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From Primer to Core : Performing Text Summarization with NLP and spaCy

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Abstract: *Automatic Text Summarization (ATS) is becoming increasingly essential because of the overwhelming growth of word-based information found online and across various domains such as news archives, academic publications, and legal documents. Manually summarizing this vast amount of content is time-consuming, labor-intensive, and often not feasible. Efforts to enhance ATS methods have been ongoing after the 1950s. ATS can be categorized into three main types: Generative, Non-Generative, and hybrid. The Non-Generative approach identifies and pick crucial sentences directly out of actual content to form a summary. In contrast, the abstractive approach generates new sentences by interpreting the meaning of the source content. The hybrid approach integrates elements from both extractive and abstractive methods. Although many techniques have been proposed, automatically generated summaries often fall short of the quality produced by human summarizers. Most existing research has been centered around extractive summarization, while abstractive and hybrid methods remain relatively underexplored. This work outlines key aspects of ATS, including its methodologies, underlying techniques, datasets, evaluation metrics, and directions for future research, offering a clear understanding of the field for those interested in further development and exploration.*

Keywords: Automated Text Summarization; Python NLP; spaCy; Text Processing ; Natural Languauge Processing ; Evaluation Metrices

I. INTRODUCTION

The internet contains a vast and growing amount of textual information—ranging from websites, reviews, news articles, blogs, and social media posts to archives of novels, books, scientific papers, legal records, and biomedical literature. This content continues to increase rapidly every day. As a result, people often spend a significant amount of time trying to find the specific information they need. In many cases, it's not possible to read and understand all the available material, especially when much of it includes repetitive or less relevant content. Because of this, summarizing and reducing text becomes a necessary task.

Manual summarization requires time, effort, and resources, making it difficult to apply at scale (Vilca & Cabezudo, 2017). Automatic Text Summarization (ATS) offers a practical way to address this problem. The purpose of an ATS system is to create a brief version of the input text that captures its main ideas while minimizing repetition (Radev, Hovy, & McKeown, 2002; Moratanch & Chitrakala, 2017). This helps people understand the key points of a document without having to read the entire content (Nazari & Mahdavi, 2019).

Maybury (1995) described a summary as a shortened version of one or more sources that keeps the most important information, adapted to a specific user and task. Similarly, Radev et al. (2002) defined a summary as a text created from other text(s), containing the most relevant information in a shorter format— typically less than half the length of the original. The term "text" may also include spoken language, multimedia, and hypertext.

ATS systems are generally divided into two types: single-document summarization, which works with one text at a time, and multi- document summarization, which combines content from multiple sources. These systems apply one of three main approaches:

• Non-Generative summarization: selects key sentences directly from the source text.

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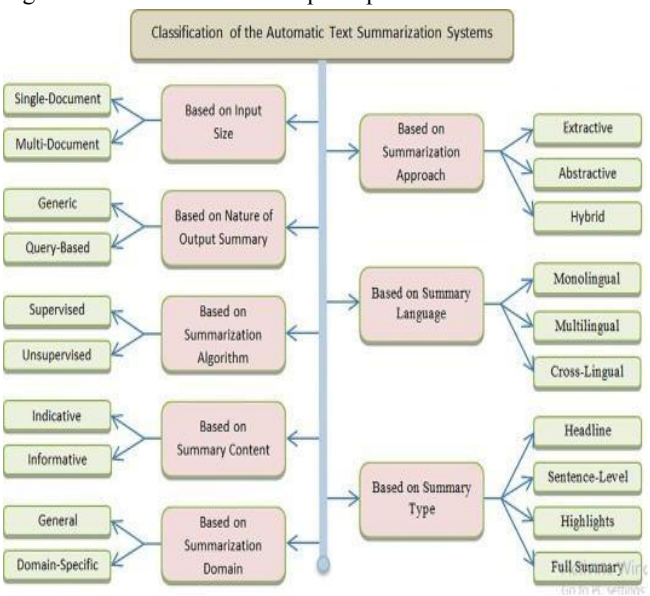
• Generative summarization: rewrites the content using new phrases and language.
• Hybrid summarization: blends both extractive and abstractive methods.
A typical ATS system follows three main stages:
1. Pre-Processing: The input text is cleaned and prepared through processes such as sentence splitting, tokenization, stop-word removal, part- of-speech tagging, and stemming (Gupta & Lehal, 2010).
2. Processing: A summarization technique is applied to convert the pre-processed text into a summary. Sections 3 and 4 discuss various approaches and technical components used during this step.
3. Post-Processing: Adaptation are made to refine the clarity and correctness of the created abstract, posting any issues in content structure .

II. CATEGORIZATION OF ATS

Automatic Text Summarization systems can be divided in many methods depending on factors like input type, output format, motive, abstract length, applied algorithms, empire accuracy, and language. Various researchers may distinct on different characterstics, leading to a scale of classification principle.



2.1 Based on Number of Input Documents

A ordinary method to distribute summarization systems is by the component of report used to create a abstract. This direct to two major types:

- Single-Document Summarization: In this proceed toward, the summary is caused from a single actual document
- It's mainly used in situations like abstracting reading passages or imposing a headline to a single article. Since it give out with only single document, it learn to be easier to execute and direct.
- Multi-Document Summarization: This practice created abstracts by unites content from multiple records. It's helpful in framework where different outlook or sources required to be combined, such as adding up information from various opening or concising user analysis from different platforms.

Multi-document summarization conduct extra dispute. One vital problem is repitition, where the alike content appears multiple times in the result. To post this, Carbonell and Goldstein (1998) proposed the Maximal Marginal Relevance method, which is useful in bring down recurrence. Another problem lies in diversity, as uniting data from different sources can introduce contrast content and unfairness, especially during the use of non-generative methods. In such

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cases, generative summarization frequently handles the complications more focusfully by creating new, symmetric sentences that consider multiple outlooks.

2.2 Based on Summarization Methods

Another method to distribute Automated Text Summarization systems is by the method used to create the abstract. This refers to whether the system straight selects subsist sentences, generates up-to-date ones, or unites both methods. Based on this, summarization can be classified into three major types:

- Non-generative Summarization: This method involves posting main information or phrases straight out of the actual content and putting them together to form a abstract . It's alike to using a highlighter to point lead information in a passage—what's pointed is what gets inserted in the abstract.
- Generative Summarization: In this technique, the system find out and writes the information, then rephrases it in new content that may not appear word-for-word in the original text . This is more like writing notes in your own words after reading a chapter.
- Hybrid Summarization: This unites elements from both non-generative and generative strategies. Some parts of the abstract are taken straight out from the actual content, while others are caused using natural language generation methods .

2.3 Based on Output Style

ATS systems can generate summaries tailored to either a general audience or based on specific user queries:

- General Summarization involves creating a short version of a record (or many records) by finding out its crucial points without picking out a particular subject.
- Query-Based Summarization works by range the abstract with a user's particular search or question. It highlights sentences or sections that are mostly related to the client's query by allocated higher significance to clauses closely aliking the query terms. This approach is mainly useful when studying a group of records to find out focused perceptions.

2.4 Based on Language Usage

Turning on how the language of input and output is grasped, ATS systems comes into the various categories:

- Monolingual Summarization: The terminology used in the actual record and the abstract is the same.
- Multilingual Summarization: Handles papers in various terminology and creates abstracts in those particular languages.
- Cross-Lingual Summarization: Interpret the information while concising. For example, it might take a document in any language and produce an abstract in another language.

2.5 Based on Algorithmic Approach

The method of summarization algorithm mainly impacts system behaviour:

- Supervised Learning: This method is based on manually known training data. The system learns patterns from human-curated examples before concising new texts.
- Unsupervised Learning: These systems do not require pre-known data. Despite of it, they investigate patterns and crucial content based on accurately or structural attribute of the data.

2.6 Based on Content Depth

The nature of the content in a abstract also differ by purpose:

- Indicative Summaries: Offer a high- level overview or gist of the document without going into detail.
- Informative Summaries: Aim to capture the full scope of the document's main arguments and data.
- Evaluative Summaries: Reflect a crucial stance, often containing explanations or penalty—such as an author's outlook on the subject.

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2.7 Based on Summary Length

ATS systems can customize output to contest various length constraints or user needs:

- Headline Summarization: Creates ultra-brief outputs—sometimes just a clauses or a few crucial words, often used in information.
- Single Sentence Summarization: Produces a one-liner summary that encapsulates the entire document's essence.
- Highlight Summarization: Creates bullet-pointed summaries that compress the core content in an easy- to-read format.
- Full Summarization: Generates detailed summaries that vary in length based on the desired compression level or the user's preference.

2.8 Based on Domain Scope

ATS systems can also be differentiates according to the estate or type of content they are planned for:

- Genre-Specific Systems: Work with structured content types like scientific articles, legal documents, or medical reports.
- Domain-Dependent Systems: planned to perform ideally within a specific subject area .
- Domain-Independent Systems: Built to handle general content from various fields without needing tuning for a specific topic.

2.9 Based on Depth of Processing

How deeply the text is analyzed during summarization also defines the system:

- Surface-Level Methods: These rely on easily identifiable text features—like word frequency, sentence location, or key phrases—to build summaries quickly. These techniques work well for simple extractive methods.
- Deeper-Level Methods: These involve more nuanced analysis, such as understanding semantic structures, entity relationships, or discourse structure. This method allows for more abstract and coherent summaries that better mimic human understanding.

III. DETAILED ABOUT NTS, GTS AND HTS

3.1 Non-Generative Text Summarization (NTS)

- Non-Generative summarization works by picking the most appropriate sentences directly out of source text without rewriting them. This method began with early work by Luhn (1958) using term frequency-based techniques to identify key information.
- Over time, systems like SCISOR (Rau et al., 1989) and SUMMARIST improved summarization by adding basic NLP capabilities and multilingual support. These tools pointed a shift from easy occurence counts to more sophisticated language concern.
- Machine learning methods such as Naïve Bayes and C4.5 (Neto et al., 2002) framed summarization as a classification problem— deciding if a sentence belongs in the summary or not. Some systems also used lexical chains (Silber & McCoy, 2002) to link related words for better coherence.
- Unsupervised models (Nomoto & Matsumoto, 2003) emerged to remove the need for manually labeled data, while hybrid techniques (Binwahlan et al., 2010) combined diversity, fuzzy logic, and swarm intelligence to improve sentence scoring and reduce redundancy.
- Evaluations of summary quality shifted from word count to concept retention (Ye et al., 2007b), with tools like Document Concept Lattice (DCL) optimizing the sentence selection process.

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3.2 Generative Text Summarization (GTS)

Generative summarization recreates sentences that represent the basic meaning of the actual content, rather than copying exact phrases. This technique gained structure through competitions like DUC-2003 and DUC-2004, where news articles were summarized with the help of human-written references. One top- performing system was TOPIARY (Zajic et al., 2004).

Earlier work used techniques from machine translation, such as phrase tables (Banko et al., 2000) and quasi-synchronous grammar (Woodsend et al., 2010). These methods laid the foundation for what would later evolve into deep learning-based models.

With the rise of sequence-to-sequence (Seq2Seq) models, text summarization saw major progress. Rush et al. (2015) used a convolutional encoder and attention mechanism to summarize news datasets like Gigaword and DUC. Similarly, Chen (2015) created a large Chinese dataset and used RNN- based encoders and decoders for short summaries.

Nallapati et al. enhanced this by using ranked observation to model crucial words and rare words. However, the model still scrap to totally express hidden information relationships. Later, Miao & Blunsom (2016) introduced a generative model to survey these hidden arrangement, followed by Li et al. (2017) who attach logic-based arrangement like "what, "what happened", and "who did what."

To get closer to real-world understanding, Abstract Meaning Representation (AMR) (Banarescu et al., 2013) was introduced, focusing to show "who is doing what to whom" in a graph form. However, it wasn't used for full distraction until Doha et al. (2017) put forward working with multiple abstract graphs to cover various information.

Song et al. (2019) combines non-generative generative approaches in their ATSDL model. This system first extracted key clauses using a method called MOSP and then find out how these clauses could form grammatically right abstract.

CTRLsum (He et al., 2020) brought managable to abstract by letting users input crucial words, while EdgeSumm (El-Kassas et al., 2020) unites multiple non-generative methods using graphs to refine abstract quality. These models proved qualitative but had restrictions like domain particularity or language dependency.

More new improvement include CNN-based abstract by Zhang et al. (2019) that enhance parallelism and WEI et al. (2018) who added normalization to converse semantic regularity. Still, one major responsibility remained— factual correctness.

To post this, Kryściński et al. (2019, 2020) developed models to find and fix factual unsuited between summaries and actual content. Their method identifies if a summary sentence can be proved using parts of the actual document and adjusts when instability are found.

Finally, GAN-based models like PGAN-ATSMT (Wang et al., 2020) and HH-ATS (Yang et al., 2021) introduced opposed training—where a generator creates summaries and a discriminator scores them. These models mimic human-like reading and concising using various-step reasoning processes such as studying, core reading, and revision.

3.3 Hybrid Text Summarization

Both non-generative and generative summarization approaches have their cons and pros. Extractive summarization is typically simpler to build, but it often fails to arrange with how humans naturally expect abstract to read. On the other hand, generative summarization, while more human-like, is challenging to implement effectively.

To overcome the individual limitations of these two methods, researchers have explored hybrid summarization techniques, which aim to combine the strengths of both. These methods attempt to maintain the structural simplicity of extractive models while improving coherence and readability through abstraction.

Before the 1990s, most automated summarization systems focused mainly on extraction—reproducing crucial parts of the text without generating new content. A key development during that time was the SUMMARIST system (Hovy & Lin, 1996), which used natural language processing (NLP) tools to improve summarization. Its movable structure made it flexible, containing for multilingual purposes.

Later on, researchers began combining semantic and statistical methods for hybrid summarization. For example, Bhat et al. (2018) introduced emotion-based features into their summarization process. By finding out the emotional tone of information, the system sort lines that carried meaningful sentiment, assuming they had more related to the reader or writer.

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Once key sentences were selected, Bhat's method used a hybrid generation model that combined tools like WordNet, the part-of- speech as well as Lesk algorithm tagging to rephrase and restructure the extracted content. This helped produce summaries that were both factually grounded and more natural-sounding.

IV. ATS SYSTEM EVALUATION AND EVALUATION PROGRAMS

a) Extrinsic Evaluation

This type of evaluation checks how useful the summary is when performing another task, such as text grouping, information recapture, or response. In this approach, an abstract is considered successful if it helps improve performance on these related tasks.

Some common areas of extrinsic evaluation include:

• Relevance Testing: This checks whether the summary includes the most important information related to the topic, compared to the full original text.

• Reading Comprehension: This measures how well someone can understand a topic or answer questions after reading the summary, often using tests like multiple-choice questions.

b) Internal Evaluation

Internal evaluation size up the quality of the summary by itself, without tying it to any other task. It focuses on how clear, informative, and well-structured the summary is.

There are two main types of intrinsic evaluation:

• Comparison with Human-Written Summaries: The generated summary is compared to a reference summary written by humans to see how closely they match.

• Comparison with the Original Text: This checks how much important content the summary captures from the original document.

4.1 Evaluating Summary Quality and Coherence

To make sure a summary is useful and readable, it's important to check for certain qualities that make the text coherent and easy to understand:

• Grammatical Correctness: The summary should be free of grammar mistakes, weird symbols, and incorrect punctuation or word choices.

• No Repetition: Good summaries avoid repeating the same information more than once.

• Clear References: Pronouns like "he" or "she" must clearly point to someone or something mentioned in the summary.

• Logical Flow and Structure: Sentences should be well-connected and follow a logical order so that the summary reads smoothly.

These language-based checks help ensure the summary feels natural and easy to follow. In fact, evaluations of summaries at conferences like Records Understanding Conference and Data Analysis Conference used 5 main questions related on these factors: clarity, grammar, structure, relevance, and repetition. Experts would read the summary and rate it on a five-point scale based on how well it scored in each of these areas (Gambhir & Gupta, 2017).

Another way to test summary quality is by using readability measures. These look at things like vocabulary variety, sentence structure, and how well the ideas connect. For example, vocabulary can be judged by counting unique words (unigrams), while syntax can be assessed by looking at how often verbs and nouns appear. These features are then compared to human readability scores to see how well they align.

4.2 Programs and Conferences for Summary Evaluation

Over the years, several programs and events have helped researchers test and improve their summarization systems. One of the earliest was SUMMAC, part of the TIPSTER program in the late 1990s. It evaluated summaries using both task-based (extrinsic) and standalone (intrinsic) criteria.

Following this, the DUC (Document Understanding Conference) series ran from 2001 to 2007. Each year, the challenges became more complex:

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• DUC 2001–2002: Focused on creating general summaries from single and multiple documents.
• DUC 2003: Introduced query-based summarization for multiple documents.
• DUC 2004: Added topic-based and cross-language summaries.
• DUC 2005–2006: Evaluated multi- document summaries based on user queries.
• DUC 2007: Took it a step further with update summarization—producing new summaries that reflect only what's changed since the last one.

After 2007, DUC was merged into the TAC (Text Analysis Conference). TAC continues the tradition of encouraging progress in Natural Language Processing, especially summarization. Each year, TAC hosts tracks and workshops where systems are tested on their ability to create short, meaningful, and well- structured summaries. The summarization track remains a key part of this initiative, helping teams build smarter, more human-like summarization tools.

V. COMMONLY USED DATASETS FOR AUTOMATIC TEXT SUMMARIZATION (ATS)

Data is at the heart of any Automatic Text Summarization system. No matter how advanced the method is, without the right kind of dataset, it's impossible to train or evaluate a summarization model effectively. However, raw data can't be used as-is. It often needs to go through preprocessing steps like cleaning, formatting, and tokenizing before it's ready for use.

Machine learning approaches especially need large, well-structured datasets that contain ideal examples of summaries. These examples, often written by people, serve as the gold standard that models try to learn from. Over time, several datasets have become widely used in the field. Here are some of the most popular ones:

- DUC (Document Understanding Conference): Released by the National Institute of Standards and Technology , these datasets are among highly recognized in summarization research. They were shared as part of summarization challenges held between 2001 and 2007. Each set includes documents and human- written summaries for benchmarking systems.
- TAC (Text Analysis Conference): After 2007, DUC evolved into TAC, which continued the work with its own summarization track. These datasets are still widely used, but you'll need to fill out a request form on the TAC website to get access.
- Gigaword: Created by Rush et al. in 2015, this dataset contains millions of English news articles. Each article is paired with a headline, making it ideal for training models on headline generation—a type of summarization.
- Large-scale Chinese Short Text Summarization: This datafile comes from Sina Weibo, a Chinese social media platform. It includes over 2 million posts along with summaries written by the original posters. Since it's in Chinese, it's mainly used in Chinese-language summarization tasks.
- WikiHow: Introduced by Koupaee and Wang in 2018, this dataset is built from the WikiHow website, a how-to guide written by users. Articles are paired with short, bolded lines that serve as summaries. It's useful for studying summarization in instructional or procedural text.
- CNN/Daily Mail: This dataset contains around 310,000 English-language information articles put down by CNN as well as Daily Mail journalists. Originally created for machine comprehension, it now supports both extractive and abstractive summarization tasks. It's commonly used in deep learning models for summarizing news content.

VI. APPLICATIONS OF AUTOMATIC TEXT SUMMARIZATION

Automatic Text Summarization has a wide range of real-world applications that span across industries, domains, and platforms. As ATS techniques have evolved into various types—like extractive, abstractive, and hybrid—their practical uses have expanded just as quickly.

This section explores some of the key areas where ATS is making an impact. Whether it's helping people save time, simplifying large volumes of text, or making digital platforms more user-friendly, ATS systems are becoming essential tools in today's information-rich world.

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Here are some notable applications:

- Boosting Information Retrieval (IR) and Extraction (IE) Systems: Integrating ATS with systems like question answering tools improves their efficiency. Summaries help quickly extract relevant details.
- Information Summarization and Creation: ATS helps condense long news articles into brief highlights or generate news summaries from multiple sources (Tomek, 1998; Bouras & Tsogkas, 2010).
- RSS Feed Summarization: Summarizing news from RSS feeds helps users scan through multiple headlines and pick what's most important (Zhan et al., 2009).
- Summarizing Blogs and Social Media Posts: Platforms like blogs and Twitter produce tons of text. ATS tools make it easier to digest this content quickly.
- Mesh Page Summarization: ATS can extract the core content from web pages, helping users find what they need without reading the entire page .
- Email as well as Thread Summarization: ATS can automatically summarize long email chains, making business communication more manageable (Muresan et al., 2001).
- Professional Report Summarization: Busy professionals—like politicians, researchers, or business executives— benefit from summaries that distill large documents into brief overviews (Lloret et al., 2013).
- Meeting Summarization: ATS tools are used to summarize key discussion points from recorded or transcribed meetings, aiding follow-up actions.
- Biographical Summaries: Quickly generates key life highlights of individuals, often used in media and research.
- Legal Document Summarization: Law professionals use ATS to simplify lengthy legal documents, making case reviews faster and more efficient (Farzindar & Lapalme, 2004).
- Book Summarization: ATS can provide short versions of entire books, which is useful for academic or casual reading (Mihalcea & Ceylan, 2007).
- Medical Document Summarization: In healthcare, ATS is used to summarize patient records, research articles, and clinical findings to support faster decision-making (Feblowitz et al., 2011; Ramesh et al., 2015).

VII. CONCLUSION

- Automatic Text Summarization (ATS) focuses on reducing lengthy text content into shorter versions while preserving its key meaning and valuable information. With the growing volume of digital content and the rise of internet technologies, ATS has become a vital tool in text analysis and processing. It plays a central role in the area of Natural Language Processing as well as continues to gain momentum both in research and real-world applications.
- To bridge the gap between the two, hybrid methods have emerged— combining the strengths of both non-generative and generative techniques to build more competent concise. This paper presents a detailed contrast of these approaches along with a thorough observe of ongoing research and methods.
- Looking ahead, there's great potential for developing summarization systems that are robust, domain-agnostic, and capable of handling content in multiple languages across various document types. A major challenge that remains is improving the objectivity of summary quality evaluation. While metrics like grammaticality and coherence exist, human judgment can vary, leading to inconsistencies in assessment.
- In the future, automating these evaluations and refining ATS systems to generate more coherent and contextually accurate summaries will be key goals for researchers in this space.

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