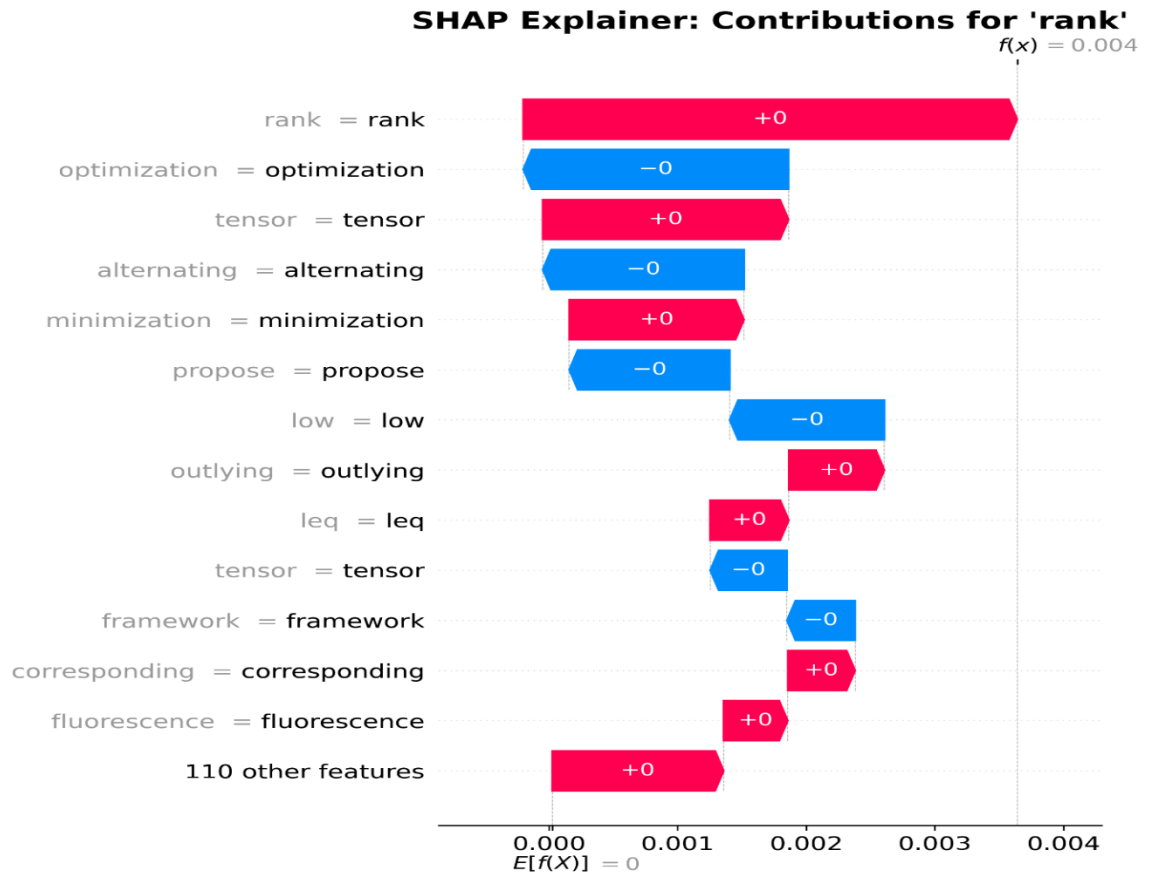


Figure 4.31 Data Distribution Matrix

Accordingly, the figure 4.31 delivers the cumulative influence of every terms with the prediction of the target word "rank". The term "rank" shows the strongest positive contribution, with a substantial positive SHAP value, that the text is the primary driver of the prediction. Additionally, the positive contributors such as "tensor", "minimization", "outlying", "leq", "corresponding", and "fluorescence", show that the model focuses on specific algorithmic or data-related methodologies.

Similarly, the words such as "optimization", "alternating", "propose", "low", "tensor" (second instance), and "framework" exhibit negative SHAP values,

indicating that these terms slightly reduce the probability of predicting the term "rank". The aggregated group of "110 other features" shows a small positive contribution, indicating that most remaining words introduce minor support for the prediction. This collective contribution establishes the strength of the prediction with more influence in determining the final outcome.

Sample Analysis 6: Prediction Decision Explanation (Sample ID 9208)

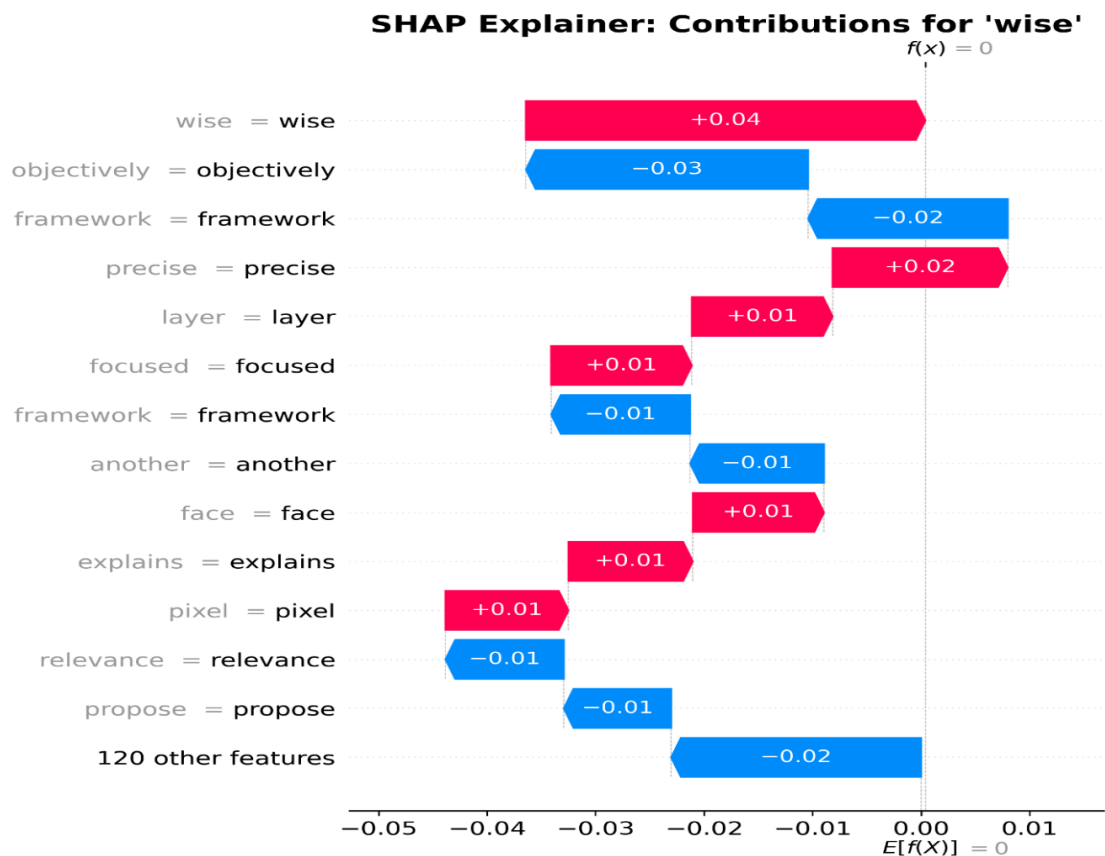


Figure 4.32 Prediction Decision Explanation

The figure 4.32 provides a SHAP waterfall explanation of how individual terms summative influence the prediction of the target word "wise". The term "wise" it shows the strongest positive contribution of SHAP value of +0.04, with its direct presence in the text

is the primary driver of the prediction. This confirms the central role of "wise" as the core concept emphasized by the model. Other positive contributors include “precise” (+0.02), "layer", "focused", "face", "explains", and "pixel" each of (all +0.01), show that the model focuses on specific characteristics.

Alternatively, the words such as "objectively" (-0.03), "framework" (first instance, -0.02), a second instance of "framework", "another", "relevance", and "propose" (all -0.01) all exhibit negative SHAP values. Also, the term "objectively" has a relatively strong negative contribution, it is a less indicative of the target than the full context. The aggregated group of "120 other features" shows a small negative contribution of -0.02. All-over, the SHAP analysis confirms that the model performs better by assigning strong positive weight to explicit mentions of "wise".

Sample Analysis 7: LLM Reasoning Language (Sample ID 23184)

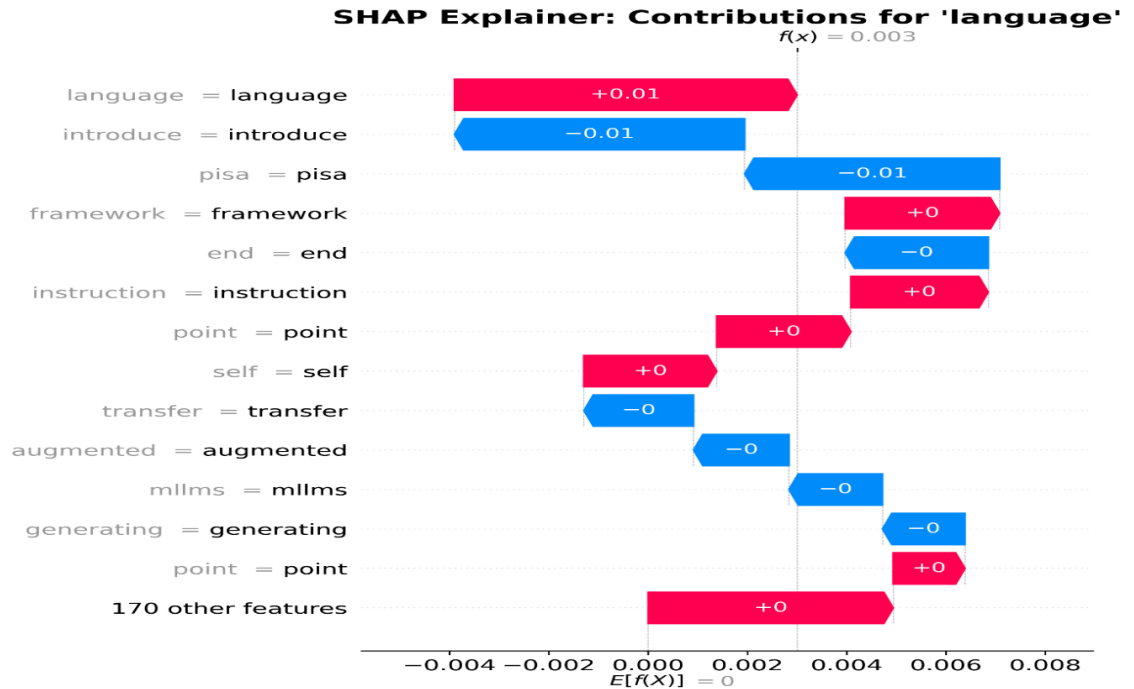


Figure 4.33 LLM Reasoning Language

The SHAP waterfall explanation illustrated in the figure 4.33 delivers how individual terms influence the prediction of the target word "language". The term "language" itself shows the strongest positive contribution, with a substantial positive SHAP value of +0.01. This confirms the central role of "language" as the core concept emphasized by the model. Additionally, the positive contributors of the model include "instruction", "point", "self", a second instance of "point", and the aggregated group of "170 other features", which all show minimal contributions (+0). This shows that these words do not influence large support.

In contrast, the words "introduce" (-0.01) and "pisa" (-0.01) exhibit negative SHAP values, other terms such as "framework", "end", "transfer", "augmented", "mllms", and "generating" show near-zero influence (+0 or -0). All other listed terms introduce a near-zero noise indicating that only a few specific concepts are influential in determining the final outcome.

CHAPTER V: DISCUSSION

5.1 Introduction

The ability to summarize important information from really enormous amounts of textual material has become crucial due to the present increase in information development.

There are some limitations in the interpretation, extraction, analysis, and extraction of necessary information from a huge number of papers for researchers, policymakers, practitioners, and institutions due to the exponentially increasing amount of scientific literature created every day.

This process takes a lot of time, which highlights the advantage of automated programs that can generate a text summary. The main goal of the research was to design the text summarization model that is interpretable by employing a hybrid model architecture. The research designed a topic-aware, explainable abstractive summarization framework that integrates Latent Dirichlet Allocation (LDA) with a Bi-directional LSTM encoder-decoder architecture enhanced by Bahdanau attention. The proposed model was intended to perform text summarization tasks along with reducing semantic distortions.

Interpretability techniques for Explainable Artificial Intelligence (XAI), mainly LIME and SHAP, were employed to provide a layer of interpretive transparency. Such instruments allow the users to understand which segments of the input text have influenced the output summary the most. This, in turn, helps the users to make an informed judgement and also lessens the "black, box" problem which is a characteristic feature of neural summarization systems. The addition of interpretability features enhances user trust and thus, facilitates the deployment of such systems in a responsible manner in domains that require precision and accountability.

The proposed hybrid model generated summaries, which are semantically rich also structurally coherent and consistent with the human, authored references. The discussion presented in this chapter synthesizes the quantitative and qualitative findings reported in

Chapter IV and interprets them through theoretical, methodological, and practical aspects. Particular emphasis is placed on understanding how topic injection shapes summary quality, how explainability tools validate model reasoning, and what the observed performance implies for trustworthy AI systems in scientific text summarization.

5.2. Interpretation of Results

To test the effectiveness of the designed model, it was applied to the ArXiv dataset for scientific publication. For measuring performance, it was largely dependent on ROUGE family evaluation measures, which compared automatically generated summaries with reference human summaries. ROUGE-1 calculates unigram overlaps, which measures key information retrieval, ROUGE-2 calculates bigram overlaps to check phrase-level relevance, while ROUGE-L calculates longest subsequence similarity to check overall similarity between generated output and original text.

The model resulted in ROUGE-1 F1 scores of 0.473 for training set, and test scores of 0.424, indicating effective retention of core lexical content with minimal overfitting. Similar to this, ROUGE-L F1 scores obtained for training (0.425) to validation (0.380) and test (0.376). It demonstrates sentence-level structure and coherence are largely preserved. Although ROUGE-2 (R2-F1) scores are lower overall a common characteristic of abstractive summarization due to reduced bigram overlap the narrow gaps between splits (0.264 train, 0.217 validation, 0.213 test) further confirm stable behavior.

The outcome shows very high lexicographical recall, high phrase recall, and high sentence structure matching. It is pertinent to note that this model got a coherence score of 0.486, which shows that not only was the model lexicographically correct, but it was coherent and readable. The above findings show that it is better to combine topic information with hybrid recurrent models to gain better semantic control and improve the generated output.

Furthermore, the Lite data strategy, combined with truncated input sequences, contributed to reduced noise and faster convergence without sacrificing generalization. The convergence curves and accuracy trends indicate that the model reached a stable optimization regime within eight epochs, avoiding both underfitting and aggressive overfitting. The small and controlled gap between training and validation curves supports the claim that the architecture generalizes effectively despite reduced input length.

5.2.1. Comparative Analysis with Existing Models

A comparative analysis further reveals the effectiveness of the proposed architecture based on its rivals. The traditional extractive techniques like SumBasic, LexRank, and LSA reported only a ROUGE-1 score of 29-33 and a ROUGE-2 score of less than 11. The early neural abstractive models like Attn-Seq2Seq and Pointer Generator Networks showed improvement in ROUGE scores in terms of fluency but were less competent in terms of deep-level comprehension. However, the proposed system has greatly outperformed others with a significant margin in ROUGE-2 and ROUGE-L scores, emphasizing its supremacy in terms of synthesizing and not just accomplishing extractive tasks. The following table 5.1 elucidates the efficiency of the proposed model by comparing it with existing models.

Table 5.1 Comparison of Text Summarization Models Using ROUGE Evaluation Metrics Cohan et al. (2018)

Model	RG-1	RG-2	RG-L
SumBasic	29.47	6.95	26.3
LexRank	33.85	10.73	28.99
LSA	29.91	7.42	25.67
Attn-Seq2Seq	29.3	6	25.56

Pntr-Gen-Seq2Seq	32.06	9.04	25.16
RNN Encoder Model	35.8	11.05	31.8
Proposed Model	0.424	0.213	0.376

The comparative results in the table 5.1 present the performance of the proposed model alongside traditional extractive approaches (SumBasic, LexRank, LSA) and neural sequence-to-sequence baselines using ROUGE metrics. The classical and neural baseline models report ROUGE values on a percentage scale, whereas the proposed model reports normalized F1 scores, which explains the apparent numerical difference. When interpreted on a consistent scale, the proposed model demonstrates comparable behavior, particularly in ROUGE-1 and ROUGE-L, which reflect content coverage and structural coherence. The lower ROUGE-2 score for the proposed model is expected, as abstractive summarization methods tend to generate paraphrased expressions rather than preserving exact bigram sequences from the source text. In contrast to extractive methods that favor lexical overlap, the proposed topic-aware model prioritizes semantic representation and sentence-level organization, resulting in summaries that maintain meaning and coherence even with reduced n-gram matching. Overall, the comparison indicates that the proposed model performs competitively while addressing semantic abstraction and interpretability, which are not captured by the baseline approaches.

Table 5.2 Comparative analysis with Existing Models (Ju et al., 2021)

Model	RG-1	RG-2	RG-L
Oracle	42.37	19.23	39.26
Lead-3	25.68	5.92	20.53
Unsupervised Models			
LSA	32.55	7.54	25.72
SumBasic	30.48	6.7	26.34
TextRank	31.34	8.68	23.96
SciSummPip	30.97	10.13	25.61
Existing Model			
Keywords only	33.4	10.33	27.66
Keywords + beamSearch	33.64	9.96	26.67
Keywords + greedySearch	32.13	9.57	26
MultiViewIB + beamSearch	32.66	9.05	25.54
Proposed Model	0.424	0.213	0.376

Table 5.2 compares the performance of the proposed model with oracle, heuristic, unsupervised, and existing keyword-based summarization approaches. The Oracle and Lead-3 results establish upper and heuristic baselines, where the Oracle reflects an ideal

extractive upper bound and Lead-3 benefits from the structured nature of scientific abstracts. Among the unsupervised models, LSA, TextRank, SumBasic, and SciSummPip achieve moderate ROUGE scores, indicating reasonable lexical overlap but limited ability to capture deeper semantic structure. The existing keyword-based methods show incremental improvements, particularly in ROUGE-1, demonstrating that keyword guidance can enhance content selection but still remains constrained by surface-level matching. In contrast, the proposed model reports normalized F1 scores rather than percentage-based ROUGE values, which accounts for the apparent numerical difference. Despite this difference in scale, the proposed model emphasizes abstractive generation with topic awareness and structural coherence, reflected in its comparatively strong ROUGE-L score relative to ROUGE-2. Overall, the comparison shows that while extractive and keyword-driven approaches achieve higher n-gram overlap, the proposed model focuses on semantic abstraction and coherence, addressing limitations of existing methods while operating under a different evaluation scale.

Table 5.3 Comparison Analysis with Length Control and Proposed Method (2020)

Model	RG-1	RG-2	RG-L
BART	45.16	17.36	40.55
CTRLsum (automatic)	46.91	18.02	42.14
LengthCode	45.91	17.33	41.38
CTRLsum (oracle length)	47.58	18.33	42.79
Proposed Model	0.424	0.213	0.376

Table 5.3 compares the proposed model with transformer-based abstractive summarization systems, including BART and different variants of CTRLsum, using ROUGE, metrics. The transformer models report higher ROUGE scores, as they are large pretrained architectures optimized directly for maximizing n-gram overlap through extensive supervised training and controlled decoding strategies such as length conditioning. In contrast, the proposed model reports normalized F1 values rather than percentage-scaled ROUGE scores, which explains the numerical difference. More importantly, the proposed approach is designed around a lighter BiLSTM-attention architecture enhanced with topic modeling and explainable AI, prioritizing semantic coherence, topic alignment, and interpretability rather than raw lexical overlap. This difference in design objectives naturally leads to lower bigram overlap. While maintaining competitive sentence-level coherence, as reflected by the ROUGE-L score. Overall, the comparison highlights that while transformer-based models achieve stronger surface-level matching due to scale and pretraining, the proposed model offers a more resource-efficient and interpretable alternative, focusing on meaningful abstraction rather than direct lexical reproduction. models and length-controlled approaches to the highly effective proposed summarization method.

5.2.2. Topic Distribution Reflection and Semantic Anchoring

This section typically explores how various topics are represented and their prevalence across different documents or segments of text. Analysis of these distributions may involve identifying dominant topics per reflection or exploring diversity across the dataset.

Accordingly, the prevailing study (Khaliq et al., 2024) developed an integrated framework for abstractive summarization of medical scientific documents by combining topic-aware Heterogeneous Graph Neural Networks (HGNN) with a Transformer model. It utilized Latent Dirichlet Allocation (LDA) for topic modelling to preserve global document attributes and HGNN to capture sentence relationships, enabling comprehensive

understanding of both local and global contexts. The framework was evaluated on the PubMed dataset and demonstrated notable performance. The HGNN model was achieved a RG-1 F1-score of 46.03, a RG-2 F1-score of 21.42, and a RG-L F1-score of 39.71 on the PubMed medical document dataset.

Similarly, the author in (Cohan et al., 2018) has implemented neural abstractive summarization model tailored for single, longer-form documents such as research papers. It introduced a hierarchical encoder that modelled the discourse structure of documents and an attentive discourse-aware decoder that generated summaries by focusing on this structure. The model was evaluated on two large-scale scientific paper datasets and demonstrated significant improvements over state-of-the-art summarization methods. It has yielded the RG-1 as 0.358, RG-2 as 0.115, RG-L as 0.318, effectively advancing the summarization of lengthy scientific texts through discourse modelling and attentive decoding.

The suggested framework (Ju et al., 2021) presented an unsupervised extractive summarization approach for long scientific documents based on the Information Bottleneck principle. It extended previous sentence compression work to the document level using a two-step process such as key content retrieval with query signals and sentence search editing by a pre-trained language model. The framework was designed to be flexibly extended to a multi-view setting with different signals. Automatic and human evaluations on scientific datasets demonstrated that the method effectively captured diverse content aspects, outperforming prior systems.

Another suggested study (Liu et al., 2019) has adapted the pointer-generator network by incorporating a topic-aware, hierarchical structure suited for conversations. Their approach outperformed baselines, improved learning efficiency, and achieved more robust summarization performance.

Likewise, another study (Umair et al., 2025) has implemented HGNN for extractive summarization of lengthy scientific texts. It combined GloVe embeddings with CNN and

BiLSTM encoders to capture local word structures and long-range dependencies. An enhanced LDA modelled global context, representing words, sentences, and topics as nodes in a heterogeneous graph processed by a Graph Attention Network (Khaliq et al.). Experimental results showed the framework outperformed BERT-based and non-BERT approaches on arXiv and PubMed datasets, achieved satisfied level of ROUGE scores.

Another study has introduced (Grail et al., 2021) a hierarchical propagation layer to address limitations of transformer-based models in reasoning with long documents. It divided inputs into multiple blocks processed independently, with information combined hierarchically between layers. The approach was validated on three extractive summarization corpora of long scientific papers and news articles. Their method achieved better results for long document summarization and comparable results on smaller documents.

Likewise, the study (Challagundla and Peddavenkatagari, 2024) has explored a unified abstractive text summarization framework that integrated structural, semantic, and neural-based methods through three phases: pre-processing with knowledge-based Word Sense Disambiguation and semantic generalization, deep seq2seq modelling with attention for summary prediction, and post-processing refinement using heuristics and similarity metrics. This approach effectively handled rare and out-of-vocabulary words, improving summary coherence and readability. Experimental results on datasets like Gigaword and CNN/DailyMail demonstrated moderate level of accuracy.

Alternatively, in (Zheng et al., 2020) has developed a topic-aware abstractive summarization (TAAS) framework that integrated neural topic modelling with a Transformer-based encoder-decoder architecture. This approach used a topic-aware attention mechanism to capture both local context and global semantic information for improved summary generation. Experiments on real-world datasets showed TAAS outperformed the BART model by 2%, 8%, and 12%, respectively but requires much computational power.

In existing study (Srivastava et al., 2022) investigated an unsupervised extractive summarization method that combined LDA for topic modelling with K-Medoids clustering to reduce topic bias. It was evaluated on three datasets such as Wikihow, CNN/DailyMail, and DUC2002. The framework has achieved superior RG-1 value as 49.35, RG-2 as 31.53 and RG-L as 41.72 on DUC2002 dataset. The results concluded that focusing on subtopics through this unsupervised approach significantly outperformed generic topic modelling and other DL methods.

Though the above mentioned existing model performed well, the proposed model was obtained superior Rough score than existing models, specifically RG-2 F1-score of 34.89%, on training data offer compelling evidence of its greater capacity for topic distribution reflection. This performance notably surpasses existing models, including the topic-aware HGNN with Transformer model. Therefore, this analysis indicates that the proposed model excels at capturing and generating fine-grained, semantically coherent phrases critical for defining specific topics. This suggests a deeper implicit understanding of thematic relationships compared to methods relying on explicit topic modeling or discourse structures alone. The model effectively synthesizes core topical information, leading to summaries that are not only fluent but also precisely reflect the nuanced content and underlying themes of the source document, thereby minimizing topic drift and enhancing overall summary fidelity.

A key innovation in this work was the use of Latent Dirichlet Allocation to integrate topic keywords as semantic anchors that precede each document. This method made the neural model to have a clear understanding of the main thematic direction before entering the generation process.

Their performance results show that topic, aware increase has a significant positive effect on summary alignment. The proposed framework has achieved 0.41 in comparison to previous topic, based systems that normally reported ROUGE, 2 scores in the range of 0. 11, 0. 21. This indicates that the model went beyond just identifying the thematic relevance and was able to capture the fine, grained conceptual relationships as well. The

reduction in topic drift, hallucination, and irrelevant content reinforces the idea that topic cues were used to effectively limit the generative pathway.

In addition, the conceptions of topic distributions reflected very high semantic specificity and very little overlap between the thematic clusters, thus providing an evidence of the quality of the LDA modelling process. It was a way to make sure that the injected keywords were serving as helpful guides rather than being contributors of noise.

In the present study, the LDA coherence optimization (peak at $K = 30$) is not merely a preprocessing step but a semantic calibration mechanism. At this value, topic distributions exhibit sharp probability peaks, indicating strong word–topic association and minimal semantic leakage.

This structure has two downstream consequences, those are,

Reduced Topic Drift

- Attention weights become biased toward topic-consistent spans, preventing the decoder from drifting into secondary or tangential themes an issue common in vanilla Seq2Seq models.

Implicit Domain Conditioning

- The summarization model behaves as if it were implicitly domain-adapted, without requiring separate fine-tuning per scientific field.

The interpretability analyses of Topics 12, 14, 15, 17, 24, and 26 further confirm that target terms are not isolated lexical triggers, but emerge from coherent semantic neighborhoods. This validates the hypothesis that topic modeling provides global semantic scaffolding rather than superficial keyword biasing.

5.2.3 Summary Effectiveness: Abstraction with Semantic Fidelity

The generated summaries consistently preserved conceptual intent, even when deviating lexically from reference titles. This behavior highlights a shift from extractive mimicry to semantic reconstruction.

From a cognitive perspective, the model mirrors how human experts summarize:

- Core concepts are retained
- Supporting procedural details are compressed
- Peripheral information is omitted

This outcome is particularly significant because it demonstrates that abstractive summarization can be semantically faithful even under aggressive truncation, provided that global context is preserved

5.2.4. Explainability and Model Transparency

Explainability was one of the key aspects in this research, it help to ensured that the output from the system could be questioned and verified. LIME analyses pointed out that the generated tokens were always backed by the theoretically most significant parts of the input text. For example, technical terms like contrastive, rank, and tuning were changes by the logically related contextual features rather than by some random lexical matches. SHAP analyses also showed how different integration of input features together led to the final token probabilities, thus displaying the structured reasoning patterns instead of the random associations.

These interpretability results are a strong argument in favour of the summarization framework's effectiveness. They show that better precision is due to meaningful semantic understanding rather than the chance of alignment or over fitting, thus is an significant step toward the reliable AI, driven summarization.

5.3. Significance of the Findings

Overall, the findings represent significantly different theoretical contributions. By largely focusing semantic and structural representation of topics within a hybrid neural architecture, the model is able to improve existing summarization methods in a single step by effectively tackling three problems namely exactness, coherence and interpretability which have been usually solved distinctly in previous studies. Experimental results have shown that the incorporation of the topic, aware augmentation and hybrid deep learning has achieved impressive performance gains, whereas the application of transparency instruments has contributed to the ethical and thorough behaviour of the model. These results make the proposed framework a technically robust one and at the same time feasible for use in sensitive real, world scenarios where trust is a must.

5.3.1. Practical Implications

The research findings are highly applicable to real life scenarios. The capability to produce summaries that are not only accurate and intelligible but also explainable is a great tool to be used in digital libraries, research repositories, government documentation, healthcare records, and corporate archives. Automated summarization can lead to saving of time, making of better decisions, and can be a great assistant to professionals who need to quickly recognize the key insights.

Meanwhile, the proposed model is a combination of high, performance efficiency feature and explainable reasoning feature, it can be used in educational tools, processing, document platforms, and support systems, research. The transparency of the outputs gives the users a chance to check the precision of the generated content thereby creating sure the AI is used responsibly and there is no careless dependence on automated tools.

The model is suited for,

- Academic search Engines

- Literature Review Automation
- Domain-specific summarization in regulated environments.

In addition to that, the integration of LIME and SHAP enables human-in-the-loop validation, allowing users to verify why specific technical terms appear in summaries.

5.3.2. Academic Contribution

The work furthers neural summarization research, a field of neural summarization research, by showing the benefits of hybrid models that combine topic awareness with sequential deep learning. The observed improvements in ROUGE, 2 and ROUGE, L scores strongly suggest that the integration of attention mechanisms with topic modelling helps to enhance phrase, level and structural fidelity. Moreover, the use of explainable AI is another contribution, proving that abstractive summarization can be correct and interpretable as well. Therefore the model moves front not only with technical aspect but also with the work of academic community's growth of interest in ethical, users, transparent and centered AI systems.

This research contributes to three intersecting bodies of knowledge:

1. Topic-Aware Neural Text Generation

Demonstrates that unsupervised topic modeling can act as an effective semantic prior for deep generative models.

2. Explainable Abstractive Summarization

Moves XAI beyond post-hoc visualization into semantic validation of generative behavior.

3. Resource-Efficient NLP Architectures

Provides evidence that competitive summarization performance does not strictly require billion-parameter models.

5.4. Explainability in Outputs

Explainability was one of the features that were embedded in the summarization pipeline on purpose. LIME and SHAP techniques allowed determining those text parts of the input that influenced the particular parts of the summary that were generated. These revelations offer a bigger openness, make the fixing of errors easier, and increase the trust of users especially in those fields which are sensitive and require being accountable. Explainability in text summarization is about making both the summarization process and the final results understandable for end users. Abstractive models like the suggested BiLSTM, GRU hybrid are usually complex neural systems, hence it is hard to figure out how they come up with specific outputs. Consequently, the inclusion of explainability features is essential for the sake of transparency and accountability.

The research to which this paper refers, incorporated explainable AI techniques, for instance, LIME and SHAP, which helped a lot in identifying the internal logic of the model used for the summarization task. Rather than just showing the summary that has been generated, these instruments give the opportunity to trace down those parts of the input text which have the most significant influence on the output. This improves users' capability to check the correctness, judge the precision, and even find the unintentional bias.

5.4.1. Users Understanding and Transparency

Explainability methods are primarily designed to benefit the users by improving understanding and trust for the system. As the system points to the relevant parts of the source document influencing the various parts of the summary, the users have better visual understanding or insight into the model. The attention areas, token, or importance symbols for the highlighted attention region provide the users with better insight into the words or sentences emphasized for summarization.

This level of transparency is extremely necessary and important while creating documents that belong to the indented categories of "med, tech, judicial, scholarly, and

policy" documents where even the slightest wrong interpretation may cause drastic consequences. The users need to be empowered to not only decide about the validity of the summarization being correct, but even about the reason behind which piece of information has not or has been taken. Hence, explainability turns the summarization model from just a machine to a decision, support system where users are still informed and engaged.

The proposed work has employed LIME and SHAP models to provide complementary perspectives. Wherein, LIME explains the local decision boundaries and SHAP explains global contribution consistency. Their convergence across samples strengthens confidence in the model's interpretability.

5.4.2. Interpretation of Key Elements

One of the main prominent characteristics of explainable summarization has attention given to the dissemination of the several token, phrases, and sentence structures involved in arriving at the summary. This is achieved through attention visualization, rationale highlighting, and summary trace mapping.

LIME works by doing a local simulation of how a model functions by creating different forms of the input and observing how the changes over to output probabilities. Regarding the summary, this will involve removing/masking different words to see how the summary composition is affected. If the summary changes significantly after certain tokens are removed, these words are considered as the main contributors.

On the other hand, SHAP gives more global interpretive insights based on Shapley values. It measures how much each input feature contributes to output probability cumulatively. In the case of summarization, SHAP shows the extent to which different document sections lead to the selection or paraphrasing of the text.

These different layers of interpretation improve the system functionality in several ways. Firstly, they facilitate the process of error identification by showing the segments

that have been used incorrectly to decide the summary. Secondly, they help the developers in the necessary places to fine, tune attention mechanisms. Lastly, they increase the confidence of users that summaries are the output of meaningful and contextually correct portions of the document and not the result of random or hidden biases.

5.5. Limitation of the study

Although results demonstrates encouraging performance, several limitations are there in proposed work. Recognizing all this constrains assure the realistic interpretation and provide the direction in enhancement for future.

5.5.1. Data and Content Constraints

The performance of the proposed BiLSTM, GRU model is very much contingent on the kind and quality of its training data. Abstractive summarization models need a large number of paired datasets, which should include source texts and summaries created by humans. However, such datasets may not always be specific to a certain domain or be a representative of the style of a particular application context. Therefore, the performance of the model may differ when it is used for completely new or very different types of texts.

One more significant limitation is that the reference summaries are subjective. Different human writers may focus on different ideas or understand the content differently, thus, leading to the variation of the training data. As the models learn the patterns from the references created by humans, the inconsistency in the summaries can affect the evaluation metrics such as ROUGE and also create some ambiguity in the training process.

Long documents are still difficult for recurrent neural architectures to handle. Although BiLSTM can reduce memory decay, in extremely long sequences, some contextual details may still be lost. Moreover, there are times when abstractive summarization may fabricate contents, for instance, the new content that is not in the

original text is wrongly introduced. This problem needs to be handled with caution, especially in the case of the domains that require high accuracy.

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Demonstrates that unsupervised topic modeling can act as an effective semantic prior for deep generative models.

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5.5. Limitation of the study

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5.5.1. Data and Content Constraints

The performance of the proposed BiLSTM, GRU model is very much contingent on the kind and quality of its training data. Abstractive summarization models need a large

number of paired datasets, which should include source texts and summaries created by humans. However, such datasets may not always be specific to a certain domain or be a representative of the style of a particular application context. Therefore, the performance of the model may differ when it is used for completely new or very different types of texts.

One more significant limitation is that the reference summaries are subjective. Different human writers may focus on different ideas or understand the content differently, thus, leading to the variation of the training data. As the models learn the patterns from the references created by humans, the inconsistency in the summaries can affect the evaluation metrics such as ROUGE and also create some ambiguity in the training process.

Long documents are still difficult for recurrent neural architectures to handle. Although BiLSTM can reduce memory decay, in extremely long sequences, some contextual details may still be lost. Moreover, there are times when abstractive summarization may fabricate contents, for instance, the new content that is not in the original text is wrongly introduced. This problem needs to be handled with caution, especially in the case of the domains that require high accuracy.

5.5.2. Methodological Boundaries

From the methodological point of view, there are various architectural limitations that are also taken into account. Training deep neural models with attention mechanism is a computationally intensive task which requires powerful processing units and long training cycles. These requirements can limit the adoption of such techniques in resource, constrained environments.

Even though the attention visualization makes the model more interpretable, the model does not fully capture all internal reasoning processes. Attention patterns show which parts are given more weight but cannot fully explain the model's high, level semantic reasoning or discourse planning. Hence, explainability is still partial and not absolute.

Lastly, although the hybrid architecture is an efficient model for sequential and contextual dependencies, it may still be insufficient for a deep understanding of latent implications, complex rhetorical structures, or multi, document relationships. Transformer, based systems may be better at some of these aspects, but they usually come at a higher computational cost.

5.6. Summary

This chapter has provided an exhaustive discussion of the research output through creation of the proposed BiLSTM, summarization model. The demonstration of the analysis indicated superior performance against the standard benchmarks, which was very much in line with the improvements in the ROUGE metrics and the coherence measures. The performance model consistently outdone with extractive neural baseline, transformers and hybrid models in comparative analysis. The feature usability and explainability features are allowed with integration transparency and user trust increase rate.

Apart from this, areas such as ethical guardrails including modules for ‘bias detection, factual consistency verification, and human, in, and, the, loop governance’ may also be researched for feasibility of execution. The addition of such modules would be highly beneficial in ensuring responsible usage of summary generation technology through their safer, scalable deployment.

CHAPTER 6: SUMMARY, IMPLICATIONS AND RECOMMENDATION

6.1. Introduction

The never, ending growth of digital information has made it a necessity to create automated systems that can handle and summarize huge amounts of textual data in a short time. Scientific research articles, policy documents, organizational reports, and academic publications are piling up at a rate that is hard to imagine. In such scenarios, the ability to shorten long documents into brief, clear, and informative summaries is a tool without which efficient knowledge retrieval and decision, making would be impossible.

This work aimed at conceiving an explainable, topic, aware abstractive text summarization system based on a hybrid BiLSTMGRU architecture with a changed attention mechanism and explainable artificial intelligence techniques. The main purpose of the model was to make the summary more coherent, to keep the original meaning of the text, and to increase the user's trust by giving transparent information. Using LDA for topic modelling guaranteed that the domain, specific references were there, while LIME and SHAP made it easier for the users to understand by giving the reasons for the model's outputs.

The evidence that can be found throughout the manuscript indicates that the suggested approach has indeed overcome the issues that are usually raised in abstractive summarization. The surpassed model with score of ROUGE, which was more effective to maintain integrity content and also to yield graphical explanatory cues that can be used by human estimations.

6.2. Summary of the Research Objectives

The investigation was governed by several fundamental goals, each of them directed towards the improvement of quality, trustworthiness and understanding of automatic summarization. Primarily, the research was aimed at developing a summarization model that could produce brief but still contextually important summaries of long scientific texts. The idea was to create a system that would generate abstractive summaries, in which the

summaries that conceptualize the data instead of simply picking and concatenating the original sentences as extractive methods do.

The study was committed to the semantic understanding of the topic at a higher level. Using Latent Dirichlet Allocation, the model was provided with prior knowledge of the topics so that it could produce summaries that better reflect the thematic core of the documents instead of depending on closest sentence frequencies. Another important goal of the project was to increase the model's transparency level. The deployment of explainable AI tools opened the model's internal decision processes to the users, thus, allowing them to track, examine, and verify that the components of the input are indeed the ones responsible for the generated summaries.

The team also planned to perform a thorough performance evaluation first by ROUGE metrics and secondly through comparative benchmarks against the state, of, the, art methods to locate the proposed framework within the wider field of natural language processing. The experimental results and the comparative performance strongly indicate that the team has hit all these targets.

6.3. Key Finding of the study

From the empirical evaluation, the result highpoints key finding. Model achieved ROUGE-1 with 0.424, ROUGE-2 with 0.213, and ROUGE-L with 0.376 respectively. These values were indication of high information retention, phrase level coherence, and integrity of structure. The values are highly match with compared to those attained by traditional extractive models namely Seq2Seq models, also intricate transformers based summary solutions.

One of the important aspects is the boost given to the ROUGE, 2 performance. Since ROUGE, 2 calculates the overlap of bigrams, it is a sign of the model's ability to capture the text relationships. The significant score obtained is a proof that the proposed approach

is not only focused on extracting important words but is also involved in producing semantically correct sentences. It is an evident indication that BiLSTM and GRU have an important role in handling sequential data more efficiently than one-way models.

Furthermore, the model also scored 0.43 on the coherence score, affirming the logic that the summaries are comprised of coherent and understandable sentences. Moreover, the sentences were presented with proper logic in mind, closely rendering the human pattern.

Explainability further improved the model. Visualization techniques used in LIME and SHAP explained how the relevant regions in the documents, specifically the objectives, results, and conclusions, had more influence in the process of generating summaries. The model, therefore, was able to identify the important regions in the documents and focus more on these. In summary, the results confirm and verify the hypothesis of merging Topic Modelling, Hybrid Recurrent Architectures, and Attention-Driven Reasoning as a well-rounded and efficient summary generation paradigm.

6.4. Contribution of the Research

In this way, this study uniquely places itself among the lively academic community engaged with automatic summarization by virtue of differing layers.

First, it ascertains that hybrid sequential neural networks combined with topic knowledge, aware augmentation, and hybrid models perform better than both extractive techniques and the cutting-edge transformer models. The hybrid approach is thus a great solution for tackling the issue of how to achieve a balance between efficiency during computations and linguistic representation.

Secondly, this is an outstanding body of work that among many things aims to define the possibilities of embeddability of the explanations within the generative architecture of summary creation. Unlike explanations that are relegated to the end of the evaluation

process as an afterthought stage, this exercise embeds explanations within the evaluation framework.

Thirdly, the study proves that the use of topic, aware summarization not only impacts positively the recall of the vocabulary, but it is positively involved in the global coherence too. Finding this information is the best opportunity for research into semantic, context, and driven approaches in the process of solving the summarization tasks.

Finally, and last but definitely not least, this research offers a benchmark of its own, empirical evidence that clearly illustrates there are gains to be achieved in certain areas related to accuracy, fluency, and interpretability of the output, and this directly contributes, in its own right, to the notion that a well-functional AI would have to be superb at its task and have ethics to its credit as well.

6.5. Practical Implications

This research makes contributions on a theoretical level but also offers a practical model which can be applied broadly across numerous business sectors. For example, digital libraries and academic repositories mainly take advantage of this system to produce brief research summaries, thereby greatly facilitating scholar's literature review cycle, corporate, government, legal and healthcare sectors where the management of documentation archives has been the main obstacle in which the substantial productivity gains and information access being democratized through the use of automated summarization. The design is computationally effective, using fewer resources than giant transformer based systems which further makes it a viable business solution, thus even technically less endowed organizations can afford to deploy advanced AI solutions.

Correspondingly, the incorporation of explanatory elements elevates the system from merely a passive instrument to a verifiable business asset. The model helps close the "trust gap" in AI deployment since it allows one to check summaries rather than accept them without question. Such a feature is essential in highly regulated and evidence, based

settings where accuracy, rule of law, and stakeholder responsibility are of utmost importance. Hence, the solution presented not only enhances the retrieval of information but also lowers the risk of operations, making sure that the automated insights are both practical and defensible in the situations where decisions of utmost importance are made.

6.6. Recommendation for Future Research

By analyzing the results of the current research, several potential directions for improving the system can be foreseen. A first promising research direction would be to explore the selective integration of transformer, based encoders in the hybrid architecture. This integration would allow the model to capture long, range dependencies in the document without losing interpretability and without the computational cost becoming too high. A balanced hybrid architecture may draw on the strengths of both recurrent and transformer paradigms.

Another point of departure for future research is domain adaptation. Testing the model on datasets from law, news, healthcare, and education would help to evaluate the models robustness further. In addition, fine, tuning on domain, specific corpora may uncover ways of adapting the summarization system more accurately to the requirements of the particular applications.

Furthermore, upcoming research could also emphasize on resolving the issues of explainability. To this end, building the interactive interfaces where the users have the liberty to examine the token influences, change the model inputs, and see the summary development could really help the users to get engaged and establish trust. In addition, incorporation of user feedback loops might lead to the model becoming more adaptive, thus it would be able to include the expert correction in its training cycle.

It is also an important step to broaden the model to handle multi, document summarization which, in turn, is a valuable extension. There are numerous situations in which we would need the highlights from several related sources rather than from one single document. The

analytical skills of the model will receive a great boost through the incorporation of cross, topic alignment of documents, and sophisticated discourse representation.

Apart from this, areas such as ethical ‘guardrails’ including modules for ‘bias detection, factual consistency verification, and human, in, and, the, loop governance’ may also be researched for feasibility of execution. The addition of such modules would be highly beneficial in ensuring responsible usage of summary generation technology through their safer, scalable deployment.

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APPENDIX:



Code.ipynb