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"An Extensive study of Symantic and Syntatic Approaches to Automatic Text Summarization"

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Abstract: - Automatic text summarization (ATS) has emerged as a crucial research domain in the discipline of natural language processing (NLP) and information retrieval. The exponential growth of digital content has necessitated the need for efficient techniques that can automatically generate concise and informative summaries from lengthy documents. This article provided a comprehensive recap of automatic text summarization, covering both abstractive and extractive methods. Using extractive techniques, prime phrases or keywords from the original text are identified and chosen, while abstractive methods involve producing summaries by paraphrasing and synthesizing content in a more human-like manner. Discussed the advantages and limitations of each approach, including the challenge of ATS, which arises when summarizing content from external sources. Furthermore, reviews common evaluation metrics used for assessing the quality of summaries and discusses recent advancements in neural network-based approaches for text summarization. This survey aims to provide an overview of automatic text summarization which acts as a useful resource for researchers and practitioners in the fields of information retrieval and NLP.

Keywords: Abstractive method, Extractive techniques, hybrid method,Automatic text summarization, Evaluation metrics,Natural Language Processing.

I. INTRODUCTION

Websites and other digital resources are enormous providers of textual data. The different collections of news items, novels, books, documents, etc. also provide a richness of textual material. The structured observations day after day, the Web, and other resources are expanding tremendously. When a user searches for some information, the obtained texts contain a lot of redundant or insignificant text. Compacting as well as summarizing the text materials becomes crucial and necessary as a result. Summarizing manually is a complicated process that takes a considerable amount of effort and time. Realistically speaking, it is exceedingly challenging for people to physically summarize such an enormous volume of literary texts (Yao, Kaichun, et al. 2018). Text summarization aims to draw out underlying meaning from lengthy texts. The action of automatically building a brief synopsis of a document that gives the user meaningful data is referred to as summarization (Sun et al.2018). In the current information age, a large number of scientific articles are published in various disciplines of research. People prefer to read article summaries rather than the complete item in today's hectic world, which keeps them up to date on recent occurrences. The hardest challenge in NLP remains ATS, despite the development of various techniques. Text summarization aims to draw out underlying meaning from lengthy texts. Long texts or other sources are distilled of essential information to save readers time, money, and effort.

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1.1. Extractive text summarization:

This techniques take the text as input, rate or score each sentence according to how relevant it is to the text, and then present you with the most crucial passages. The most crucial text from the existing text is simply highlighted, rather than new words and phrases being added. There are numerous techniques for extracting text summaries, including statistical, topical, discourse-based, graph-based, structural, semantic, deep learning-based, machine learning-based, and optimization-based techniques. The technique of choosing and combining significant text or phrases from a given textual source is named as extractive text summarization. It refers to underlining crucial passages in a manuscript. Using extractive text summarization, key passages and phrases from the original textual are removed.

1.2.Abstractive Text Summarization: Abstractive text summarizing is the creation of a summary of a textthat goes beyond only extracting and rearrange existing phrases. Instead, it entails comprehending the text's meaning, interpreting its meaning, and coming up with fresh, succinct sentences that sum up its important points. Abstractive summary involves the synthesis of fresh sentences that might not be present in the original text, in contrast to extractive summarization, which chooses and reuses sentences from the source text. This method focuses on natural language production and understanding algorithms, frequently using transformer-based designs like GPT (Generative Pre-trained Transformer) or deep learning models like recurrent neural networks (RNNs).The summary of an abstractive.

1.3. Hybrid text summarization:

In order to produce summaries, a method known as hybrid text summarizing combines aspects of extractive and abstractive summary approaches. In hybrid summarizing, similar to extractive summarization, the system may use extractive methods to recognize and highlight significant sentences or phrases from the source material. But it also uses abstractive strategies to reword and come up with new sentences that perfectly summarize the original text.

1.4 ATS Classification

ATS is a NLP activity that requires reducing a lengthier text's content to a shorter one while preserving key details and ideas. Text summary is divided into multiple categories depending on various criteria, as shown in figure 3.

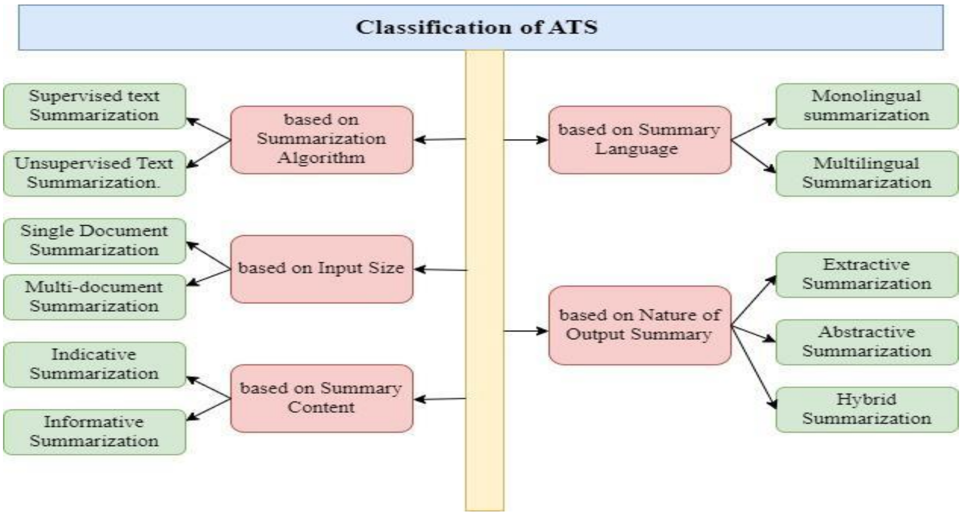

Figure 3: ATS classification

The ATS is classified on the basis of summarization algorithm, Input size,summary contents, summary lamguage, nature of output summary. ATS is principal NLP activity that tries to provide short and logical summaries of long texts or text passages. Text summarising has become increasingly relevant for a diversity of applications, consisting of news summary, summarization of documents, and summarization of social media, as digital information has grown exponentially. With the development of numerous methodologies and approaches in most recent years, there has been substantial progress in the field of ATS. This paper present a detailed review of the developments, challenges, and methodologies of ATS, focusing on the key approaches, assessment measures, and applications.

Syntactical and semantical summarization are two crucial aspects of natural language processing that stand out as essentials for realising the full potential of textual data. Syntactical summary is the lighthouse that guides us through the complex web of language, revealing the subtle structural and grammatical details that constitute a text's core meaning. In addition, symantical summarization explores the semantic foundation, revealing the connections and underlying meaning of words, sentences, and concepts.

These two foundational elements combine together to create an essential distillation framework that helps us reduce language's complexity to incisive and succinct summaries. Exploring the domains of syntax and semantics not only offers a more sophisticated understanding of language but also provides access to powerful artificial intelligence and information retrieval applications.

II. KEY APPROACHES OF AUTOMATIC TEXT SUMMARIZATION:

To automatically produce succinct and relevant summaries of text documents or sentences, two major approaches in NLP are syntactic and semantic text summarizing.

A] Syntactic summarization: Syntax: What Is It? Syntax is the term for the grammar principles that govern sentence construction, or how words are arranged to form sentences. Syntactic summarization, as the name suggests, relies on the syntactic features of the language, such as sentence structure, grammar, and word order, to extract relevant information from text. It aims to retain the original grammar and sentence construction in the summary while extracting key information based on syntactic patterns and relevance to the topic. Syntactic summarization techniques are often extractive in nature, where sentences or phrases are selected based on syntactic rules or patterns to construct the summary (Mihalcea et al.2004).

B] Semantic summarization: Semantics: What Is It? The meaning of a statement is referred to as semantics. Without appropriate semantics and a deliberate, grammatically sound word order a sentence's meaning would be quite different. Lexical semantics, which is the study of word meanings and relationships, is one of the categories into which linguists divide semantics. Contrarily, conceptual semantics examines how speakers of a language understand and pick up semantic concepts. Semantic summarization delves deeper into the meaning or semantics of the text. Semantic summarization techniques may involve paraphrasing, rephrasing, or restructuring sentences to effectively capture the meaning of the text. Abstractive summarization, a type of semantic summarization, goes beyond extraction and generates summaries that may not necessarily retain the original sentence structure or grammar, but aim to convey the overall meaning of the text in a more human-like manner(See et al.2017). table 1 gives difference between Syntactic Summarization and Semantic Summarization.

Table 1: Comparison of Syntactic and Semantic Summarization.

Approach	Syntactic Summarization	Semantic Summarization
Focus	Sentence structure, grammar, and word order.	Meaning, context, and relationships between words or concepts.
Technique	Extractive: Selecting sentences or phrases based on syntactic patterns and relevance to the topic.	Extractive or Abstractive: Paraphrasing, rephrasing, or restructuring sentences to capture the meaning of the text.
Output	Retains original sentence structure and grammar.	May not retain original sentence structure or grammar, aims to convey overall meaning in a more abstract and conceptual manner.
Goal	Extraction of key information based on syntactic features.	Conveyance of meaning and context of the text
Strengths	Good for extracting key information or facts.	Captures the overall meaning and context of the text.
Limitations	May miss underlying meaning or context.	May require more advanced NLP techniques for understanding meaning.

III. SYNTACTIC TEXT SUMMARIZATION METHODS.

There are number of syntactical methods are available for text summarization among hat top important methods explained below.

3.1. Method of Sentence Scoring:

One common way for summarizing syntactic text is the Sentence Scoring method. In order to choose the most pertinent and significant sentences for the summary, it entails scoring sentences according to a number of criteria.

3.1.1.Criteria for Scoring:

Sentence scoring involves evaluating sentences based on different criteria, which can vary depending on the specific requirements of the summarization task. Common scoring criteria include:

•**Sentence Length:** Longer sentences may be scored lower, as they often contain more details and may not be as concise.

•**Position in the Document:** Sentences appearing at the beginning or end of a document may receive higher scores because they often introduce the topic or provide a conclusion.

•**Word Importance**: Important words or phrases within a sentence can contribute to a higher score. Keyword extraction techniques may be used for this purpose.

•**Content Relevance:** Sentences that directly address the core topic or contain key information are considered more relevant and may receive higher scores.

•**Semantic Importance:** Sentences that contain concepts, facts, or arguments critical to the document's main message are rated higher.

3.1.2..Scoring Algorithms: Various algorithms can be used to calculate the scores. These algorithms can be as simple as assigning numerical values to each criterion and summing them to get a total score. Alternatively, more complex algorithms like TF-IDF (Term Frequency-Inverse Document Frequency) can be employed to measure the importance of words and their frequency in the document.

3.1.3.Threshold Selection: After scoring, a threshold value is chosen. Sentences scoring above this threshold are selected for the summary.

Example:Let's consider a simplified example of how sentence scoring might work. Imagine we have a document discussing the advantages of renewable energy sources. We'll score two sentences from this document:

Original Sentence 1: "Solar energy is a clean and sustainable source of power that reduces greenhouse gas emissions."

Original Sentence 2: "Additionally, it has the potential to save costs and create job opportunities in the energy sector."

Now, use a simple scoring method based on criteria like sentence length, keyword importance, and content relevance (on a scale of 1 to 10, with 10 being the highest):

Table 2: Scoring of sentence1 and sentence 2.

Criteria for Scoring	**Sentence 1 scores:**	**Sentence 2 scores:**
•Length:	**6** (moderate length)	**7** (moderate length)
Position:	**8** (introduces the main topic)	**5** (additional information)
Keyword Importance:	**9** (contains "solar energy," a key phrase)	**7** (contains "renewable energy")

Content Relevance:	**9** (directly addresses the topic)	**8** (relevant but not as focused as sentence 1)
Total Score:	**32**	**27**

If we set a threshold score of 30, then only Sentence 1 would be selected for inclusion in the summary.

3.2.Graph-Based Methods:

Example: Construct a sentence similarity graph where sentences are nodes, and edges represent their syntactic similarity. Important sentences are selected based on their centrality in the graph.

Original Sentence 1: "The new product launch generated significant buzz in the market."

Original Sentence 2: "Customers praised the product's innovative features and competitive pricing."

Summary (Graph-Based): Both sentences are considered important in capturing the product's success in the market.

3.3.Methods of Dependency Parsing:

Example: Analyze the grammatical structure of sentences using dependency trees. Sentences are ranked based on their position in the tree and the presence of critical dependencies.

Original Sentence 1: "The research team conducted experiments to assess the impact of climate change on local flora."

Original Sentence 2: "Their findings highlighted the vulnerability of certain plant species to temperature fluctuations."

Summary (Dependency Parsing): The second sentence is chosen because it describes the significance of the research findings.

3.4. Method of Part-of-Speech Tagging:

Example: Identify sentences that contain specific parts of speech (e.g., nouns, verbs, adjectives) relevant to the topic.

Original Sentence 1: "The athlete's outstanding performance secured a gold medal in the 100-meter sprint."

Original Sentence 2: "Spectators cheered loudly, celebrating the victory of the hometown hero."

Summary (Part-of-Speech Tagging): Both sentences are included as they provide essential information about the athlete's achievement.

3.5.Compression-Based Methods:

Example: Apply text compression algorithms to reduce the text size while retaining essential content.

Original Sentence 1: "The company announced its expansion plans into new markets, including Europe and Asia, during the quarterly meeting."

Original Sentence 2: "This strategic move aims to capitalize on emerging opportunities and increase global market share."

Summary (Compression-Based): A compressed summary might combine these sentences: "The company revealed expansion plans in Europe and Asia to seize emerging opportunities."

3.6. Methods of Redundancy Elimination:

Example: Remove redundant references or repeated information from the text.

Original Sentence 1: "The novel presents a gripping story. The story captivates readers with its engaging narrative."

Summary (Redundancy Elimination): Only one sentence is retained in the summary to eliminate redundancy: "The novel presents a gripping story."

3.7.Methods of Grammar Rule Application:

Example: Apply syntax rules to simplify complex sentences while maintaining their meaning.

Original Sentence: "Despite the inclement weather, they embarked on the hike, determined to enjoy the beauty of nature."

Summary (Grammar Rule): The sentence can be simplified while preserving the structure and meaning: "Despite the bad weather, they were determined to enjoy nature on their hike."

3.8. Methods of Lexical Chaining:

Example: Identify chains of related words or concepts and select sentences containing words from the same chain.

Original Sentence 1: "The company's stock soared as profits reached an all-time high."

Original Sentence 2: "Investors celebrated the remarkable performance."

Summary (Lexical Chaining): Both sentences are included in the summary as they are part of the same chain emphasizing financial success.

3.9. Methods of Positional Importance:

Example: Select sentences based on their position in the document, such as introducing the topic or providing a conclusion.

Original Sentence 1: "In this report, we will discuss the causes of air pollution."

Original Sentence 2: "To conclude, measures to mitigate air pollution are of utmost importance."

Summary (Positional Importance): Both sentences are included to provide an introduction and conclusion to the report.

3.10. Methods of Topic Segmentation:

Example: Divide the text into topical segments and select sentences from each segment for the summary.

Original Sentence 1: "Introduction: This chapter outlines the main objectives of the research."

Original Sentence 2: "Methodology: The study employed a mixed-methods approach to collect data."

Summary (Topic Segmentation): Both sentences are included to represent different sections of the document.

These syntactic text summarization techniques help in generating summaries that maintain the grammatical structure and coherence of the original text while highlighting essential information.

IV. SEMANTIC TEXT SUMMARIZATION METHODS

Semantic text summarization aims to capture the meaning and essence of the text. Below are given techniques and methods of semantic text summarization, along with examples for each.

4.1. Method of Topic Modeling:

Technique: Identify topics within a text and select sentences that represent these topics.

Example: Apply Latent Dirichlet Allocation (LDA) to identify topics in a collection of documents and select sentences that best represent these topics.

Original Sentence 1: "Climate change is a pressing global issue with environmental and economic implications."

Original Sentence 2: "Rising temperatures lead to more frequent extreme weather events."

Summary (Topic Modeling): Sentences from different topics are selected based on LDA results to create a multi-faceted summary.

4.2. Method of Graph-Based Summarization: **Technique:** Use graphs to represent the relationships between sentences, where nodes are sentences and edges represent semantic similarity

Example: Use TextRank to create a graph where sentences are nodes and edges represent semantic similarity. Important sentences are selected based on their centrality in the graph.

Original Sentence 1: "The recent study on biodiversity loss highlights the urgent need for conservation efforts."

Original Sentence 2: "Biodiversity is crucial for ecosystem stability and human well-being."

Summary (Graph-Based): Sentences are chosen based on their importance in capturing key concepts related to biodiversity and conservation.

4.3.Method of Clustering:

Example: Group similar sentences into clusters and select representative sentences from each cluster.

Original Sentence 1: "The health benefits of regular exercise are well-documented."

Original Sentence 2: "Exercise can reduce the risk of chronic diseases."

Original Sentence 3: "Physical activity also improves mental well-being."

Summary (Clustering): Representative sentences are selected from each cluster, covering different aspects of the topic (e.g., physical health and mental well-being).

3.4. Method of Word Embeddings:

Technique: Utilize word embeddings to measure semantic similarity between sentences and select those with the most related content.

Example: Utilize word embeddings like Word2Vec or BERT to measure the semantic similarity between sentences and select sentences that are most related.

Original Sentence 1: "The new vaccine has shown remarkable efficacy in preventing the spread of the virus."

Original Sentence 2: "Vaccination campaigns are crucial in controlling the pandemic."

Summary (Word Embeddings): Sentences are selected based on the semantic similarity of their content, ensuring comprehensive coverage.

4.5.Method of Deep Learning Models:

Technique: Employ neural networks like Transformers for abstractive summarization, where the model generates summaries by understanding the context and semantics of the text.

Example: Employ neural networks, such as Transformers, for abstractive summarization, where the model generates summaries by understanding the context and semantics of the text.

Original Sentence: "The advancements in artificial intelligence are reshaping various industries, from healthcare to finance, by automating processes and improving decision-making."

Summary (Deep Learning): The model generates an abstractive summary that captures the key ideas and implications of AI advancements.

4.6.Method of Named Entity Recognition (NER): Technique: Identify and prioritize sentences containing important entities such as people, organizations, or locations.

Example: Use NER to identify and prioritize sentences containing important entities such as people, organizations, or locations.

Original Sentence 1: "Elon Musk's SpaceX achieved a historic milestone with the successful Mars mission."

Original Sentence 2: "The company's innovations are revolutionizing space exploration."

Summary (NER): Sentences mentioning Elon Musk and SpaceX are prioritized for inclusion.

4.7.Method of Entity-Based Summarization: Technique: Summarize text by focusing on specific entities or concepts mentioned in the document.

Example: Summarize text by focusing on specific entities or concepts mentioned in the document.

Original Sentence 1: "Blockchain technology is transforming the financial sector."

Original Sentence 2: "Bitcoin and Ethereum are popular cryptocurrencies built on blockchain."

Summary (Entity-Based): The summary highlights the impact of blockchain technology and mentions specific cryptocurrencies as examples.

4.8 Method of Conceptual Overlap:

Technique: Measure the overlap of concepts and ideas in sentences and select those with the most interconnected content.

Example: Measure the overlap of concepts and ideas in sentences and select those with the most interconnected content.

Original Sentence 1: "The impact of deforestation on wildlife is a major concern for conservationists."

Original Sentence 2: "Conservation efforts aim to protect biodiversity in threatened ecosystems."

Summary (Conceptual Overlap): Sentences are selected for their interconnectedness in conveying the importance of conservation and the impact of deforestation.

4.9.Method of Hierarchical Summarization:

Technique: Create a hierarchical summary that includes a title or headline followed by multiple levels of summaries, each providing varying levels of detail.

Example: Create a hierarchical summary that consists of a title or headline followed by multiple levels of summaries, each providing varying levels of detail.

Title: "The Impact of Artificial Intelligence on the Labor Market"

Level 1 Summary: "AI is changing the job landscape with automation and new opportunities."

Level 2 Summary: "Automation is replacing routine tasks, while AI creates demand for new skills."

4.10 Method of Discourse Analysis:

Technique: Analyze discourse markers and cohesive devices to select sentences that contribute to the overall coherence and flow of the summary.

Example: Analyze discourse markers and cohesive devices to select sentences that contribute to the overall coherence and flow of the summary.

Original Sentence 1: "The study found a strong link between diet and cardiovascular health."

Original Sentence 2: "Moreover, it emphasized the role of exercise in preventing heart disease."

Summary (Discourse Analysis): Sentences are chosen to maintain a coherent flow, as indicated by the use of "moreover."

These techniques help create semantic text summaries that focus on the meaning and essence of the content, making them suitable for conveying complex information concisely and accurately.

V. STANDARD DATASETS

4.1. CNN/Daily Mail : The CNN/Daily Mail dataset is a widely used benchmark dataset for text summarization tasks. It consists of news articles from the CNN and Daily Mail news websites, along with human-generated summaries for each article. The dataset is commonly used for both single document and multi-document summarization tasks.

4.2. Gigaword : The Gigaword dataset is a widely used benchmark dataset for text summarization tasks. It consists of news articles collected from the New York Times (NYT) and Associated Press (AP) news wires. The dataset is commonly used for single document summarization tasks.

4.3. PubMed dataset: The PubMed dataset is a widely used and publicly available dataset for biomedical and life sciences research. It contains a vast collection of bibliographic records of articles from journals in the field of biomedicine, including topics such as medicine, biology, pharmacology, genetics, and more. The dataset is commonly used for text summarization tasks related to biomedical literature.

4.4. DUC 2002-2007 dataset: The Document Understanding Conference (DUC) dataset is a collection of datasets that were used in the Document Understanding Conferences held from 2002 to 2007. These datasets are commonly used for text summarization evaluation and benchmarking purposes. The DUC datasets consist of sets of documents along with reference summaries that can be used to train and evaluate automatic text summarization systems.

4.5. Newsroom dataset: The Newsroom dataset is a large collection of news articles from various news sources, which can be used for text summarization tasks. The dataset covers a wide range of topics and is suitable for both single document and multidocument summarization. It can be accessed from the following reference link: https://summari.es

4.6. TAC 2008-2011 dataset: The Text Analysis Conference (TAC) datasets are a popular choice for text summarization evaluation and benchmarking. TAC is an annual conference that hosts various tracks, including the Document Understanding Conference (DUC) track, which focuses on text summarization.

4.7. LCSTS dataset: The LCSTS dataset, which is extensively utilized for Chinese text summarization tasks, is a widely recognized collection in the field. It was created by scholars from the Harbin Institute of Technology in China and is commonly employed for summarizing individual Chinese language documents.

4.8. **Inspec dataset:** The Inspec dataset, which is extensively utilized in the domains of computer science and engineering, is widely acknowledged for its significance in text summarization tasks. It is commonly employed for summarizing individual documents and serves as a prominent resource for assessing and comparing the performance of various summarization algorithms.

4.9. New York Times dataset: The New York Times dataset, extensively employed in the domains of NLP and information retrieval, is highly regarded for text summarization tasks. It encompasses a substantial collection of news articles sourced from The New York Times, serving as a prevalent resource for single-document as well as multi-document text summarization endeavors.

4.10. WikiHow dataset: The WikiHow dataset, widely utilized for text summarization tasks, specifically targets instructional articles sourced from the WikiHow website. This dataset is frequently employed in single-document and multi-document text summarization tasks, particularly for producing succinct and well-organized summaries of step-by-step guidance.**4.11**. **ACL Anthology dataset :** The Anthology dataset, often associated with NLP and text summarization, specifically pertains to the ACL Anthology. This anthology serves as an extensive compilation of research papers in computational linguistics and NLP.Table 3 shows various datasets were utilised to summarise the text.

Table 3: Different datasets used for text summarization

Dataset Name	Size	Multidocu ment	Single Document	Language	Reference Link

CNN/Daily Mail	Large	Yes	Yes	English	[1]
Gigaword	Large	No	Yes	English	[2]
PubMed	Large	No	Yes	English	[3]
DUC 2002-2007	Small/Medium	Yes	No	English	[4]
DUC 2008-2016	Small/Medium	Yes	No	English	[5]
TAC 2008-2011	Small/Medium	Yes	No	English	[6]
LCSTS	Medium	No	Yes	Chinese	[7]
Inspec	Small/Medium	No	Yes	English	[8]
New York Times	Large	Yes	Yes	English	[9]
WikiHow	Large	No	Yes	English	[10]
ACL Anthology	Large	Yes	Yes	English	[11]

Sources

[1] CNN/Daily Mail dataset: https://github.com/abisee/cnn-dailymail

[2] Gigaword dataset: https://catalog.ldc.upenn.edu/LDC2003T05

[3] PubMed dataset: https://pubmed.ncbi.nlm.nih.gov/about/

[4] DUC 2002-2007 dataset: https://duc.nist.gov/data.html

[5] DUC 2008-2016 dataset: https://www-nlpir.nist.gov/projects/duc/data.html

[6] TAC 2008-2011 dataset: https://tac.nist.gov/data/index.html

[7] LCSTS dataset: https://www.cs.cmu.edu/~jwieting/

[8] Inspec dataset: https://www.theiet.org/publishing/inspec/

[9] New York Times dataset: https://archive.ics.uci.edu/ml/datasets/New+York+Times

[10] WikiHow dataset: https://github.com/mahnazkoupaee/WikiHow-Dataset

[11] ACL Anthology dataset : https://www.aclweb.org/anthology/

VI. EVALUATION METRICS

Automatic text summarization systems are evaluated using various metrics to assess the quality of generated summaries in comparison to reference (human-created) summaries. The choice of evaluation metrics depends on whether the summarization task is extractive or abstractive. Below are given common evaluation metrics used for automatic text summarization:

5.1.ROUGE (Recall-Oriented Understudy for Gisting Evaluation): The ROUGE measure counts the overlap between the generated summary and the reference summary for words, n-grams (sequences of 'n' words), or even word sequences. ROUGE-N, which measures unigrams, bigrams, etc.; ROUGE-L, which measures the longest common subsequence; and ROUGE-W, which measures weighted word overlap, are examples of common ROUGE metrics.

5.2. BLEU (Bilingual Evaluation Understudy): Based on the accuracy of the n-grams in the generated summary and the reference summary, BLEU calculates a similarity score. Although text summarization is one of its uses, machine translation was its initial purpose..

5.3. METEOR (Metric for Evaluation of Translation with Explicit ORdering): METEOR uses several matching techniques, including as stemming, synonyms, and more, to compare a generated summary to a reference summary in order to assess the quality of the latter.

5.4. CIDEr (Consensus-based Image Description Evaluation): Although it has been modified for text summary, CIDEr is mainly utilised for captioning images. It uses consensus-based scoring, IDF weights, and n-grams to quantify the level of agreement between the generated and reference summaries..

5.5. NIST (Normalised Information Retrieval Score): Based on n-gram overlap with reference summaries, NIST assigns a higher weight to higher-order n-grams, which are frequently more significant in establishing summary quality.

5.6. F1 Score: A popular metric that combines recall and precision is the F1 score. It determines how closely the generated summary adheres to the length and content of the reference summary.

5.7. Precision and Recall: Recall gauges how thorough the created summary is in comparison to the reference, while precision assesses how pertinent the material is in the summary. Recall and precision can be used alone or in combination to evaluate a summary's quality

5.8. ROUGE Word Embeddings, or ROUGE-WE: By embedding sentences or phrases into a continuous vector space, ROUGE-WE calculates semantic similarity. It encapsulates the produced summaries' semantic quality.

5.9. ROUGE-S: ROUGE-S compares the generated summary's sentence structure to the reference summary in order to assess sentence-level coherence. It assesses the coherence and flow of sentences.

5.10. Human assessment: Using human judges to review the quality of summaries that are generated is known as human assessment. Summaries may be graded by judges according to their overall quality, informativeness, coherence, and fluency. This method offers insightful but subjective comments.

The particular objectives of the summary assignment and the qualities of the summaries that are produced determine the assessment metric that is chosen.

VII. CONCLUSION

This research article has offered a thorough overview of the field of automatic text summarization. We have reviewed the key concepts, methods, and challenges associated with this task, including extractive and abstractive approaches, evaluation metrics, and recent improvements in deep learning and NLP techniques. ATS has emerged as a critical research area aimed at addressing the information overload problem by generating concise and coherent summaries from large volumes of text. Extractive methods have been widely used due to their simplicity and effectiveness, but they may lack the ability to produce summaries that are truly coherent and informative. Abstractive methods, on the other hand, offer more flexibility in content generation but pose challenges in maintaining coherence and factual accuracy. Evaluation metrics for example ROUGE, METEOR, and CIDEr have been proposed to evaluate the quality and effectiveness of generated summaries, but they have restrictions and do not always correlate fine with human findings. Recent advancements in deep learning, including transformer-based models, show promising results in text summarization, but challenges such as data limitations, handling long documents, and ethical considerations remain open research areas.

ATS has applications in many fields, containing news summarization, document summarization, social media summarization, and personalized summarization for individuals with different information needs. As technology continues to advance, further research and innovation in ATS is required to address the limitations of current approaches and unlock the full potential of this field for real-world applications. This survey paper has provided a comprehensive overview of automatic text summarization, highlighting its significance, challenges, and recent advancements. It is hoped that this survey serves as a valuable resource for researchers, practitioners, and stakeholders in the field of NLP and information retrieval, and inspires further advancements in the field of ATS.

REFERENCES

[1] Chatterjee, Niladri, and Raksha Agarwal. "Studying the effect of syntactic simplification on text summarization." IETE Technical Review 40, no. 2 155-166, 4 mar. 2023.

[2] Agarwal, Raksha, and Niladri Chatterjee. "Votesumm: A multi-document summarization scheme using influential nodes of multilayer weighted sentence network." IETE Technical Review 40, no. 4,535-548 jully 2023.

[3] Yao, Kaichun, et al. "Dual encoding for abstractive text summarization." IEEE transactions on cybernetics 50.3 985-996, 2018.

[4] Sun, Xiaoping, and Hai Zhuge. "Summarization of scientific paper through reinforcement ranking on semantic link network." IEEE Access 6, 40611-40625, 2018.

[5] Al-Sabahi, Kamal, Zhang Zuping, and Mohammed Nadher. "A hierarchical structured self-attentive model for extractive document summarization (HSSAS)." IEEE Access 6 (2018): 24205-24212.

[6] Li, Sheng, et al. "Visual to text: Survey of image and video captioning." IEEE Transactions on Emerging Topics in Computational Intelligence 3.4 (2019): 297-312.

[7] Zhuang, Haojie, and Weibin Zhang. "Generating semantically similar and human-readable summaries with generative adversarial networks." IEEE Access 7 (2019): 169426-169433.

[8] Saini, Naveen, et al. "Extractive single document summarization using binary differential evolution: Optimization of different sentence quality measures." PloS one 14.11 (2019): e0223477.

[9] Li, Wei, and Hai Zhuge. "Abstractive multi-document summarization based on semantic link network." *IEEE Transactions on Knowledge and Data Engineering* 33.1 (2019): 43-54.

[10] Liu, Yang, and Mirella Lapata. "Text summarization with pretrained encoders." *arXiv preprint arXiv:1908.08345* (2019).

[11] 9. W. Kai and Z. Lingyu, "Research on Text Summary Generation Based on Bidirectional Encoder Representation from Transformers," *2020 2nd International Conference on Information Technology and Computer Application (ITCA)*, Guangzhou, China, 2020, pp. 317-321, doi: 10.1109/ITCA52113.2020.00074.

[12] 10. Stein, Aviel J., et al. "News article text classification and summary for authors and topics." *Comput. Sci. Inf. Technol.(CS & IT)* 10 (2020): 1-12.

[13] 11. Hernández-Castañeda, Ángel, et al. "Extractive automatic text summarization based on lexical-semantic keywords." *IEEE Access* 8 (2020): 49896-49907.

[14] You, Fucheng, Shuai Zhao, and Jingjing Chen. "A topic information fusion and semantic relevance for text summarization." *IEEE Access* 8 (2020): 178946-178953.

[15] Yang, Min, et al. "An Effective Hybrid Learning Model for Real-Time Event Summarization." *IEEE Transactions on Neural Networks and Learning Systems* 32.10 (2020): 4419-4431.

[16] Yang, Min, et al. "Hierarchical human-like deep neural networks for abstractive text summarization." *IEEE Transactions on Neural Networks and Learning Systems* 32.6 (2020): 2744-2757

[17] Bhargava, Rupal, Gargi Sharma, and Yashvardhan Sharma. "Deep text summarization using generative adversarial networks in Indian languages." *Procedia Computer Science* 167 (2020): 147-153.

[18] Zaheer, Manzil, et al. "Big bird: Transformers for longer sequences." *Advances in neural information processing systems* 33 (2020): 17283-17297.

[19] Ma, Tinghuai, et al. "T-bertsum: Topic-aware text summarization based on bert." *IEEE Transactions on Computational Social Systems* 9.3 (2021): 879-890.

[20] Y. Chen, C. Chang and J. Gan, "A Template Approach for Summarizing Restaurant Reviews," in *IEEE Access*, vol. 9, pp. 115548-115562, 2021, doi: 10.1109/ACCESS.2021.3103512.

[21] Jang, Heewon, and Wooju Kim. "Reinforced Abstractive Text Summarization With Semantic Added Reward." *IEEE Access* 9 (2021): 103804-103810.

[22] Jiang, Jiawen, et al. "Enhancements of attention-based bidirectional lstm for hybrid automatic text summarization." *IEEE Access* 9 (2021): 123660-123671.

[23] Paharia, Naman, Muhammad Syafiq Mohd Pozi, and Adam Jatowt. "Change-Oriented Summarization of Temporal Scholarly Document Collections by Semantic Evolution Analysis." *IEEE Access* 10 (2021): 76401-76415.

[24] Abdel-Salam, S.; Rafea, A. Performance Study on Extractive Text Summarization Using BERT Models. *Information* 2022, *13*, 67. https://doi.org/10.3390/info13020067.

[25] Alomari, Ayham, et al. "Deep reinforcement and transfer learning for abstractive text summarization: A review." *Computer Speech & Language* 71 (2022): 101276.

[26] Pang, Bo, et al. "Long document summarization with top-down and bottom-up inference." *arXiv preprint arXiv:2203.07586* (2022).

[27] Yadav, Divakar, Jalpa Desai, and Arun Kumar Yadav. "Automatic Text Summarization Methods: A Comprehensive Review." *arXiv preprint arXiv:2204.01849* (2022).

[28] Zhu, Haichao, et al. "Transforming wikipedia into augmented data for query-focused summarization." *IEEE/ACM Transactions on Audio, Speech, and Language Processing* 30 (2022): 2357-2367.

[29] Aliakbarpour, Hassan, Mohammad Taghi Manzuri, and Amir Masoud Rahmani. "Improving the readability and saliency of abstractive text summarization using combination of deep neural networks equipped with auxiliary attention mechanism." *The Journal of Supercomputing* (2022): 1-28.

[30] Park, Hyun, and Yanggon Kim. "Finding the Optimal Ratio of Summaries to NEWS Articles and Establishing a Hybrid NEWS Summary System." *2022 IEEE/ACIS 7th International Conference on Big Data, Cloud Computing, and Data Science (BCD)*. IEEE, 2022.

[31] Chitty-Venkata, Krishna Teja, et al. "Neural architecture search for transformers: A survey." *IEEE Access* 10 (2022): 108374-108412.

[32] Mao, Qianren, et al. "Fact-Driven Abstractive Summarization by Utilizing Multi-Granular Multi-Relational Knowledge." *IEEE/ACM Transactions on Audio, Speech, and Language Processing* 30 (2022): 1665-1678.

[33] Laban, Philippe, et al. "SummaC: Re-visiting NLI-based models for inconsistency detection in summarization." *Transactions of the Association for Computational Linguistics* 10 (2022): 163-177.

[34] Aote, Shailendra, Anjusha Pimpalshende, and Archana Potnurwar. "Multi-Document Extractive Text Summarizer for Hindi Documents Using Swarm Intelligence Based Hybrid Approach." *Available at SSRN 4019476.*

[35] Srivastava, Ridam, et al. "A topic modeled unsupervised approach to single document extractive text summarization." *Knowledge-Based Systems* 246 (2022): 108636.

[36] Shi, Kaile, et al. "StarSum: A Star Architecture Based Model for Extractive Summarization." *IEEE/ACM Transactions on Audio, Speech, and Language Processing* 30 (2022): 3020-3031.

[37] Biswas, Pratik K., and Aleksandr Iakubovich. "Extractive summarization of call transcripts." *IEEE Access* 10 (2022): 119826-119840.

[38] Ahmed, Rowanda DA, Mansoor AbdulHak, and Omar Hesham ELNabrawy. "Text Summarization Clustered Transformer (TSCT)." *2022 International Conference on Frontiers of Artificial Intelligence and Machine Learning (FAIML)*. IEEE, 2022.

[39] Kong, Yuqi, Fanchao Meng, and Benjamin Carterette. "A Topological Method for Comparing Document Semantics." *arXiv preprint arXiv:2012.04203* (2020).

[40] Joshi, Akanksha, et al. "RankSum—An unsupervised extractive text summarization based on rank fusion." *Expert Systems with Applications* 200 (2022): 116846.

[41] Mahalakshmi, P., and N. Sabiyath Fatima. " Summarization of Text and Image Captioning in Information Retrieval Using Deep Learning Techniques." *IEEE Access* 10 (2022): 18289-18297.

[42] Koh, Huan Yee, Jiaxin Ju, Ming Liu, and Shirui Pan. "An Empirical Survey on Long Document Summarization: Datasets, Models, and Metrics." *ACM computing surveys* 55, no. 8 (2022): 1-35.

[43] Asad Abdi, Norisma Idris, Rasim M. Alguliev, Ramiz M. Aliguliyev, “Automatic summarization assessment through a combination of semantic and syntactic information for intelligent educational systems”,Information Processing & Management,Volume 51, Issue 4,2015,Pages 340-358,ISSN 0306-4573,https://doi.org/10.1016/j.ipm.2015.02.001.

[44] Mihalcea, R., & Tarau, P. (2004, July). Textrank: Bringing order into text. In *Proceedings of the 2004 conference on empirical methods in natural language processing* (pp. 404-411).

[45] See, A., Liu, P. J., & Manning, C. D. (2017). Get to the point: Summarization with pointer-generator networks. *arXiv preprint arXiv:1704.04368*.

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