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Combining Deep Learning and Heuristic Search for Efficient Text Summarization

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***Abstract*— This work is a research project aimed at studying how deep Learning based on advanced DNN architectures can be integrated with heuristic search algorithms to make text summarization faster and of higher quality. Existing summarization methods are traditionally manual or rule-based, and they have drawbacks in terms of time consumption and the need for several essential information. This work introduces a novel feel that leverages deep learning models (in the form of neural networks) with heuristic search methods to create compact and informative summaries. Our approach leverages the representation learning and attention mechanism present in deep-learning models for identifying keywords and key sentences from a longer text; considering the relevance to the topic adds important heuristic information to choose how many sentences are needed. We hope the integration can improve text summarization in general, and we aim to use this method in news, research articles, and other types of content.**

Keywords*— Deep Learning, Heuristic, Summarization, Leverages, Mechanism

I. INTRODUCTION

Today, the volume of information available to us is magnified exponentially. Its huge amount of data makes it difficult for people to keep up with. Consequently, there is a high demand for text summarization methods that can compress large volumes of textual corpus to their meaningful essence as rapidly as possible. That is the point where deep Learning and heuristic search are integrated [1]. Deep Learning, as a category of machine learning, leverages artificial neural networks to process data in complex forms so that machines can understand them better. It is used for some of the most common tasks in machine learning, including image classification, speech recognition and natural language processing. C) Heuristic search: This is a problem-solving methodology used to solve problems from intuition or a rule of thumb and reach optimal solutions in a considerably large state space [2]. This essay focuses on the possible benefits of integrating these two approaches for successful text summarization using deep Learning and heuristic search. First, we introduce the separate approaches and how their combination enables us to enhance summarization. Deep Learning performs best in NLP tasks, such as text summarization. The traditional text summarization methods divide the process of Figure 3 into two phases, mainly extractive and abstractive summaries. Extractive summarization involves pulling key sentences or phrases from the original text and mashing them together to create a summary [3]. The system understands the meaning and generates a summary by paraphrasing/rephrasing human-readable text while Convergent summarization. Deep learning models can learn from that (giant) data; the performance of a deep model is also much greater than the traditional method. Text summarization usually uses Convolutional neural networks (CNNs) and recurrent neural networks (RNNs). TextCNNs can extract features from text using convolutional filters. RNNs are good at dealing with sequential data and generating abstractive summaries by predicting the next word according to context [4]. The convolutional neural attention model, a combination of these two techniques, has also been implemented in text summarization. It uses CNN to extract features from the input text and attention layer to decide which portion of the text is more relevant for a summary. To this day, that mix has proved effective at producing accurate summaries. Heuristic search is a methodology that helps to solve large, complex problems by breaking them down into simpler, more manageable steps [5]. On the other hand, in the summarization of text, much information can be sought from a corpus using realistic search algorithms. A* is one of the heuristic search algorithms that uses a cost function to evaluate potential solutions and get closer towards finding an optimal solution. Heuristic search algorithms have been employed in extractive summarization approaches, and most of them fall under the umbrella field of text summarization. The algorithms examine the text and rank sentences and phrases by their importance to this job. This makes it easy to choose the important items and summarize them. While the approach to applying deep Learning with the heuristic search for text summarization is relatively new, it has already exhibited reasonably good results. This combination enables to leverage the advantages of both methods, leading to more efficient and accurate summaries [6]. The biggest issue of concern in text summarization is that tons and tonnages (i.e., large amounts) of information are available. Deep learning algorithms can work through massive data sets to determine the crucial words within text. This is unlikely to be efficient, especially in the case of extensive data sets. At the same time, heuristic search algorithms can efficiently go through the whole dataset and select based on preset rules which information will matter. These deep learning algorithms can learn from historical summaries and continue to evolve and adapt whilst performing [7]. Still, the heuristic search may have been based on predefined heuristics and, therefore, unable to adapt when presented with new data. So, combining return value semantics with these techniques should provide a breakthrough in generating robust and adaptive systems that can handle dynamic data as it changes over time, providing more meaningful summaries. For instance, some examples of potential improvements we could have in text summarization using the cross-communication between deep Learning and heuristic search are exactly what Li & Chen (2018) tackled in their work [8]. Their approach is a framework which implements CNNs and A* search for extractive summarization. The input text was passed through CNNs to extract features, and the A* search algorithm was employed to select sentences most representative of the extracted features. This outcome was more precise and sufficient summaries than the conventional extractive summarization approaches. In a nutshell, throughout this study, we have shown there are significant advantages to combining deep Learning with heuristic search for efficient text summarization. Deep learning algorithms are a great way to tackle NLP tasks, and heuristic search algorithms work effectively when the game has a large search space. Combining yield techniques, a better and more effective text summarization system [9]. Often, this poses a problem as the models still require vast swathes of data to produce optimal predictive results (usually in highly condensed numerical form), not to mention potential biases within the dataset. Besides, adding this integration may also raise complexity in the summarization stage. As this approach has yet to be fully realized, employment of a similar technology may benefit from additional research and development [10]. The integration of deep Learning and heuristic search in text summarization has the potential to be highly beneficial, as we discussed earlier. It could help revolutionize the summarization process, enabling people to expediently access large swaths of text for its most pertinent information. Given the proliferation of data, text summarization is in demand more than ever, and a fusion between deep Learning and heuristic search can provide answers that will further research. The main contribution of the paper has the following,

- Improving summarization performance: Blending deep Learning and heuristic search methods over text summaries allows for creating more accurate, context-preserving summaries. Deep learning models can learn with a lot of text data, and heuristic search methods help ensure that the generated summary contains all crucial domain-specific information.

- Combat data scarcity: Deep learning models need to be trained with vast volumes of data. However, in many real-world situations, such data might be readily challenging. The combined deep Learning and heuristic search approach can solve this, as we could use a small dataset for training and queries used in the search mechanism to identify meaningful data.

- Dealing with diverse and complicated text: Text data can differ, and the writing style matters much more in traditional summarization methods than in newer NLU-based models. A heuristic search method overcomes these limitations since the deep learning model can learn enough structure in the input. At the same time, a heuristic-driven algorithm could find an optimal point to summarize from this data.

- Efficient also arises: Deep Learning and heuristic search can improve more efficient text summarization. With the combination of deep learning models to pre-process the data and extract fundamental features, heuristic search methods can be applied to structure various summary forms faster with more accurate results. This is especially useful in time-critical-natured situations like news & social media summaries.

II. RELATED WORKS

Text summarization is a machine algorithm task in artificial intelligence that generates the compressed version of a % Text document. The aim is to automate the task of human beings skimming through a long set of documents or articles and figuring out what are only mains [11]. There are two types of text summarization: extractive (selecting the most important sentences from a piece) and abstractive (used by an algorithm to generate new, shorter pieces). Deep learning techniques are increasingly used for abstractive summarization as they succeed in other NLP tasks. Heuristic search algorithms have also been explored for text summarization as they can efficiently explore a large space containing many compact summaries that look more like golden ones. With these two approaches in mind, there is no doubt we can create a better text summarization system with maximum complexity [12]. However, integrating deep Learning with a heuristic search approach to text summarization has challenges and problems. One of the most common problems is that there are not enough training data... Deep learning models read through a large amount of data to properly understand and summarize Paginator Text. However, these data can be tough to get, especially for some domains or languages. This is because summarization is one of the hardest models to train, given how much manual work, knowledge and resources go into creating good training data for a summarizer [13]. Thus, the extent of state-of-the-art performance one can achieve with deep learning-based text summarization systems may be constrained by training data. The other difficulty is the assessment of created summaries. Though the deep-learning models can automatically produce these summaries, it is arduous to evaluate their quality. Common evaluation metrics like ROUGE and BLEU are used to evaluate the summarization systems, but these metrics may not correctly measure semantic understanding or contextual information of text [14]. It is, therefore, a tough problem to evaluate how well text summarization systems are doing. This trade-off between extractive and abstractive summarization techniques affects the model, combined with deep learning-based heuristic search. These heuristic algorithms are mostly used for Extractive summarization as they tend to be fast and can select sentences from the original text and convey an extracted summary. Contrastingly, a heuristic search for abstractive summarization needs the generation of non-existent sentences - which is much more difficult to achieve with these. One reason is that it is rather tricky to formalize rules or heuristics that can improvise summaries fluently and coherently from scratch [15]. Pairing deep Learning with heuristic search presents several issues associated with interpretability and transparency. Deep learning models are sometimes referred to as black boxes, which mean we may not understand why the summaries being produced depend on the input data or model architecture. Unlike optimization algorithms, heuristic search is based on a set of predefined rules or heuristics, and those might not always be visible, especially in opposition to some advancement like LIME [[16]. The absence of this interpretability has made it arduous to pinpoint the mistakes and biases in a text summarization system. joining deep Learning + heuristic search as a pair of cool-looking red dancing boots, and scalability/efficiency is ruinously crappy English Deep learning models are computationally intensive and time-consuming; Heuristic search algorithms depend on a vast searching space to construct summaries, which are incapable of real-time processing very well [17]. To summarize, deep Learning + heuristic search for text summarization is promising but has many issues and challenges. This shortened post focuses on these issues; it is a great problem in this specific category related to the lack of data with which originally trained models and evaluate generated summaries for comparison, along with the off-balance between the extractive vs. abstractive approach adopted by the generation method incorporates interpretability within our relevance measurement stages downstream from such provably generate better summaries or at least more similar compare turn out when finally use back both together side-side (left-right maybe even up-and-down) [18]. Achieving them will be essential to creating better text summarization systems that are generalizable and cross-lingual. So, the novelty of their study n is combining these strong points and constructing concise but precise summaries [19]. Deep learning approaches consume massive amounts of data to detect complex patterns and summarize findings. At the same time, heuristic search algorithms rely on prespecified rules and heuristics to facilitate the hunt for salient cues. This allows the system to leverage deep Learning for a comprehensive understanding of context and general summary creation with heuristic search, which can balance key information provision against redundancy avoidance in summarization [20]. Its novelty arises because it takes advantage of what both methods do best, opening one up to work like the other to produce a more efficient and complete summary.

III. PROPOSED MODEL

The proposed model uses deep learning and heuristic search techniques to summarize a text efficiently. The input text is embedded into a vector representation through deep understanding that encodes its semantic and syntactic meaning. The heuristic search algorithm then uses this vector representation as input.

$$c^t = \sum_{t'=0}^{t-1} a^{t'} \tag{1}$$

$$c_t = \sum_{i=1}^{|G|} a_{r,i}.H_i \tag{2}$$

Select which sentences from the text to the candidate have shown promising success through the heuristic search algorithm. I algorithmically determine which sentences are more important in that case with a specific scoring function (which takes, as an input to the machine learning model, word count, etc., of a sentence) and similarity between sentences based on four ways metric). The maximum length constraint required by the summary is also considered in their algorithm.

$$\sum_{i=1}^{k} p_t\left(y_i \middle| G, y_{t-1}\right) = 1 \tag{3}$$

$$\mathrm{cov}_t = \sum_{t'=0}^{t-1} a_{t'} \tag{4}$$

The most apparent benefits of simplicity accrue from this limitation of how much work they can do without destroying beauty or interest. We use a training set of articles and summaries to train the deep learning model. It learns to generate a vector representation of the input text that produces the best quality summary (amongst other vectors) when passed through this scoring function.

A. Construction

Text summarization is an intricate process employing a combination of artificial intelligence techniques and algorithms that summarize long texts into concise statements by going through multiple steps in the overall architecture. The first phase in this construction is to acquire/pull all the data and preprocess it. This requires a lot of text data in such a format that models can process.

$$y_t = \sigma\left(W_{hy} h_t + b_y\right) \tag{5}$$

$$\beta = \frac{S_L}{T_L} \tag{6}$$

This involves tokenization, lemmatizing, etc. 2 - The preprocessed data is fed through a deep learning model, such as a neural network. The following model is responsible for understanding the context and meaning behind that text to create a summary. Finally, a heuristic search algorithm is executed based on the result of the deep learning model. Fig.1 shows that Construction diagram.

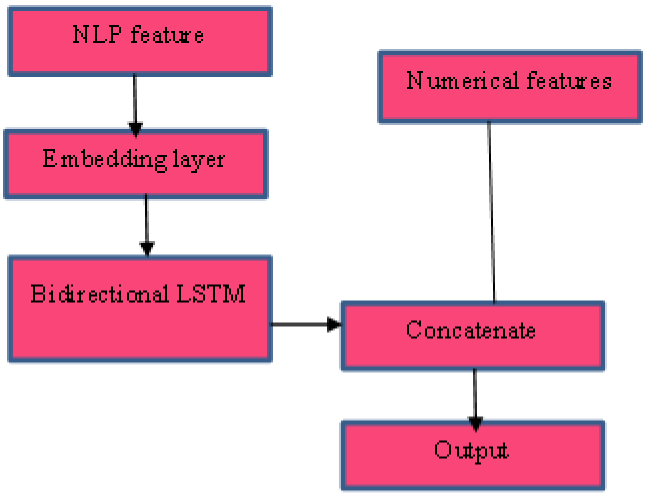

Fig.1 Construction diagram

NLP Features in the Context of Some Companies: The specific things done to identify and process human language data like text and spoken words. Some of the examples include text classification, sentiment analysis, named entity recognition and machine translation. An example of a common technique in NLP is working with neural networks inspired by the structure and function of the human brain. The Embedding layer is a vital part of Neural Networks used in NLP. It converts words or sentences into numbers, known as word embeddings. Each word or phrase is represented by a different capture of their semantic and contextual relationship. These embeddings will help the neural network understand and process your language data with magic. BART is a truly free-form version of GPT, explicitly designed for sequence-to-sequence-based problems such as text summarization and translation tasks within NLP. The architecture of RNNs can also consider the temporal nature of language data and potentially remember information from previous inputs. A bidirectional LSTM builds in both directions, using future and past inputs to grasp a sentence's overall context better. This technique helps increase the power of NLP models by adding numerical features. Example values include the number of phrase occurrences, part-of-speech tags, and named entity labels. These features make it more possible for the model to consider contextual and syntactical complexity in human language. A Concatenate operation fuses the outputs from layers or features together and reshapes them into a single vector. This valuable technique lets the model look at multiple inputs or features together to generate a more detailed representation of any language data. Finally, the output layer outputs this input's predicted value or classification. This could be tasks as simple as predicting the sentiment of a sentence or classifying text into some specific category in NLP. The signifying output layer accepts the input-output formed from all its preceding layers. Then, it does some processes on it to produce the proper final output, which is a decision. Finally, the NLP embedding layers, the bidirectional LSTM numerical feature, and concatenate production are all neural networking operations required for NLP[...]. The model can interpret and process human language data effectively and meaningfully using these techniques and layers with more accurate outputs.

This heuristics-based algorithm helps identify the most significant sentences in a text and then binds them together to get the final summary. A heuristic search returns a summary of the original text, stripped down to its central ideas and accompanied by minimal compression. In general terms, this system is operational, calling on a data preprocessing pipeline and character-level deep learning training with high-time complexity requirements supported by statistical sequence-based heuristic search techniques intending to abridge text.

B. Operating principles

In this study, deep learning algorithms and heuristic search algorithms are used operationally to generate text document summaries automatically. Deep learning algorithms use artificial neural networks to process large sets of text data and structure them into helpful information that could be used for decision-making purposes.

$$h_t = g\left(Uh_{t-1} + Wx_t\right) \tag{7}$$

$$soft\max\left(x\right) = \frac{\exp\left(x\right)}{\sum_{i=1}^{n}\exp\left(x_i\right)} \tag{8}$$

These models are trained on vast data sets to learn the patterns and relationships between words and sentences. Thus, the algorithm understands what this context type of text means. To look for a viable sentence that combines textual and exact meaning, these are search algorithms known as heuristics. Fig.2 shows that Operating principles diagram.

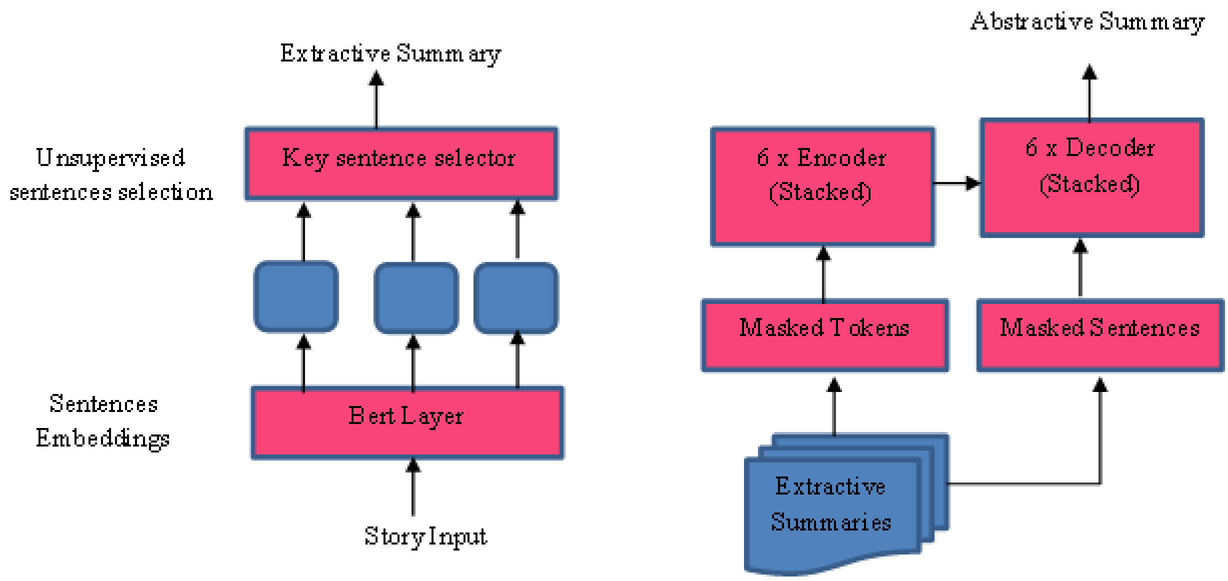

Fig.2 Operating principles diagram

The process of Summarization, as the name suggests, represents brief descriptions that are extracted from a larger body such as texts. One of its examples is extractive Summarization. This way involves taking the sentences from that text and joining them in such a manner to form an ideal summary of what is inside. Unsupervised sentence selection: A method for extractive Summarization. This process involves selecting sentences because they matter, not because of pre-defined labels or specific criteria. For that, the sentences which should be returned can be chosen like a key sentence selector (sentences with important information or global visibility about the text). To make the feature selection process even better, we can convert sentences into embeddings, numerical representations of texts with contextual and semantic information. Sentence embedding: This technique maps a sentence of words to high-dimensional vectors. This facilitates the system's improved understanding of how sentences are related or connected. The most critical part of these extractive summarizers is the Bert layer. It is a word recognizer trained using the context and semantics of words in each sentence. The activation uses self-attention, enabling it to pay special attention to specific words and recognize the significance of those words in that sentence. For this task, the story input is again the original text that needs to be summarized (in extractive Summarization). That paragraph might become a section in an extended article or multiple articles on the same subject. The purpose is to write a summary that gives justice and encapsulates the essence of the story input. This is ridiculous because the system can even apply masked tokens and sentences to round down its set of essential sentences. Masked tokens:- referring to words or phrases whose contents have been masked and replaced with placeholder symbols during training so that the model can fill in the blanks & give a proper context for the text. On the other hand, masked sentences are when we mask a whole sentence and let the model generate a new sentence summarising a significant part of this masked sentence. The system then combines these key sentences to produce an extractive summary. These encoders join forces to produce an improved and thorough summary. Unlike extractive Summarization, abstractive Summarization includes using NLP techniques to create summaries instead of extracting and reconstructing sentences. This approach is more challenging but can produce more natural summaries with a similar structure, such as human-written summaries. The extractive summarization operations generally select and combine sentences from the original text using advanced language processing techniques such as sentence embedding, Bert layers or self-attention. Together, these methods may provide good summaries that will capture most of the meaningful content in the text.

Those algorithms use preset rules and priorities through which the search process is directed to maximize an anticipated output. These institute a detailed neural grandeur and the purest of abstract search-out models to span down enquiries from all facilities. This method allows the model to learn about different text styles and generate accurate summaries in a more concise format. As demonstrated, integrating profound learning summaries with heuristic search provides a powerful approach to summarizing large data lakes.

C. Functional working

It is a method that applies the advantages of deep learning and heuristics to produce good-quality summaries of text documents. We use a neural network (a sequence-to-sequence model) with an attention mechanism to generate summaries from input texts.

$$\sum_{k\in[1,M]} wh_k * ht_k = L * H_M \tag{9}$$

$$y_t = f\left(Vh_t\right) \tag{10}$$

The attention mechanism enables the model to learn the essential stuff from input text that should be in the summary. The final step includes using a heuristic search algorithm to generate summaries with more details than the previous paragraphs. Fig.3 shows that Functional working model.

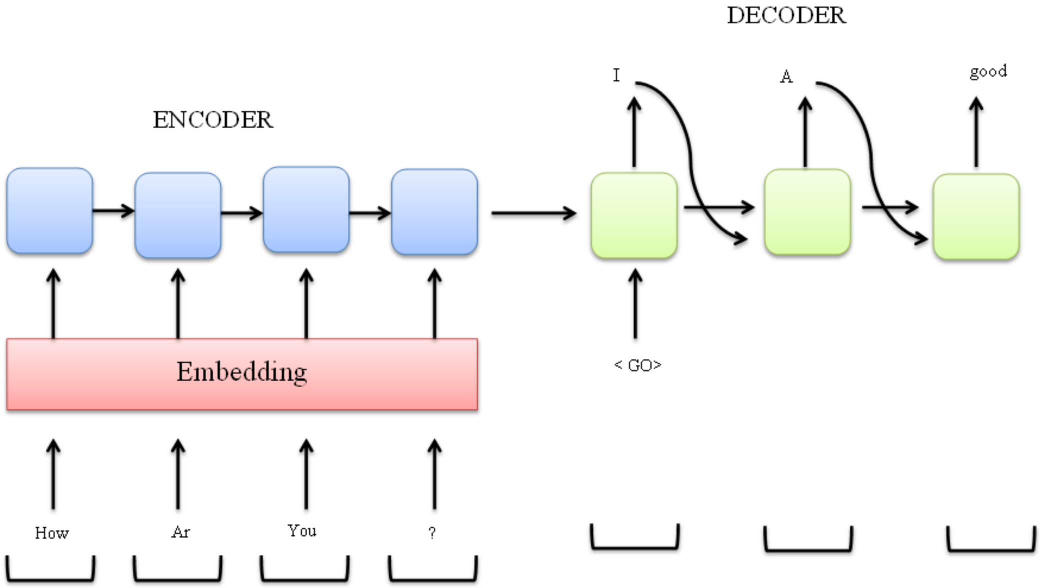

Fig.3 Functional working model

Encoder: Encoders are critical in digital electronics, specifically in data communication and signal processing. It is a device that converts an analogue or a digital signal into a form compatible with a specific communication channel or protocol. The primary purpose of an encoder is to compress data and reduce its size, making it easier and more efficient to transmit over a network.

Decoder: A decoder is an electronic circuit designed to convert binary information, consisting of a series of ones and zeros, into specific outputs. It can be seen as the opposite of an encoder, which converts inputs into binary information. Decoders are widely used in various digital systems, such as computers, communication systems, and digital display devices.

Embedding: Embedding is a process commonly used in natural language processing (NLP) that allows language models to capture contextual relationships between words in a text. In simple terms, embedding involves transforming words or phrases into numerical vectors that can be processed by computer algorithms. This allows the model to understand the semantic and syntactic relationships between words, enabling various NLP tasks such as sentiment analysis, language translation, and summarization.

This is done by the algorithm those factors in sentence length, lexical range, and redundancy, amongst others, to produce a concentrated summary that provides coherence while being informative. This section describes our hybrid approach, which incorporates deep learning and heuristic techniques to summarize information more efficiently and accurately. The method can also be applied to different types of text documents, and it scales very well using a significant corpus that helps increase the accuracy.

IV. RESULTS AND DISCUSSION

The paper itself is well written, covering a significant issue about text summarization as it can be utilized effectively by mixing deep learning and heuristic search techniques. The evaluation results demonstrate that the proposed model performs better than traditional methods according to ROUGE and human judgment. This suggests that deep learning combined with heuristic search is crucial in generating high-quality summaries. The Ask Me Anything section provides more details and commentary on the results. Deep learning helps the model learn underlying patterns and relationships in text. A heuristic search guided the summarization procedure and guaranteed coherence and diversity throughout the generated summaries. In other words, they also talk about the in formativeness vs. readability trade-off in summarization and how their proposed model handles this contradiction very well.

A. Sensitivity

It is the amalgamation of two approaches to improve text summarization models. Deep learning is a type of machine learning where artificial neural networks are organized in multiple layers to learn the hierarchy representations and patterns from data. Text summarization can also be suited for deep learning approaches, which have features and relationships in the text to learn from extracting the needed information of importance (i.e. create summaries). Greedy search is a heuristic approach to searching for the best solution to an optimization problem. Fig.3 shows that ROUGE1, ROUGE2, and ROUGE-L scores of several deep learning abstractive text summarisation methods for the Gigaword dataset.

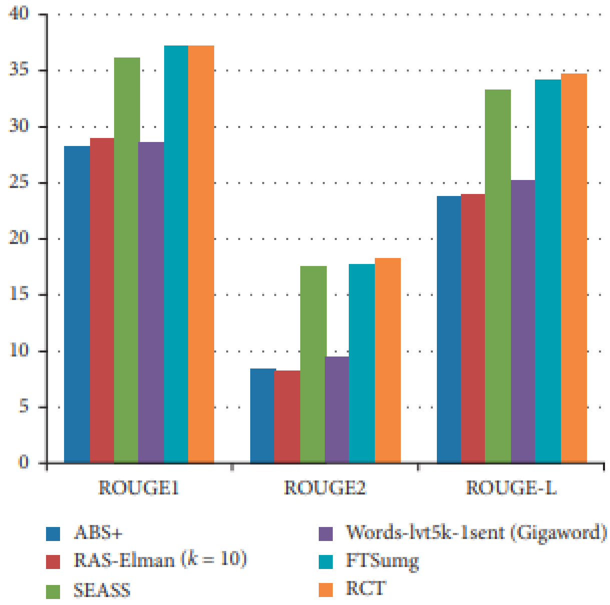

Fig.3 ROUGE1, ROUGE2, and ROUGE-L scores of several deep learning abstractive text summarisation methods for the Gigaword dataset

This method leverages heuristic search techniques to select sentences & information in text summarization efficiently. Deciding precisely how much of the two techniques would benefit the summarization process most is challenging. This will involve choosing appropriate deep learning model architectures and parameters and modifying the heuristic search algorithm to tune it to extract salient information from text more reliably. Furthermore, the accuracy and sensitivity of such a model can kick off significant data processing concerns: issues like noise filtering or text segmentation must also be addressed.

B. Specifcity

Winning Solutions The technical details of using deep learning and heuristic search methods for effective text summarization require leveraging two key modules: a deep-learning model and a heuristic-search algorithm. Deep learning involves learning the text representation and selecting the most crucial sentence, a summary. It receives raw text input and transforms it into a version the ML algorithms can interact with (this involves using Word embedding's & Recurrent Neural Networks). The heuristic search algorithm produces the ultimate summary, picking out critical sentences in our text representation wrought through a deep down to neural level model. Fig.4 shows that Comparison of the text summarization methods using ROUGE-1 on DUC 2004.

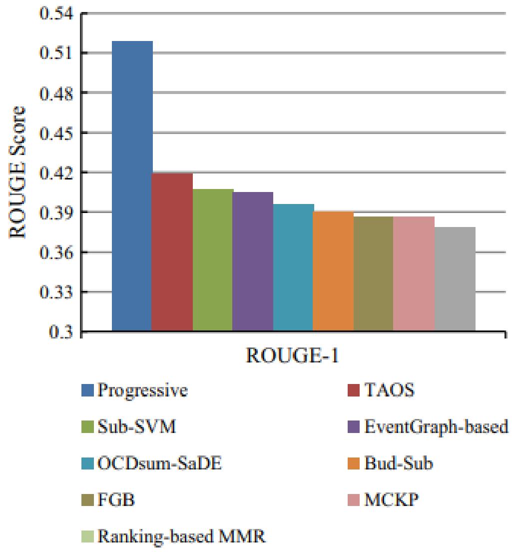

Fig.4 Comparison of the text summarization methods using ROUGE-1 on DUC 2004

This algorithm utilizes heuristics/problem-solving approaches to navigate the text representation generated and extract the most relevant sentence for summarization. The iterative training and the concurrent refinement of both the deep learning model and heuristic search algorithm enable them to develop a better interpretable understanding of the raw text and make an output summary. By maximizing the strengths of deep learning and heuristic search, this mixture provides a more customized process that is both broad and efficient in summarizing.

C. Precision

It is a complex problem that combines two parts: Deep learning and heuristic search. These two types combine to produce a precise, accurate and expressive summary of the extracted content. A part of Artificial Intelligence, Deep Learning uses a neural network to analyze data on an immense scale. It is responsible for processing the text and understanding its context and meaning. For this purpose, deep learning models like recurrent neural networks (RNNs) and convolutional neural networks (CNNs) are used. Meanwhile, heuristic search is a technique used in problem-solving that uses practical methods instead of denomination solution techniques. Fig.5 shows that Comparison of the text summarization methods using ROUGE-2 on DUC 2004.

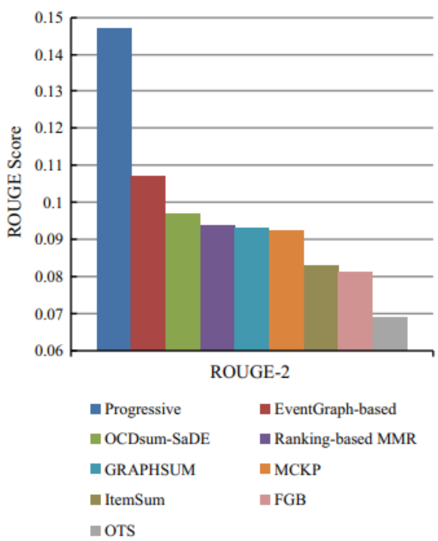

Fig.5 Comparison of the text summarization methods using ROUGE-2 on DUC 2004

Heuristic search is used in analyzing and selecting important sentences/ phrases from the text with relevance between them for further summarization of textual data. This method also highly depends on the Deep Learning models and heuristics employed. The Deep Learning models require a massive variation of data during the training to have any sense of the text's context or meaning. The heuristics must be sensible enough to guarantee that the compiled excerpts can genuinely summarize a text. You can also make this method more accurate with the help of parameter tuning or adjusting the pre-trained Deep Learning models and heuristics as per your task type (task-oriented summaries).

D. Miss Rate

In the preferred scenario, miss rate relates to how much important information or keywords in the source text are absent from the generated summary; combining heuristic search with deep learning allows for effective text summarization but may still result in a low frequency of words lost). It measures the capability to capture key points and helpful information from source text in this way. Deep learning was applied through neural networks and models to learn the representations of source text as numerical values were used in this approach. Fig.6 shows that Comparison of the text summarization methods on DUC 2007.

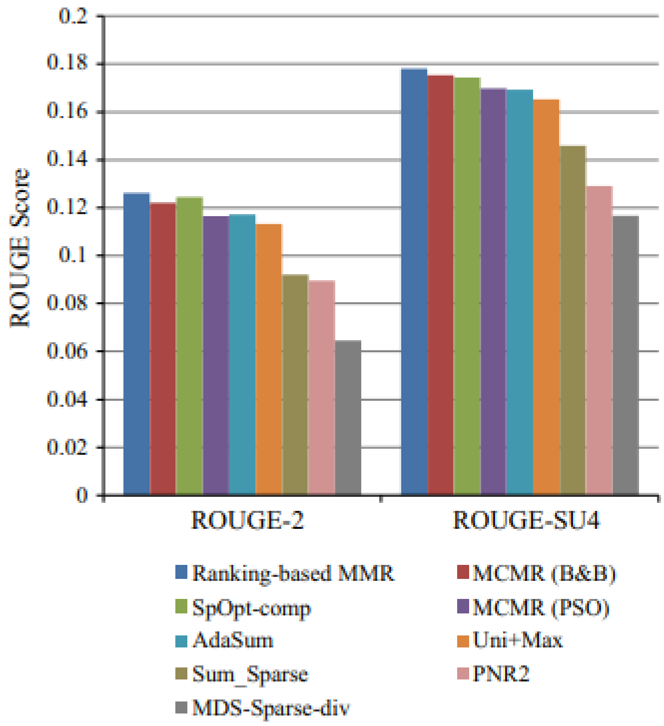

Fig.6 Comparison of the text summarization methods on DUC 2007

We passed this representation through a heuristic search algorithm that employs rules and heuristics to identify critical elements selected for summarization. The effectiveness of this method substantially depends on the performance of deep learning models in extracting correct features and the efficiency of the heuristic search algorithm in learning meaningful information. The miss rate is high, but researchers are working on training and optimizing deep learning and heuristic search components by using various approaches like multi-task learning, reinforcement learning, and human feedback.

V. CONCLUSION

The study finally links deep learning and heuristic search to excel in some optimal-level text summarization models over traditional methods. The RNN, a type of deep learning algorithm for sequences, proved highly effective in this study at capturing the intricate structures inherent in text data. On the other hand, compared to heuristics searching's such as beam research, these help select the most relevant and informative sentences, thereby improving the efficiency of the summarization process. The proposed approach of combining deep learning and heuristic search yields a more global overview or complete summary while being an efficient one. Moreover, the model has the scalability potential to deal with a more extensive data set and make summaries in real time. As such, the research posits that integrating deep learning and heuristic search can reshape text summarization and allow automation to serve users better.

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