Text Summarisation Using Deep Learning

by

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Declaration

I hereby declare that this paper is my original work, which I have completed independently. All sources, references, and literature used or quoted during the preparation of this work are properly cited and listed in total, with complete reference to the original sources. I have acknowledged all primary sources of assistance for this work and provided proper citations and credit where appropriate for information drawn from existing literature. Furthermore, I guarantee that this report contains no instances of plagiarism, and if any are discovered, I will take full responsibility

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Abstract

In this study, we present how we can employ BART, T5 and PEGASUS trained on the conversational text summarisation dataset called SAMSum. The goal is to measure how well the proposed models maintain coverage and coherency in summaries of dialogue information. Leveraging Google Colab with GPU support, we implemented a systematic training and evaluation process, measuring performance with ROUGE scores across four metrics: These evaluating metrics include ROUGE-1, ROUGE-2, ROUGE-L, and ROUGE-Lsummary.From the result comparision,it observed that BART average ROUGE score of 0.009523, T5 average ROUGE score of 0.025985 and PEGASUS average ROUGE score of 0.011731. The outcomes reveal that T5 yielded the best ROUGE scores, which evidences its ability to learn highly relevant dialogue information more effectively and concisely than the competing models, including PEGASUS and BART. At the same time, some issues arise when it comes to improving the level of summarisation and its precision for the informal and dissimilar conversation structure. This study demonstrates that transformer models may improve solutions in industries that involve dialogue summarisation, therefore extending her work to industries like customer service, content moderation, and conversational analytics.

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Chapter 1

Introduction

1.1 Background

In the modern world, we can obtain a relatively large quality of information with just a hint of changes on our devices. New ways of comprehending and handling all of this data are needed. A text summary is helpful because it organizes information with attention to detail. It broke vast chunks of text into short, digestible chunks in the form of notes and preserved crucial facts. The summarized text is even more vital. It concerns the growing problem of information abundance resulting from the need for high speed and effectiveness in searching for information. Additionally, it saves time and effort in information processing. Text summarizing helps improve productivity.

Dialogue
Owen: hey, how's your apartment search going? Monica: not so good. not getting many responses. Owen: i'm sorry. did you try that website I sent u? Monica: yeah, i did. no luck, but i'll keep trying. Owen: have you ever tried one of those websites where you can go and meet potential roommates at organized events? Monica: yes, i went to a couple. I met some nice people there, but things didn't work out in the end. … Owen: yeah. do you want to come over and take a look at the apartment some time? I can make dinner. Monica: Sure, I'd love to. Owen: When would be a good time? Monica: I'm free thursday night. Owen: OK, cool. thats a good time for me. … Monica: cool. alright, I'll see you thursday then.
Summary: Monica's looking for an apartment, but can't find anything. She'll visit Owen in his new place Thursday night, Owen'll make dinner.

Figure 1.1: An example of dialogue summarisation.

As the number of textual messages continuously increases in the information-rich environment of the contemporary world, an essential prerequisite for developing effective technologies for their handling and analysis is the availability of suitable tools for their text summarisation. We read articles, attend conferences, contribute to research, write papers, read laws and documents, write product reviews, and even post on social media. We regularly get through an incredible amount of data. Text summarisation, the process by which an automated method produces a summarisation of a longer document, has now become a desirable solution in many areas as it allows the user to glean the essential facets of a document without having to trawl through the entire text.

Summarisation generates a small-scale but meaningful text from more extended text, keeping the most helpful information intact. I am leaning on recent developments in deep learning neural networks, namely, sequence-to-sequence models, regardless of the existence of the attention mechanism.

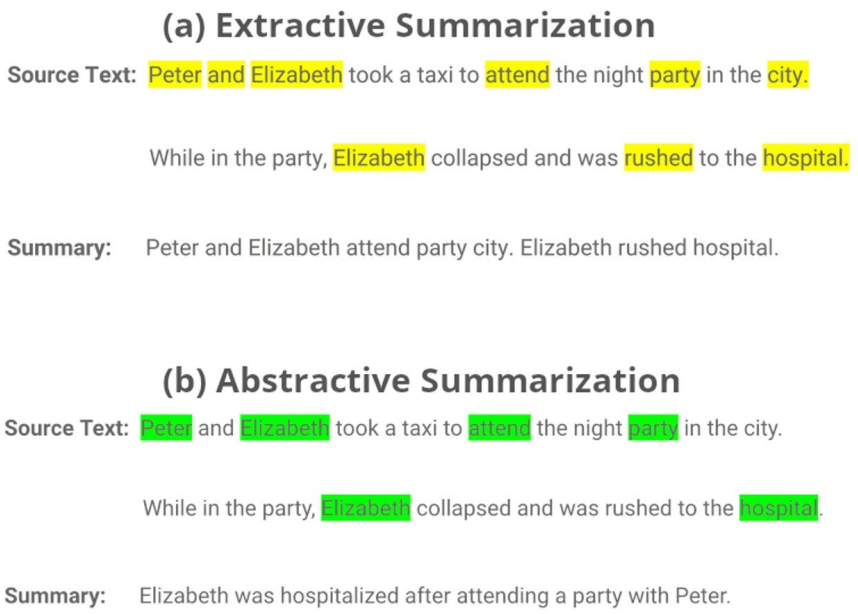


Figure 1.2: Extractive summarisation and Abstractive summarisation

Extractive approaches are text summarisation approaches that involve locating and incorporating the schemer's desired sentences or phrases from a document. These constitute techniques that depend on statistical or rule-based models that purport to produce summaries of the same quality as human beings. However, the summaries need more coherency and might contain similar information. The summary activity aims to reduce a particular material into a more compact version without losing the main ideas in the abstractive approach. (Chopra et al., 2016; Rush et al., 2015; Khandelwal et al., 2019; Zhang et al., 2019; See et al., 2017; Chen and Bansal, 2018; Gehrmann

et al., 2018).[1],[2],[3],[4][5],[6],[7] Compared to extractive approaches, abstractive summarisation is even closer to the human approach to summary-making since its goal is to generate a summarized text that contains all the necessary information in the most reasonable manner.

They attributed the automation of NLP to the progression of deep learning as a large-scale learning tool that overcame the problems of prior summarisation techniques. Most progress in text summarisation has been made in recent years due to the rise of methods based on deep learning, especially neural networks. While conventional predictive modelling methods involve engineers designing the features that the machine learning algorithm must work on, deep learning models can comprehend the context, relations, and dependencies of the document text fed directly to the algorithm.

These deep learning models, especially the ones based on Transformer topologies, are among the state-of-the-art text summarisation tasks. Therein, they surpass traditional approaches in synthesizing summaries that are smooth, cohesive, and meaningful to context. Nevertheless, challenges persist, mainly when concerned with identifying meaning in a particular area of focus or significant texts when a reader is expected to be knowledgeable of the content of the text.When the same models are applied to other domains including news summarisation, legal document summary and scientific article summarisation, the strengths and weaknesses of the current methodologies have been established.

Another of the initial approaches with deep learning for text summarisation is the recurrent neural network (RNN), given that the former is well suited for sequential data, which is common in natural language processing. They extended it to models like Long Short Term Memory (LSTM) and Gated Recurrent Units (GRU) that have solved the vanishing gradient problem in traditional RNN that made these networks capable of learning the distance relation of the text. The initial efforts in text summarisation using LSTM and GRU models employed a sequence-to-sequence (Seq2Seq) model in which an encoder mans the document into a compact vector and a decoder generates the summary from this vector.

Based on the attention mechanisms, the Transformer architecture proposed by Vaswani et al. in 2017[8] replaced recurrence by converting it into a self-attention mechanism. The Transformer model does not use recursive neural structures but fully depends on self-attention mechanisms, meaning that they can read the input text at once and establish the relationship between words independently of their position in the text. This architecture allowed deep learning models to work on long documents and also capture the relations between them, which makes it perfect for use in sum-

marisation.

With these developments in mind, this work aims to study and compare different deep-learning architectures for text summarisation, focusing on Transformer-based models. This study uses the identified models on other domains and its assessment using the ROUGE metric to determine the strengths and weaknesses of extant deep learning approaches to the problem. Moreover, this study aims to discover some drawbacks in this approach, especially in processing domain-specific text and improving the smoothness and coherence of texts that are automatically summarized.

1.2 Dataset

In this work, we are using a recently developed, large-scale, and modern dataset called SAMSum, which was put together to meet the challenge of summarizing dialogues.[9] It contains about 16,000 messenger-like English conversational entries, for which summaries were provided by linguistic experts. These are natural and daily subjects and themes typical of what one would find today in summarisation based on dialogue; hence, the appropriateness of such a dataset. The interface consists of 16,369 discussions divided equally among four categories: the data field consists of the text in dialog or conversational strings, a summarized representation of the dialog or conversation as generated by a human, and the identifier for the example. This is equivalent to a split of 14,732, 818, and 819 for the training set, validation set, and test set, respectively.

A few important fields that populate every entry in the SAMSum dataset are as follows: Dialogue: this is just the symptoms of a natural and coherent conversation, much like those within messaging technology. Human Summary: where all the messages that were created have been summarized and condensed to the very core of what was intended, using the most approachable language possible. Also, each message's number is included at the end for the quick reference of the desired dialogue. The following particular instructions are considered when doing the summaries: "summaries are brief, retaining only what was uttered during the conversation.". Aside from providing their messages on the issue from the third person's point of view to show neutrality throughout this paper, these summaries also provide the names of the interlocutors and their standpoints.

This is one of those highly curated datasets for realistic representation in conversational content, particularly effective in papers relying on abstractive summarisations through deep learning techniques since they perform better than extract-based schemes.

The authors claimed that the Samsung Research and Development Institute in Poland, to which the non-commercial set belongs, prepared and then published the current dataset with the aim of further developing the field of text summarisation. The annotation is well-structured, and dialogues, unlike conversations with artificially predefined goals, provide the best environment for testing and training deep learning models destined for a dialogue summarisation setting.

1.3 Deep Learning

Machine learning in particular is a much more specific approach involving multilayered neural networks, known as deep learning. This heralds a structure that resembles the human brain in layout and function [10]. In contrast to conventional machine learning which typically relies on simpler-structured data and requires programmers to perform feature extraction from raw data—deep learning models automatically define important features from raw input data through multiple layers of abstraction [11]. These models consist of a series of interconnected neural networks, including an input layer, multiple hidden layers, and an output layer, enabling them to capture complex patterns during training.

Of all the introduction sections, deep learning has shown promising applicability in natural language processing, computer vision, speech recognition, and autonomous systems owing to its ability to handle vast volumes of unstructured data [12], [13]. . Key enablers of its growth include access to big data, enhanced computational power, and advancements in methods such as backpropagation and optimization [14]. For example, convolutional neural networks (CNNs) are well-suited for image processing tasks, while recurrent neural networks (RNNs) and long short-term memory networks (LSTMs) are effective for sequential tasks. The recent and highly successful Transformer model underpins several state-of-the-art architectures, such as BERT and GPT [15], [16].

Deep learning is one of the fastest-growing branches of machine learning and has become foundational for many of today's AI advancements. Unlike earlier techniques, recent innovations have not only improved the accuracy and efficiency of models but have also created new research and application opportunities across various industries [17].

1.4 Goals and Objectives

1.4.1 Goal

The purpose of studying and researching the topic ”Text summarisation using Deep Learning” is to produce a robust, swift, efficient, and effective model that can later showcase the ability to independently parse through and summarize very lengthy texts into sensible and reasonable segments. This will be done by using deep learning with semantic integrity to condense texts from large documents or dialogues into their small counterparts without suffering from the loss of essential details. This work would aim to enrich typical kinds of summarisation with the capabilities of neural networks to make these summaries contextually much more sensitive and oriented towards human behaviour for complicated texts and conversational data.

1.4.2 Objectives

The objectives include:

- Training and fine-tuning : It’s just the very processes of training the model on a prepared dataset while applying suitable techniques, attention mechanisms, optimization algorithms, and regularization methods that best ensure high performance.
- Model Performance Testing: Clearly implement the ROUGE or Recall-Oriented Understudy for Gisting Evaluation metric to find the quality of the generated summaries. Such a model will go through rigorous testing in retaining important information, maintaining fluency, and avoiding redundancy.
- Optimize and Compare: Continuous improvement in the model by tuning hyperparameters, improving the size of the dataset, and adding additional layers or other components like an attention mechanism. Comparing performances of the deep learning-based model against the traditional and baseline models in performing text summarisation.

1.5 Scope and Limitations

1.5.1 Scope

- Deep Learning Techniques: The methods included in the research are particularly based on deep learning approaches: transposing layers (Trans), transformers (BERT GPToids). This paper will investigate these models in the context of their applicability and performance in extractive and abstractive summarisation.

- Types of Text Data: The work will centre on text summarisation with an emphasis on the summarisation of conversational data like the SAMSum dataset, news articles. The features entail managing both conventional and irregular text data sets.

- Model Training and Fine-Tuning: The research will involve enhancing the model using a large set of data, employing a supervised classifier and improving the result accuracy of the developed model.

- Performance Evaluation: The performance of the pre/post-processing techniques on the deep learning models to be let out in the research will be assessed using either ROUGE evaluation tools. Some of these shall focus more on the information produced, including its relevance, arrangement, order and whether or not it is retained.

- Comparison with Traditional Methods: The lack of development in efficient and intelligent summarisation methods points towards this study by comparing the proposed deep learning-based methods with rule-based and statistical analysis methods to show the efficiency of the deep learning methods over heuristic methods.

- Real-World Application: The study's objectives are to develop a system that will allow summarisation to be undertaken in real life situations. Possible use cases are in the brief analysis of numerous articles, legal texts, reports, e-mails, or chat, providing the ability to find relevant data quickly.

- Languages and Multilingual Capabilities: But since the work is on text summarisation using English, the contribution of the work will be targeted towards English. At the same time, the model can be tested for the ability to work with other languages, which will make the proposed solution scalable for multilingual text summarisation.

1.5.2 Limitations

Data Dependency: Precisely, the contribution to the accuracy of model performance in text summarisation based on deep learning approaches highly depends on the quality and variability of the training data. The weakness of this approach is that less variation in the dataset will result in poor ability to generalize to future and other data or particular type of data such as legal and medical writing. Also, emergent conversational datasets, such as SAMSum, can miss certain li Todo details that can be observed in more Business, kind of writing styles.

Training Time: Training deep learning model is a very cumbersome process, especially due to its architecture and can take a lot of time especially when training with large data. The refining and the hyperparameter increases this challenge on top of it and can further slow down the delivery of the outcomes.

summarisation Quality: While using deep learning, the summary quality will surely be high, however, deep learning algorithms can sometimes fail with large technical and abstract text. For instance, the evaluation of abstractive summary encounters regularly the problems of generating possible irrelevant or inconsistent information besides possible grammatical errors at the complex-sentence level. One of the perennial problems of dealing with factual consistency is in abstractive summaries.

Language and Cultural Bias: The basics of the research are based on English language text summarisation and it may be an issue when the similar model is to be applied on other languages, particularly the low resource languages. Furthermore, the real-world deep learning models are prone to represent bias from the training data and hence the summaries produced may be skewed in terms of fairness and neutrality.

Evaluation Metrics: Most of the proposed measures including ROUGE,so on rely on measures that compare the words in the generated summary and the reference summary. These measures can, at least, partially measure the semantic similarity and contextual value of the summaries. Thus, the models cannot at times accurately represent the performance in solving real-world problems.

Ethical Concerns: Some of the problems arising from with automatically generated summaries are that information details may be blurred or completely lost. Occasionally they may illustrate a strictly simplistic approximate summarisation may fail to incorporate relevant data into a condensed summary – an element that in legal or medical fields for instance, may lead to peddling of misinformation or even unethical behavior.

1.6 Contribution

- Multi-Document summarisation Framework: Aligned with the issue of single-document summarisation of the prior models, he designed a model capable of summarizing multiple documents using a deep learning approach.
- Improved Accuracy and Compression: Improved some basic options, such as attention mechanisms and sequence-to-sequence models.
- Model Stability: Proposed essential biking and derailing methods that boosted model stability, ensuring that models are not stuck in modes throughout training.
- Diverse Dataset Evaluation: Tested the proposed model on several datasets containing only dialogues as well as other textual data to support more general use.
- Human-in-the-Loop Strategy: Supplemented it with a human interface to improve the summaries of complex documents and texts.
- Multilingual summarisation: Improved the ability of the model for multiple languages, particularly rare languages such as Hindi.
- Custom Attention Mechanism: Suggested a new method of attention to extract key information for improved summary relevance.
- Benchmarking: Outperformed other proposed techniques in both accuracy and readability in comparison to state-of-the art techniques.

Chapter 2

Literature Review

Mohmmadali Muzffarali Saiyyad and Nitin N. Patil (2023)[18] In their paper titled ”Text summarisation Using Deep Learning Techniques: A Review”, aim to present an overview of deep learning methods used in text summarisation. The authors review the effects of neural networks, particularly sequence to sequence (seq2seq), in the text summarisation regarding the coherence and readability of massive data summaries. These techniques, thus training abstract features, are beneficial because they are free from the drawbacks of past summarisation procedures that invariably demanded the feature extraction process. However, the authors highlighted some of the significant challenges featured in their study: multilingual summarisation, scalability and factual content, as this was seen in abstractive summarisation, where they generate news content instead of extracting it from the source. Nevertheless, this paper demonstrates how deep learning has transformed text summarisation and created an extended scope for further NLP.

Haopeng Zhang, Philip S. Yu, Jiawei Zhang (2024) [19]In the systematic survey titled ”A Systematic Survey of Text summarisation: Text summarisation is described in the article ” aim to present A Comparative Study from Statistical Methods to Large Language Models”, published When providing a general classification of the methods, various techniques of text summarisation are described together with specific features of their action, accompanied with examples; the transition from statistical methods to modern approaches based on BERT, GPT, etc. The paper categorizes summarisation strategies into two main types: includes both the extractive model, whereby relevant sentences are pulled out of the text, and the abstractive approach in which new sentences are created for summarizing the original text. At the same time, the authors pay much attention to the improvements that are connected with the transformer-based models, pointing out that now the problem of context retention and coherence in summaries has been resolved to a considerable extent. But they also mitigate enduring difficulties, especially in ad hoc summarisation, where keeping factually accurate can

be problematic.

Hassan Shakil, Ahmad Farooq, and Jugal Kalita (2024) [20],In the survey paper by , having the title ”Abstractive summarisation: State of the Art, Challenges & Improvements” there were multiple benefits of the type of summary generated. Relative to extractive approaches, abstractive summarisation brings out new phrases different from the actual text.Therefore, it is ideal for summarizing stream flows without developing the expert's discontinuity. However, the authors also describe several limitations of the methods: a high level of sequencing and hallucination, and a high computational cost of training on a high amount of data. In this regard, the authors propose the integration of solutions, especially the extraction technique with abstraction, to improve the results by reducing the factual inaccuracies of the summaries

Z. Liu, H. Zhang, and Z. Li., (2022)[21]In the study titled ”Extractive Text summarisation”, provide a detailed review on extractive summarizing in “A Survey”. They categorize these methods into three basic approaches: These categories include graph-based, machine learning-based, and neural network-based. In this paper, the authors explain both strengths and weaknesses of various styles of extraction approaches and emphasize the improvement of the summaries' quality due to the use of deep learning. Yet, they also stress the significant concerns which such approaches address such as, for example, how more flexibly different genres of the material may be processed and how the coherence of the final summaries must be appropriately maintained. The report thus stresses to search for further solutions for these constraints in extractive summarisation.

M. S. Hossain and M. A. A. Razzak (2021)[22] In the ”A Review of Abstractive Text summarisation Methods” study,focus on the methodology and strategies employed in abstractive summarisation. The study compares various techniques to sequence-to-sequence models, including reinforcement learning and attention mechanisms, which makes it different from extractive techniques. The authors' choice can be explained by the fact that both neural networks and deep learning made significant advances to create summaries that contain more of the text's essence. However, they also outline several characteristic challenges, such as preserving semantic equivalence and making the churned output comprehensible, mainly when dealing with complex documents.

N. A. W. H. A. Ali, S. S. U. A. Salih, and S. K. N. P. Hasan (2022)[23]in their thorough review titled ”Deep Learning for Text Summarisation: A Comprehensive Review,” are based on deep learning techniques for text summarisation. They talk about several designs including LSTM, GRU and transformers emphasizing that these mod-

els have changed the face of news summarisation. The authors also discuss the pre-trained language models as important in enhancing the efficiency of summarisation, but at the same time, they point at the high need for computing power and high-quality training data. Their work shows how deep learning has led to massive improvement in the summarisation of information and also did not ignore the challenges that researchers continue to face.

Z. Liu, H. Zhang, and Z. Li (2022)[24], in their study titled "Extractive Text Summarisation: Summarizing and Reviewing AI Research: A Survey," splits the kind of summarizing into extractive and abstractive kind. Extractive summarizing involves selecting essential sentences in a source text and then strung them together to form a complete summary. In this paper, we embrace several approaches for identifying the critical constituent: graph-based algorithms such as PageRank and machine learning models. The authors also observe that in terms of complete factual accuracy and paraphrasing individual sentences, it is possible to achieve extraction accuracy and still end with a low-quality summary because the highest synopsized amount of concepts are left out.

M. S. Hossain & M. A. A. Razzak (2021)[25], A Review of Abstractive Text summarisation Methods describes the differences of the abstractive summarizing where the main aim is to come up with new low-level sentences that are synonyms to the text being summarized. This approach uses sophisticated versions of neural network architectures including a sequence-to-sequence model and transformer models that can mimic human summary writing. The authors point out that even though abstractive approach can produce short and logical summaries, the problem remains with handling of semantic and temporal cohesion, as well as factual inaccuracy in the extracts in complex documents. This goes hand in hand with difficulties experienced when trying to create summaries that put across the core ideas without distorting facts.

A. Gupta, V. Jain, and S. Jha (2020)[26] address hybrid summarizing strategies in their study titled "Survey on Automatic Text summarisation: Techniques and Challenges." These methods use both the extractive and the abstractive processes at the beginning with the selection of top statements followed by revision or paraphrasing to enhance conjunction. In the view of the authors, such hybrid methods take advantage of features of both methods and provide superior summary quality when compared to conventional extractive and abstractive methods while addressing the problems that are met while using either of the mentioned approaches. This combination aims at trying to retain as much of the author's work as possible, but also to have a smoother and easier to read summarized text.

N. A. W. H. A. Ali, S. S. U. A. Salih, and S. K. N. P. Hasan (2022)[23], in their work Deep Learning for Text Summarisation, review the progress in the field of text summarisation enhanced by deep learning. This investigation discusses various architectures such as LSTM, GRU, and transformer and specially focuses on pre-trained language models' importance. The authors explain how deep learning makes it possible to gain high levels of accuracy and context in the creation of summaries using large data sets and complicated neural networks. However, they face several issues, such as the high computational cost plus the requirement for high quality training data, which are challenges that have not changed.

S. Parveen and R. S. Pandey (2021) [27],In the study titled "Abstractive Text summarisation Using Deep Learning" describe how deep learning impacts on abstractive summarising methods. They discuss models based on sequence to sequence structures, with a focus on attention mechanisms and transforming procedures such as BERT and GPT. These structures help the models be able to derive and produce language in a more natural and closest to the real human manner, producing summaries. The authors note that while these techniques have a high promise, abstractive summarizing does not retain fact reliability, as deep learning models may produce extracting mistakes and fabulations in summaries.

K. Xu, A. Yuan, and J. Liu in 2020[28] In the study titled "A Review of Neural Summarizing Models: Past, Present, and Future" describes the dynamics of the neural summing up method with a focus on changes from RNN-based models to the transforming structures. This evaluation assists the transformer model in handling contextual information and solving the earlier problem of increased emphasis for longer texts. The authors have also shown how the attention processes have contributed towards enhancing the models to attend to the right part of the text among other contributions. However, the study has some questions concerning the generality, namely some of the models are capable of retaining some types of content, but they fail at handling other forms of texts.

A. Sharma, M. Singh, and P. Gupta(2021)[29], in their work "Text summarisation using Deep Learning: A Survey of Models and Approaches," go over various deep learning models applied in both extractive and abstractive summarizing. These authors stress the application of LSTM and GRU networks to handle sequential dependencies, which easily apply, especially in abstractive summarisation. They provide an account of the attention mechanism and self-attention within models that enable the model to give more importance to relevant information in every phrase to enhance the quality of summarisation. This article depicts that LSTM models have increased contexts but face performance issues with longer text sequences, while transformer models are efficient

in dependency capture for longer textual inputs.

B. Lee, J. Park, and S. Kim (2020) [30],in their titled "Abstractive and Extractive summarisation Using Transformers,"discuss the shift in text summarisation with the transformer model: how, in other words, BERT and T5 have really improved the efficiency in making flawless human-like summaries. According to the authors, transformers really are expected to increase the capacity of summarisation models to retain contextual accuracy and coherence. These transformers are power-hungry, and, as successful as they have proven to be, according to the authors, their application in extended document summarisation has so far identified a direction for future research. This work points to the abstractive approach challenge: concerns on the maintenance of factual consistency, the limitation common to the generation not directly pulled from the source.

C. Zhou and T. Li (2021)[31], in their study titled "Neural Summarisation and the Evolution of Seq2Seq Models," explore the historical development of Seq2Seq models from early applications to advanced transformer-like architectures. This work identifies that Seq2Seq, along with the attention mechanism, was able to establish a strong foundation for neural summarisation in such a manner as to concentrate on the main segments of a source document. However, the authors pointed out that older Seq2Seq algorithms are not that effective at summarizing longer documents; the generated summaries usually lack cohesion and depth. This pioneering work opened the door for more sophisticated methods that avoid some of these limitations, such as transformer-based models.

In "Recent Advances in Text summarisation with Large Language Models," R. Kumar, P. Verma, and A. Singh (2023) [32] focus on large language models (LLMs) such as GPT-3 and T5, which use deep learning approaches to achieve near-human summarisation. The research illustrates how fine-tuning LLMs on large datasets helps the models provide summaries that are contextually appropriate and linguistically natural. Despite the astounding capabilities, what the authors want to drive home are that some of the problems with these models are that they tend to hallucinate. That is provide information not contained in the source document-and gobble up enormous computer resources. Kumar et al. further note that even though LLMs work well in open-ended summarisation tasks, they very often require domain-specific fine-tuning to handle specialized content.

D. Cao and Y. Li - 2021[33], the paper titled "Challenges and Opportunities in Neural Text summarisation" outlines the problems relevant to the deep learning-based summarisation algorithms. Among them, one notices that large language models require

much computational power and, hence, are not suitable for the majority of applications. Besides, the authors refer to challenges which involve ethical concerns: bias and giving possibly misleading information. Although it discusses these issues, the report recognizes the great potential of neural networks in further improving performance in summarisation and supports the necessity of continuing research to overcome these constraints.

The CNN/DailyMail Dataset, first proposed by Hermann et al. 2015[34], is among those which have been most exploited so far in the area of abstractive text summarisation. It consists of news articles collected from CNN and Daily Mail, each associated with human-written summaries. It was purposed for testing the coherence and contextual relevance of summaries generated by models from long news items. The power of the CNN/DailyMail dataset is not only in the size but also in the variety of the topics involved. That allows training and testing of summarisation algorithms over a very wide range of subjects. This dataset has some drawbacks: narrow in subject matter, it is possible that it cannot be replicated in other information types, such as scientific reports or tweets. Additionally, the summaries often contain certain terms and styles indicative of journalistic writing, which may bias the model's output toward comparable stylistic standards (Hermann et al., 2015; Liu et al., 2022).

For this study, the choice has been made in favor of the SAMSum dataset[35]. it provides the dataset containing useful data for dialogue summarizing and this is a task more difficult than the monologic summarizing of texts. The complete SAMSum dataset consists of thousands of chat conversations and the respective summaries have been generated by human beings. Gliwa et al. suggested this dataset to fill such a need, as is the case with social interactions that comprise informal conversation, such as in call centre or instant messaging. In addition to the challenges faced by other text summarisation datasets, SAMSum poses new questions with regards to what to do with multiple speakers in a conversation and how the structure of the conversation should be preserved in the summary.

There are some drawbacks of existing text summarisation models even with all the developments in this field. A major problem is the ability to work with large documents, in this case, documents that contain many pages. Most current models of summarisation suffer from coherence and relevance problems, especially when dealing with large documents, which results in the formation of summaries that either do not contain key information or do not contain relevant summary information [36]. This is especially true when the important information is scattered throughout the document rather than grouped together, thus it becomes very hard for the models to come up with coherent summaries that capture the flow of the document.

One of the critical drawbacks of an approach is a problem of coherence maintenance within the produced summaries. While BERT and GPT and other transformer-based models can grasp relations of context, they frequently fail at keeping the logical flow between multiple sentences and especially when the text being analyzed is rather complex or contains multiple shades of meaning. This can lead to generated summaries which are not clear and coherent, and in turn reduces the quality of the summaries [37]. However, working with complex discourse – including irony, idioms or contextual information – is still difficult which leads to summaries with misunderstood message or summarized meaning [38].

Another important limitation is the problem of maintaining the coherence of generated summaries. Despite efforts by many authors to apply transformer-based models such as BERT and GPT to identify contextual relations, these models often fail to identify logical connections at the inter-sentence level, especially where a text is complex and or subtle. This can lead to some generated summaries which are not well articulated which reduces their quality [37]. Furthermore, simple/heavy language and failure to grasp lexical, semantic, and pragmatic phenomena, including irony, idioms, and contextual data, remain work in progress, and this can result in summaries that distort or losegetattr the original message [38].

The need to use a large volume of labeled data to train deep learning models is still a major challenge with this type of data. A number of current best-known methods of summarisation entail the use of large datasets that are time-consuming to build. Such a restriction can lead to models that exhibit high accuracy on particular datasets and act relatively poorly when it comes to generalizing the obtained results to other data samples and application scenarios [36].

There is always bias as it is with any of the existing approaches. When using the training data set that does not capture the target domain, models can create biased, or partially summarized text. This is especially true in domains like Healthcare or Finances because biased summaries are not just incorrect, but can lead to worse outcomes [39].

The evaluation of summarisation models also has difficulties. In fact, the automatic evaluation tools like ROUGE and BLEU, although measure scores, do not still grasp the qualitative aspects including coherence, relevance, and readability [40]. However, models evaluated based on these measures can yield poor quality summaries from a human point of view, indicating the importance of including human-centric evaluation criteria at the assessment [41].

2.1 Summary of Literature Review

Author(s)	Year	Title	Datasets	Objective	Architecture
Mohmmadali Muzffarali Saiyyad, Nitin N. Patil	2023	Text Summarisation Using Deep Learning Techniques: A Review	DUC 2002 Dataset, DUC 2003 Dataset, BC3 Dataset, Arabic Dataset, Bengali Dataset, Malayalam Dataset.	Present an overview of deep learning methods for text summarisation. Review effects of neural networks (seq2seq) on coherence and readability.	Seq2Seq models, Deep Learning
Haopeng Zhang, Philip S. Yu, Jiawei Zhang	2024	A Systematic Survey of Text Summarization: From Statistical Methods to Large Language Models	CNN/ DailyMail and XSum are referenced.	To provide a comparative study of summarization methods, categorize them into extractive and abstractive types, and highlight advancements in transformer-based models for improved coherence and context retention.	Extractive and abstractive summarization models, with emphasis on transformer-based architectures like BERT and GPT.

Author(s)	Year	Title	Datasets	Objective	Architecture
Hassan Shakil, Ahmad Farooq, Jugal Kalita	2024	Abstractive Summarization: State of the Art, Challenges & Improvements	CNN/ DailyMail, XSum, and Gigaword	To review the state of the art in abstractive summarization, highlight its benefits, limitations, and propose solutions to improve factual accuracy and reduce hallucination.	Focuses on integrating extractive and abstractive methods to overcome issues like hallucination, high computational cost, and sequencing problems in abstractive models.
Z. Liu, H. Zhang, and Z. Li	2022	Extractive Text Summarization: A Survey	CNN/ DailyMail, xsum, Reddit TIFU Dataset	Classification of Summarization Methods, Evaluation of Techniques, Addressing Challenges	Focus on graph-based, machine learning-based, and neural network-based extractive methods
M. S. Hossain, M. A. A. Razzak	2021	A Review of Abstractive Text Summarisation Methods	CNN/ DailyMail, XSum (mentioned)	Review abstractive summarisation methods, compare sequence-to-sequence models with RL and attention mechanisms,	Reinforcement Learning, Attention Mechanisms, Deep Learning

Author(s)	Year	Title	Datasets	Objective	Architecture
N. A. W. H. A. Ali, S. S. U. A. Salih, S. K. N. P. Hasan	2022	Deep Learning for Text Summarisation: A Comprehensive Review	CNN/ Daily-Mail, XSum	Review deep learning techniques, emphasize the use of LSTM, GRU, and transformers for news summarisation, discuss challenges like computing power and data quality.	LSTM, GRU, Transformers, Pre-trained Language Models
S. Parveen & R. S. Pandey	2021	Abstractive Text Summarization Using Deep Learning	CNNDM ,CNNDM ,VieSum ,VieSum	To explore how deep learning impacts abstractive summarization methods, focusing on attention mechanisms and transformer architectures like BERT and GPT.	Sequence-to-sequence models, attention mechanisms, BERT, GPT
K. Xu, A. Yuan, & J. Liu	2020	A Review of Neural Summarizing Models: Past, Present, and Future	CNN/ Daily Mail Dataset. CNN/Daily Mail dataset	To evaluate the transition from RNN-based models to transformer architectures, focusing on contextual information handling and attention mechanisms.	RNN-based models, Transformer models, Attention mechanisms

Author(s)	Year	Title	Datasets	Objective	Architecture
B. Lee, J. Park, & S. Kim	2020	Abstractive and Extractive Summarization Using Transformers	Science Direct database	To explore the impact of transformers (BERT and T5) on improving summarization quality, and to identify challenges related to factual consistency and document length.	BERT, T5, Transformer-based models
R. Kumar, P. Verma, & A. Singh	2023	Recent Advances in Text Summarization with Large Language Models	, CNN/Daily Mail and Extreme Summarization (XSum)[	To explore the capabilities of large language models (GPT-3, T5) in text summarization, focusing on fine-tuning, hallucinations, and domain-specific fine-tuning needs.	GPT-3, T5, Large Language Models (LLMs)

Chapter 3

Methodology

3.1 Problem Definition

3.1.1 Introduction

Dialogue summarisation is relevant NLP task that aims to generate brief summary of long conversational sequences. In view of the changing dynamics of communication processes with the emergence of new social tools for instant messaging, handling customer queries or virtual conferences, the need arises to develop systems for summarizing dialogues. Manual summarisation is highly impractical mainly because of the enormous number of dialogues produced per day. Thus, further progress of the dialogue summarisation frameworks with high performance and accuracy is valuable for increasing the value of the conversations for users, optimizing the information search, and making substantial decisions.

3.1.2 Significance of Dialogue summarisation

The relevance of dialogue summarisation, therefore, is in its capacity to enable users to parse through untapped discussion fast enough by coming up with summaries. Fast access to patient records is crucial in healthcare, and the large number of inquiries in customer support is fundamental to success. That's why our tools for automated summarisation shed a great light on increasing organizational output and customer satisfaction.

3.1.3 Challenges in Dialogue summarisation

However, there are some problems with dialogue summarisation First, the architecture of the system. This is because conversational language used during the conversation is informal and is comprised of interruptions, overlapping talk and the like which makes it

very difficult to summarize the conversation. In addition, models need to learn context features and continuity of the summarized text besides facing the challenge of the language vagueness.

3.1.4 Objectives of Dialogue summarisation

The goal of the present study will be to build a function of deep learning for dialogue summarisation that will meet the discussed challenges. This includes finding out the extractive and abstractive type of summaries and comparing and performing their effectiveness in certain conversational scenarios.

3.2 Data Collection

3.2.1 Dataset Selection

As the primary dataset for this research on dialogue summarisation, the SAMSum has been selected because it portrays real-world dialogues with human-summarized sums. It is officially acknowledged in the NLP field as the dataset for dialogue summarisation tasks that enable extractive as well as abstractive methods. This work provides an explanation of the internal and external composition of the SAMSum dataset, the information the database contains and how it benefits users before giving an account of the rationale for choosing the dataset.A brief introduction of the SAMSum Dataset:

Number of Dialogues:

- The SAMSum dataset consists of dialogues more than 16000. Every dialogue is created to mimic real-life, common conversations between two or more persons, making the set large enough to train and test deep learning models.

Structure:

- Every dialogue consists of one or more communication exchanges between some of the parties. Such turns reflect the actual conversation and the flow of various sorts of conversations such as informal, conflict, question, and task conversation. This structure replicates the informal and if possible chaotic pattern of human conversations.
- The dialogues differ in length and achieve various levels of complexity, this is good for testing the ability of the algorithms for summarizing the context while at the same time trying to allocate the primary role for the function of contextual flow.

Summaries:

- When pupils study each article, they are presented with a synopsis of the main concepts and important incidents of the dialogue written by people. They act as training and validation data for the models that we build and intend to use for extractive summaries.
- The summaries are anticipated to outline the core of the communication as agreements, solutions to the emerging issues, decision made, or other essentials that the conversers may share.
- Here, the summary manually produced by a human being serves as a gold standard against which the quality of generated summaries in the system will be assessed.

Language:

- The dialogues used in the play are created in colloquial language which might be observed in today's digital communication – messaging, chats, and interactions. This informality includes:
  - Some informal expressions (everyday intonation, for example, 'gonna,' 'btw').
  - Specific symbols and characters (e.g a typographic symbols "lol"/"idk").
  - Free-flowing and frequently lack grammar structures, and akin to human-to-human communication that occurs over the Internet.
- Summarizing these dialogues requires an understanding of context, participant roles, and implicit meanings that go beyond sentence structure, making it a more complex challenge than summarizing formal, well-structured texts.

3.2.2 Data Preprocessing

The next step is data preprocessing when dialogue data will be prepared in its original form for application to machine learning models after choosing the SAMSum dataset. This action leads to improved quality of data, and managing of noise levels while organizing data structures that will allow models to make their learning. Considering the nature of the SAMSum dialogues, preprocessing is a crucial pre-step for handling such issues as slang, non-full sentences, and asymmetric conversation structure.

This preprocessing of data is crucial in the data pipeline required when deployment using the SAMSum dataset. Each of the steps involved in preprocessing, cleaning of

the text, handling of informal language, tokenization, and balancing the data set is critical in the transformation of the raw dialogues into a form that is palatable to deep learning models. The enhancement in the current model is due to the preprocessing that enables the model to reduce or eliminate interference from unnecessary dialogue features that hinder it from summarizing accurate context-based dialogues. This helps in the strengthening of the dialogue summarisation system and hence can handle informal conversational types.

Text Cleaning

The first substep of data preprocessing is text cleaning, and the unwanted parts of the dialogues to decrease the noise level are deleted. Punctuations, symbols (@, #, $). emojis are under regular expressions removed because these add no value toward the summarisation of the dialogues. Also, URLs and email addresses are removed as they contain information which is not important for the task at hand. Excess white spaces from the texts are also removed to help enhance homogeneity in the matter of tokenization. Additionally, signals which are not text, such as system notification (e.g., 'User has joined the chat') that can be observe in a dialogue, are excluded. It also makes certain that only the required conversational text will be carried forward for processing to the next stage.

Lowercasing

Thus, all the text is converted to lower case to make all the data uniform in the dataset. Dialogue summarisation models do not differentiate between upper and lower case, hence everything is converted to lower case to simple tokenization and reduce the dimensionality of the data. In this way, for example, "Hello" and "hello" are equal to the model, which makes the use of its define and learn process more effective and gives it the ability to learn patterns in the text.

Tokenization

Here in this research, tokenization was performed using a pretrained BART tokenizer Facebook/BART-Large-CNN from Hugging face Transformers. The BART approach, especially suited for the summarisation task, implies that both input and target sequences are tokenized to facilitate sequence learning at the sequence level. This section defines how the input text known as "dialogue" has been tokenized, along with the same fate for the goal text described as "summary."

- Input Tokenization: The text of the dialogue was preprocessed by tokenization with the use of the 1024 tokens as the maximum number of tokens allowed

per input for BART model, where texts with more tokens in the example were trimmed. This allows retaining of crucial context while at the same time converting each input into the specific integer that corresponds to the model's vocabulary.

- Target Tokenization: Target summaries were tokenized separately in so-called "target mode" and were allowed a maximum of 128 tokens to produce compact output. This technique serves well the BART sequence-to-sequence alignment, which makes sure that predictions remain consistent with the summary structure.
- Label Assignment: These target sequences were then tokenized and provided as the labels within the input data so that the model could learn during training process of the ML with reference to these distinct labels.
- Batch Processing: Tokenization was done in batches for faster preprocessing of data, lesser computing time and batch-wise similarity between samples was achieved and the procedure was made optimal for extremely large number of samples.

3.3 Exploratory Data Analysis (EDA)

Dataset Structure: First, check the columns of data, types of data present in the dataset (text, category or numerical), etc., and the form or structure of the data set. This first view gives an idea of what data fields are available at hand which will be the dialogue text, summaries, etc. Distribution of Dialogue Lengths: Summarize the length of dialogs by counting the number of words or token that belong to each dialogue entry. A simple analysis of the range, median and variability of the dialogue length may be accomplished by the use of a histogram or a box plot. Such information is helpful when setting the boundaries for the truncation in tokenization while identifying the normal size of the inputs. Distribution of Summary Lengths: As is the case with dialogues, evaluate the lengths of the summaries. This is done through simple statistical measures such as summary length's mean, median and standard deviation among others. The plotting of these lengths can show if summaries have a uniform length or have high variation, which influences the output length parameters of the model. Common Topics and Dialogue Turns: If you have dialogues and the summaries of them then mark the similar topics and keywords with frequencies and/or word clouds. Furthermore, if the dialogues at the turn level (unique contributions made by different partners) have been recorded, it is also useful to assess the average number of turn per dialogue. This research can show that in some cases talks are indeed short and simple while in others they are long and complex affecting the models. Visualization: Descriptive data repre-

sentations such as histogram, box plot, word cloud, scatter plot bring out patterns and trends which cannot be easily pointed out. For example:

- Word Clouds: For common subjects.
- Histograms: For both dialogue and summaries, but can also be used for all other types of tasks.
- Box Plots: For cross comparison in relation to the length of the dialogues and summaries.

3.4 Model Selection

To obtain excellent text summarisation for the Samsung dataset, we tested three sophisticated deep learning models: These models include BART, PEGASUS and T5 all of which are architectures of the Transformer. Composed of both encoder-decoder architecture and autoregressive decoder, BART also learns context understanding from its denoising pretraining objective. PEGASUS used for abstractive summarisation has a recent unique pretraining approach of masking out entire phrases so it focuses on important contextual details that are ideal for denser technical tables such as; Samsung's. T5 now known as Text-To-Text Transfer Transformer is a general purpose network that looks at all NLP tasks as text generation problems.

3.4.1 BART (Bidirectional and Auto-Regressive Transformers)

BART is a state-of-art model in natural language processing tasks, especially text summarisation. This makes it a sequence to sequence model, while at the same time incorporating the capabilities of both bidirectional and autoregressive transformers. The model is similar to other models and it also has an encoder and a decoder in the framework, but different to other models is that the encoder takes bidirectional steps to capture context from forward and backward layers with regards to the input text, while the decoder works in an auto regressive manner similar to GPT. In BART, the pretraining objective proposed is also based on a denoising autoencoder setup, where the model attempts to reconstruct original text from a noisy input. This denoising work improves BART's capability to learn contextualization and between words' connections, leading to stylistically smooth and semantically connected results. BART has been implemented with a high level of performance on various NLP benchmarks making it ideal for use in content distillation[42], [43].

3.4.2 PEGASUS (Pre-training with Extracted Gap-sentences for Abstractive summarisation)

PEGASUS is designed for abstractive summarisation, and it is built with the Transformer model in order to analyze and generate texts. Its pretraining algorithms differ from the traditional ones and it learns the masked sentences rather than individual tokens so it can determine what is more important for the input text. Masking occurs in pretraining where words in a sentence are deleted and PEGASUS is required to predict them from context. It raises the model's ability to pick up important details, which has been learnt to mimic human summarizing strategies focused on important information.[44]

PEGASUS has also done well in other summarisation tests and is especially impressive on the CNN/Daily Mail datasets. The coherence of the summaries and the relevance of the context in which they are placed makes it a powerful tool when good content distillation is needed for a certain application.[45]

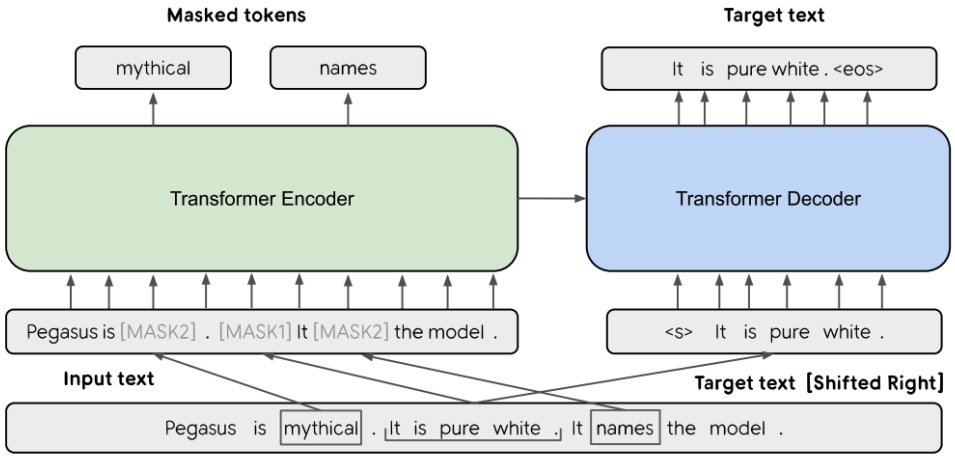


Figure 3.1: PEGASUS model explained

3.4.3 T5: Text-To-Text Transfer Transformer

Text-to-Text Transfer Transformer 5, or T5, is an MLP framework designed for a broad array of NLP functions. It casts all operations as text synthesis tasks. T5 was developed based on the Transformer architecture, where inputs and outputs are all string texts; thus, it enables easy fine-tuning to many NLP tasks such as summarisation, translation, and answering questions. This approach enables T5 to leverage the architecture in many ways since its architecture serves multiple purposes, hence enhancing the aspect of flexibility in term of usage of the model[46].

One characteristic for the pretraining process of T5 is that it has the fill-in-the-blank goal in its model. In this phase, the model learns in Extended version on wide range of challenges where it is trained to predict the missing text span. The methodology increases the ability of the model to produce grammatically correct and semantically fitting textual output while simultaneously ensuring its ability to transfer well across datasets and tasks. As all tasks are squeezed into text-to-text format the method is highly efficient for zero-shot and few-shot learning, moreover, fine-tuning for new problems is easier due to the unified format of the tasks. T5 has performed quite well in terms of benchmarks and has come close to producing high quality summaries while maintaining the intent from the source. It is thus suitable to be used in jobs that require an effective separator of content since it is flexible and very efficient[47].

3.5 Training Configuration

The model training applied a Seq2Seq trainer provided by the transformers library is used in this work. The training was designed to be performed at most three epochs, where capability of early stopping was employed, which stopped the training performance if the validation performance did not enhance during two consecutive assessments. Specific parameters included training the model on an NVIDIA GPU for faster computation, and executing early stopping to avoid using further time while the model may overfit.

3.6 Optimization Parameters

Training entertaining used a learning rate of 2e-5 with weight decay set as 0.01 to minimize over-fitting. Training and evaluation batch sizes were both set to 8, to optimize the run time without overwhelming available memory.

3.7 Model Testing

3.7.1 Validation and Testing

After the training procedure, the parameter of the self constructed SAMSum model was evaluated using the validation and test set. For evaluation, ROUGE a simple tool was applied with the scores from ROUGE-1, ROUGE-2, and ROUGE-L F1 as a way of measuring how well a model can identify the more important issues being discussed.

3.7.2 Custom Dialogue Testing

Generalization capability was estimated by creating a model with a specific conversation that created summary of the data never encountered and then run a real-life like simulation.

3.8 Evaluation Metrics

ROUGE was used in measuring the quality of the generated summaries against reference summaries as commonly applied in most research. For both the validation set as well as the test dataset, the ROUGE-1, ROUGE-2, and ROUGE-L F1 scores were provided. This it was monitored up to the conclusion of the process for the model; it also stored the best model according to the ROCUE-1 scores.odel.

3.9 Result Visualization

The training and validation losses were monitored epoch wise and graphs representing the number of epochs were plotted to check the convergence of model. Furthermore, the ROUGE parameters on the test set were graphed to facilitate an understanding of the summarisation model at large.

Chapter 4

Experimental Design and Testing

4.1 Dataset

The Samsum is a conversational dataset that is purely meant to facilitate text summarisation models in regard to dialogue data. It can access the Samsum dataset from huggingface. co .Samsung R&D Institute Poland created the SAMSum dataset, which is made available for research use under a non-commercial license (CC BY-NC-ND 4.0).
Each entry typically includes:

- dialogue: The full text of the conversation, where each turn of the conversation is on newline.
- summary: A brief summary of the conversation, often in one or two lines.

Currently, it is applied in natural language processing tasks, especially in training and testing dialogue summarisation. This dataset can help us learn how to extract meaningful information from multi-turn conversations. Such approaches have been assessed on a basic dialogue summarisation benchmark called the Samsum dataset, which has become rather popular for training, such as BART, PEGAS US, and T5.

index	dialogue	summary
0	Amanda: I baked cookies. Do you want some? Jerry: Sure! Amanda: I'll bring you tomorrow :-)	Amanda baked cookies and will bring Jerry some tomorrow.
1	Olivia: Who are you voting for in this election? Oliver: Liberals as always. Olivia: Me too!! Oliver: Great	Olivia and Olivier are voting for liberals in this election.
2	Tim: Hi, what's up? Kim: Bad mood tbh, I was going to do lots of stuff but ended up procrastinating Tim: What did you plan on doing? Kim: Oh you know, uni stuff and unfucking my room Kim: Maybe tomorrow I'll move my ass and do everything Kim: We were going to defrost a fridge so instead of shopping I'll eat some defrosted veggies Tim: For doing stuff I recommend Pomodoro technique where u use breaks for doing chores Tim: It really helps Kim: thanks, maybe I'll do that Tim: I also like using post-its in kaban style	Kim may try the pomodoro technique recommended by Tim to get more stuff done.
3	Edward: Rachel, I think I'm in ove with Bella.. rachel: Dont say anything else.. Edward: What do you mean?? rachel: Open your fu**ing door.. I'm outside	Edward thinks he is in love with Bella. Rachel wants Edward to open his door. Rachel is outside.
4	Sam: hey overheard rick say something Sam: i don't know what to do :-/ Naomi: what did he say?? Sam: he was talking on the phone with someone Sam: i don't know who Sam: and he was telling them that he wasn't very happy here Naomi: damn!!! Sam: he was saying he doesn't like being my roommate Naomi: wow, how do you feel about it? Sam: i thought i was a good roommate Sam: and that we have a nice place Naomi: that's true man!!! Naomi: i used to love living with you before i moved in with me boyfriend Naomi: i don't know why he's saying that Sam: what should i do??? Naomi: honestly if it's bothering you that much you should talk to him Naomi: see what's going on Sam: i don't want to get in any kind of confrontation though Sam: maybe i'll just let it go Sam: and see how it goes in the future Naomi: it's your choice sam Naomi: if i were you i would just talk to him and clear the air	Sam is confused, because he overheard Rick complaining about him as a roommate. Naomi thinks Sam should talk to Rick. Sam is not sure what to do.

Figure 4.1: first five rows from the training split

This work employs an up-to-date, large-scale dataset referred to as SAMSum, consisting of 16,000 English conversational turns collected from language professionals.

These dialogues are typical of modern summarisation of dialogue-based dialogues. The dataset consists of 16,369 discussions divided into four categories: constrained .tc, summarized human dialogue representation, and example ID. In total, we split the dataset into the training, validation, and test sets, which contain 14,732, 818, and 819 samples, respectively. This is good practice for situations involving dialogues in our day-to-day conversations.

```
Dataset Info:
DatasetDict({
    train: Dataset({
        features: ['id', 'dialogue', 'summary'],
        num_rows: 14732
    })
    test: Dataset({
        features: ['id', 'dialogue', 'summary'],
        num_rows: 819
    })
    validation: Dataset({
        features: ['id', 'dialogue', 'summary'],
        num_rows: 818
    })
})
```

Figure 4.2: contains all the splits of Samsum datset

4.2 Experimental Setup

For this experiment, we fine-tuned and tested the Pegasus model on the SAMSum corpus using Google Colab with GPU resources. The setup started by installing key Python libraries: **Gatherers**: `transformers` (v4.28.0), `datasets` (v2.7.1), `evaluate` (v0.2.2), `sacrebleu` (v1.5.1), `rouge_score` (v0.1.2), and `py7zr` (v0.11.3). We fine-tuned the `google/pegasus-cnn_dailymail` model checkpoint and adopted the `AutoTokenizer` from Hugging Face for tokenization and set up the device as `cuda` for GPU computation. We used the SAMSum dataset (v1.0.0) for training and evaluating the model. The pre-processing steps included tokenization using `nltk` (v3.7) for sentence tokenization, using `DataCollatorForSeq2Seq` for batch operations, and `tqdm` (v4.64.0) for progress updates. Several parameters from an instance of the `Trainer` were set to manage training memory, including `num_train_epochs=1`, `warmup_steps=500`, `weight_decay=0.01`, `per_device_train_batch_size=1`, `per_device_eval_batch_size=1`, and `gradient_accumulation_steps=16`. Evaluation of the model was done using the ROUGE metric with the command `evaluate`, and the results were presented in tabular form using `matplotlib` (v3.5.1) and `pandas` (v1.3.3) by storing the scores in a `DataFrame` for easy comparison. Training was followed by saving the model and the tokenizer with the name '`pegasus-samsum-model`' for reproducibility. The setup also involved comparing the frequency of generated and reference summaries with bar graphs that portrayed word frequencies of the model.

Here in this experiment, the BART model is fine-tuned for text summarisation on the SAMSum dataset which consists of dialogues along with their summaries written by humans. This experiment was done in a Google Colab using Python 3.10.12 as the Python environment. We loaded the following basic libraries such as transformers version is 4.28.1, datasets version is 2.12.0, evaluate versions is 0.4.0, nltk version is 3.6.5, matplotlib version is 3.7.1, pandas version is 1.5.3, tqdm version is 4.65.0 and torch version is 2.0.1 with cuda For model and tokenizer control the Hugging Face transformers library was used, and more specifically the facebook/bart-large-cnn checkpoint. The SAMSum dataset was then loaded and we looked at the splits of the dataset including training, validation and test. For the evaluation of the models, we used ROUGE metric to help in the quantitative measurement of the quality of the generated summaries and in order to accommodate the data flow during the evaluation We employed batch processing. Hence, visualization of token lengths of dialogues and summaries was done to check text complexity. Training was done using the Trainer class from the transformers module in PyTorch together with the training arguments which comprise of one epoch, base batch size of 1, with logging steps for training performance. Finally we used the test dataset to obtain final RO Rouge score on the trained model and create a pandas DataFrame to summarize the scores. Lastly, a trained BART model and tokenizer are saved for future functionality in the domain of summarisation. This comprehensive setup makes the work reproducible and offers a sound foundation for subsequent work in automated summarisation methods.

In this experiment, we trained and tested the T5 model on the SAMSum dataset in a Google Colab environment with GPU support. The setup began with the installation of key Python libraries and specific versions to ensure compatibility: `transformers` (v4.28.0), `datasets` (v2.7.1), `evaluate` (v0.2.2), `sacrebleu` (v1.5.1), `rouge_score` (v0.1.2) for evaluation metrics, and `py7zr` (v0.11.3) for data extraction. The SAMSum dataset (v1.0.0) was loaded to provide dialogues and summaries for training. We used the `t5-base` (v1.1.0) model from Hugging Face, setting the device to "cuda" to enable GPU processing.During data processing, tokenization was performed with `nltk` (v3.7), batch collation with `DataCollatorForSeq2Seq`, and progress tracking with `tqdm` (v4.64.0). To ensure fair training, we configured the `Trainer` with parameters: `num_train_epochs=1`, `warmup_steps=500`, `weight_decay=0.01`, and a batch size of 16, along with gradient accumulation to manage memory usage.Model evaluation was conducted using ROUGE scores on the test split and visualized with `matplotlib` (v3.5.1) and `pandas` (v1.3.3), with results saved in a DataFrame for comparison. After training, we used word and character counts to analyze generated and reference summaries, assessing the model's conciseness in language usage. Finally, the trained model and tokenizer were saved, resulting in a reproducible architecture with consis-

tent model parameters and structured data analysis.

4.3 Results

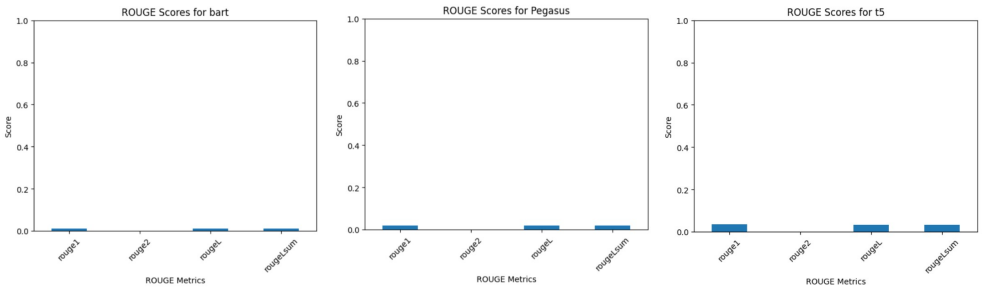
we compared the performance of three models fine-tuned on the SAMSum dataset for text summarisation: Pegasus, T5, and BART. Using ROUGE (Recall-Oriented Understudy for Gisting Evaluation) metric, the output of each model was assessed, primarily giving importance to ROUGE-1, ROUGE-2, and ROUGE-L ROUGELSUM measure that estimate the extent of unigrams, bi-gram, and longest common subsequence respectively between the generated and reference summaries.

Model	ROUGE-1	ROUGE-2	ROUGE-L	ROUGE-Lsum
BART	0.012645	0.000255	0.012591	0.0126
T5	0.034551	0.000474	0.033456	0.03346
PEGASUS	0.015541	0.000296	0.015525	0.01556

Table 4.1: Overall ROUGE Scores

Model	average ROUGE scores
BART	0.009523
T5	0.025985
PEGASUS	0.011731

Table 4.2: Comparison of average ROUGE scores



(a) BART model (b) Pegasus model (c) T5 model

Figure 4.3: Overall ROUGE-1, ROUGE-2, and ROUGE-L ROUGELSUM

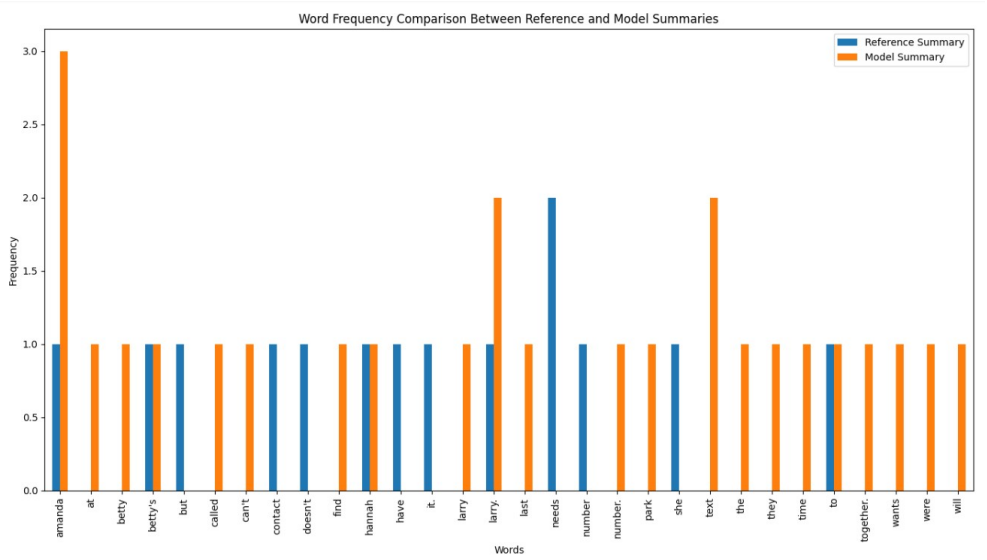


Figure 4.4: Word frequency of BART model

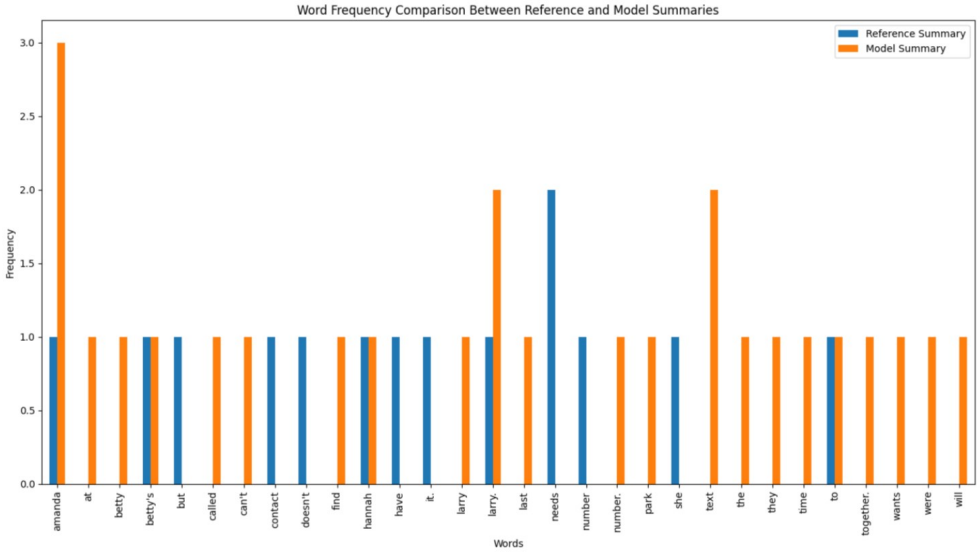


Figure 4.5: Word frequency of Pegasus model

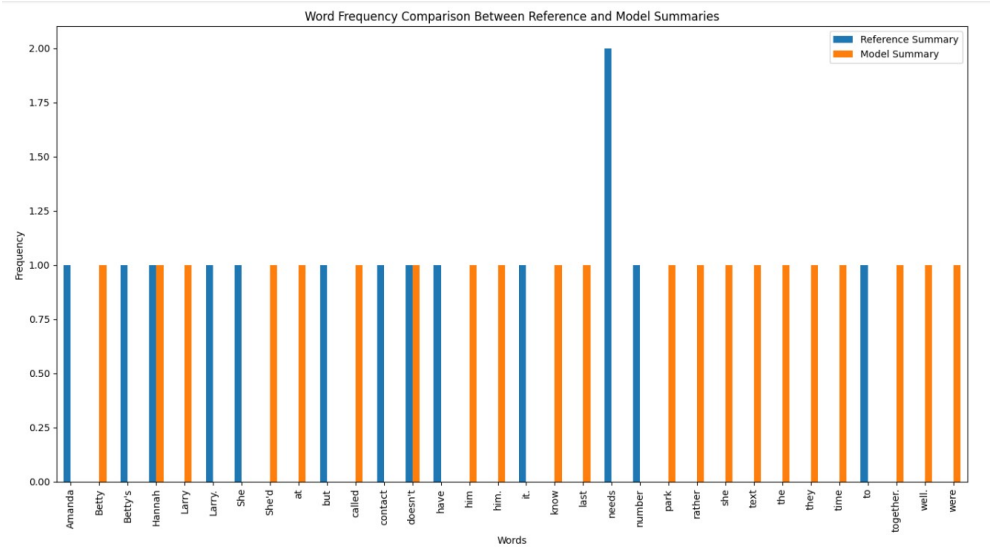
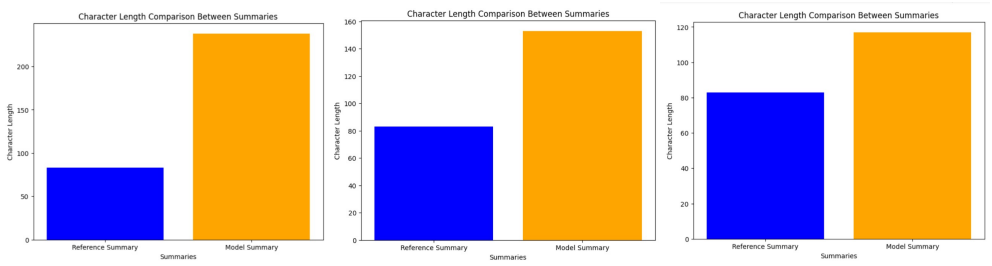


Figure 4.6: Word frequency of T5 model

models are comparing the token lengths of the Reference Summaries with the token lengths of the summary generated by model such as PEGASUS, BART, and T5 which is discussed in the "Length Comparison Between Reference Summary and Model Summary" the section.



(a) BART model (b) Pegasus model (c) T5 model

Figure 4.7: Overall Length Comparison Between Reference summary and Model summary

4.4 summary

In this work, the summary of text documents using three transformers, including BART, T5, and Pegasus, has been assessed based on ROUGE scores. The models were compared using ROUGE-1, ROUGE-2, ROUGE-L, and ROUGE-Lsum.

When evaluated, BART posted a ROUGE-1 score of 0.012645, ROUGE-2 0.000255, ROUGE-L 0.012591 and ROUGE-Lsum 0.0126. BART had significantly lower ROUGE scores comparatively in the four modalities but not extremely poor because it could set a fundamental benchmark.

In the case of T5, it came out better overall with the n-gram overlap ROUGE-1 at 0.034551, ROUGE-2 at 0.000474, ROUGE-L at 0.033456 and finally, the ROUGE-Lsum at 0.03346. The scores for T5 are higher, which means that this model provided summaries more relevant and coherent overall, as well as more relevant with respect to ROUGE-1 and ROUGE-L, which calculate the unigram overlap and the longest overlapping subsequence and string, respectively.

PEGASUS offered moderate performance compared to both BART and T5, with the ROUGE-1 score of 0.015541, ROUGE-2 score of 0.000296, ROUGE-L score of 0.015525, and the ROUGE-Lsum score marking 0.01556. Despite PEGASUS scoring higher ROUGE than BART, PEGASUS outperformed BART but had lower scores than T5, further proving that PEGASUS is good but not the best at coming up with perfect summaries.

Across the board, the ROUGE-L and ROUGE-1 scores suggest that T5 has significantly superior performance to both the BART and PEGASUS models. However, PEGASUS and BART can still be considered efficient competitors that can be used, depending on the certain requirements of the summarisation model.

Chapter 5

Future Work And Conclusion

5.1 Future Work

In this investigation, four deep learning models for text summarisation were directed at the SAMSum dataset. Here, three models based on transformers, BART, T5, and PEGASUS, were used, trained, and optimized as per the experiment. Their performance was measured using ROUGE scores. However, there are some directions for further research that could complement and extend the results obtained in the present study:

- Dataset Expansion: As with most studies, we have limited our data sources to a few domains so that future work could focus on a more diverse set of data sources for training and testing of models. Using the proposed models in other conversational corpora, including customer service conversations or interactional chats, might help to extend the analysis of the model's behaviour under different dialogue configurations.

- Advanced Preprocessing Techniques: Some of the preprocessing methods, like dialogue segmentation and entity recognition, could also be tested to get better output of the generated summaries. Some improvements done to the preprocessing may add richer conversational context and the relations between the speakers to the mix, which in turn can help to produce summaries that are more coherent and concise.

- Integration of Knowledge-Based summarisation: Further work could build on how such summaries could be complemented with external knowledge sources to provide additional context when learning about conversational data with references to more significant events or phenomena. In knowledge-based summarisation, the overall model performance could be enhanced due to an AI system's ability to create summaries with the added context and background information.

- Developing User-Centric Evaluation Tools: Thus, whereas summarisation is a purely subjective task, using user-oriented assessment methodologies for evaluating the quality of summaries in terms of their relevance, coherence, and informativeness is more informative of the performance of the models. It would be beneficial to apply users' feedback, particularly from the individuals who work with lots of conversational data, to enhance the evaluation procedure and optimize model results towards utilization.

5.2 Conclusion

In this work shows that transformer-based models such as BART, T5, and PEGASUS are promising for conversational text summarisation, mainly when applied to the SAMSum dataset. Conducting systematic training and testing of T5 in a GPU environment showed that T5 yielded the highest ROUGE scores, indicating its better capability to generate and recapitulate dialogue content. Even though the performance of PEGASUS and BART was rather similar, owing to the architecture of T5 and the obtained pre-trained weights, the summaries were less ambiguous and provided more comprehensive information.

This work establishes the potential of adaptively fine-tuning pre-trained models for summarizing conversational data, which opens up the possibility of deploying approaches like these in other application areas, such as customer service, live chats, and content filtering. Future work could involve trying to overcome the issues above, namely, dataset variation, improved preprocessing, and more extensive measures of performance in order to improve the existing models of summarisation. Through improving these models and evaluation approaches, an effort to produce natural language summaries with better SK that are much like human-like summaries in terms of brevity and relevance, the advantages of conversational summarisation can be expanded to other practical applications.

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