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Presented by:

Sl. No.	Name	Year	Section	Roll No.	Enrollment No.
1	Aritra Ghosh	2nd	A	74	12021002002137
2	Subhojit Ghosh	2nd	B	97	12021002002160

Mentor: Dr. Anupam Mandal

Abstract:

Text summarisation is the method to reduce the source text into a compact variant, preserving its knowledge and the actual meaning. Here we thoroughly investigate automatic text summarization (ATS) and summarize the widely recognized ATS architectures. A manual text summarization process is undoubtedly an effective way to preserve the meaning of the text; however, this is a time-consuming activity. Another approach is to utilize automatic text summarization (ATS). In ATS, different practical algorithms can be programmed into computers to produce information summaries. Thus, text summarization creates a brief and accurate overview of a lengthy text document by concentrating on the essential parts that provide valuable details by maintaining the overall context.

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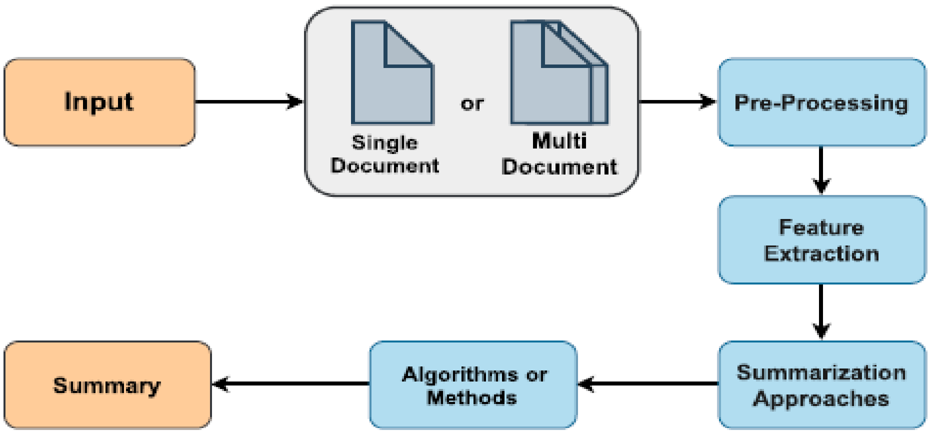
Introduction:

How does Text summarization work?



A basic structure of an ATS. The figure illustrates seven steps where the input (single or multi-document) is pre-processed and follows feature extraction. The next section follows summarization approaches and methods which concludes with a summary of the document.

A. **Pre-Processing**
   The pre-processing phase uses linguistic techniques to prepare input text documents. This includes techniques like sentence segmentation, removal of punctuation marks, filtering stop-words, and stemming (reducing common root words)
B. **Feature Extraction**
   The extraction of sentences is vital for the entire summarization process by selecting different features within the source document. Selected features are applied to each sentence, and the highly scored sentences are chosen for the summary in the feature extraction phase.
C. **Summarization Approaches**
   The first and most crucial step in the summarization strategy is to determine efficient methodologies. Some methods involve selecting the essential words and lines from the texts, while others involve paraphrasing one sentence and condensing the original content.
D. **Algorithms**

Algorithms or methods are a more definite way of denying text summarization. Different algorithms and methods under various approaches are applied to obtain a better version of the summarized text.

Features extraction of ATS:

Collecting the essential features is the first phase of the feature extraction process. Some features are used as attributes to dene the text for this task. The most prevalent features for calculating the score of a sentence and indicating the degree to which it belongs to a summary are given below:

1. **Term Frequency (TF)**: The TF metric is used to determine the importance of terms in a single document. It is commonly used to determine a word's weight.
2. **Term Frequency-Inverse Sentence Frequency (TF-ISF):** One of the most significant feature extraction methods for text summarization involves measuring the term frequency-inverse sentence frequency across all documents.
3. **Position Feature:** Typically, the initial and concluding sentences are deemed to contain more significant information about the document. Therefore, researchers have a greater likelihood of having their sentences included in the summary by placing them at the beginning or end of the document.
4. **Length Feature:** The length of a sentence can serve as an indicator of its suitability for inclusion in a summary. However, it would be incorrect to assume that a sentence is summary-worthy based solely on its length. Typically, very long or very short sentences are not included in the summary when compared to the length of other sentences in the source material.
5. **Sentence-Sentence Similarity:** This feature refers to sentence-sentence similarity and can aid in summarization by identifying sentences that are similar to other sentences in the text.
6. **Title Feature (Tif):** Sentences that contain keywords or phrases from the document's headline are more likely to be included in the summary as they can provide an indication of the document's overall theme.
7. **Phrasal Information (PI):** Including a proportion of phrases is considered useful in the summarization process. A set of phrases, denoted by P, comprises of adjective phrases (ADJP), noun phrases (NP), prepositions (PPM), and verbal phrases (VP).
8. **Sentence Position (SP):** This feature, known as Sentence Position (SP), determines the location of a sentence within the text. The significance of a sentence is influenced by its position in the text, such as being the first of five sentences in a paragraph.
9. **Thematic Word (TW):** The thematic word feature is linked to specific phrases in a particular field that frequently occur in the text and are likely related to the document's subject matter. The score is calculated by comparing the number of these words in the phrase to the maximum sum of thematic terms in the sentence.
10. **Numerical Data (ND):** A sentence that contains numerical data is typically considered important and is often included in a document summary. The score for this feature is calculated by dividing the numerical data in a sentence by the length of the sentence.

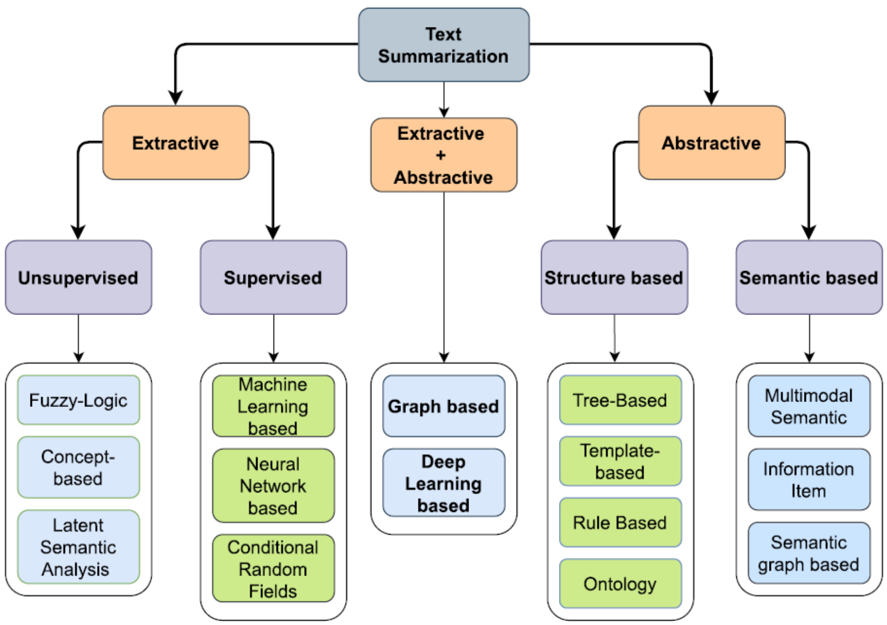
Text Representation:

Text representation models are being increasingly used to enhance the representation of input documents. In the field of natural language processing (NLP), these models involve converting words into numerical form to enable computers to recognize and identify patterns within language. Typically, these models establish a relationship between a selected phrase and the contextual words within the document. Popular text representation methods include bag-of-words, n-gram, and word embedding, which are further elaborated on below.

1. **N-gram:** N-gram is a text representation method that is particularly suitable for multilingual operations as it does not require any linguistic preprocessing. It involves grouping words or characters into N components to create a model. The resulting vector representation is typically of reasonable size, making it easy to work with. The set of text N-grams includes unigrams, bigrams, trigrams, quad grams, and other types]. However, the N-gram model has some limitations, such as the fact that it becomes more effective as N increases, but this also results in increased processing requirements, which demand significant amounts of RAM. Additionally, N-grams result in a sparse representation of language as they rely on the probability of terms co-occurring. Any words not present in the training corpus are given a probability of zero.
2. Bag of words (BoW): This can lead to sparsity in the vectors and can affect the performance of the model. In addition, the BoW model does not take into account the order of the words in a sentence, which can be important for understanding the meaning of a text. Therefore, more advanced models such as n-gram and word embedding have been developed to overcome these limitations.
3. Term Frequency-Inverse Document Frequency(TF-IDF): IDF measures the importance of a word by taking into account how frequently it appears in the corpus, while TF measures the frequency of a term in a specific document. By combining both, the TF-IDF method can determine the importance of a term in a document relative to its importance in the corpus. However, TF-IDF has some limitations, such as being slow with large vocabularies and assuming that the counts of various terms are independent evidence of similarity.
4. Word Embedding: Word embedding algorithms learn to map words or phrases into vectors of fixed dimensions in a continuous space, where similar words or phrases are represented by vectors that are close to each other.
   Some popular word embedding algorithms are:
   - Word2Vec
   - Global Vectors for Word Representation (GloVe)
   - FastText

Conventional methods:

Here we take a look at some of the pre-existing methods used for text summarization.



A. **Extractive Text Summarization** - The extractive text summarisation method involves selecting important sentences from text material to create a summary. This is achieved by identifying words and sentences that are essential to the original document and replicating them word for word. The process involves three independent tasks: identifying important sentences, selecting these sentences, and replicating them to create the summary. They are as follows:

1. **Splitting** the source document into sentences and then creating an intermediate representation of the text highlights the task. Intermediate representation has two main types, such as Indicator representation and topic representation
2. **Assigning** scores in each sentence for specifying their importance depending on their performance after the representation creation. Topic representation scores on the topic word and the text content. On the other hand, indicator representation scores depend on the features of the sentence.
3. **Selecting** the highest-scoring sentences to form the summary.

B. **Abstractive Text Summarization**- Abstractive text summarization is a newer method that automates the traditional approach. It involves identifying key sections and main ideas of a text document through paraphrasing. The process uses a different vocabulary set from the source and NLP models to create a summary that includes all the important points. Abstractive summarization can be achieved through two types of approaches: structure-based and semantic-based, which are based on NLP techniques.

1. **Structure-based** abstractive summarization approaches use abstract or cognitive algorithms to filter the most important information from a text document. The most commonly used algorithms include tree-based, template-based ontology, and rule-based ontology.
2. **Semantic-based** abstractive summarization methods refine sentences using NLP on the entire document, using techniques like multimodal semantic method (MSM), semantic graph-based method (SGM), information item-based method (IIM), and semantic text representation model (STRM).

Now Let us take a closer look at **Automatic text summarization algorithms.**

A. <u>Unsupervised Learning Methods-</u> Unsupervised extractive text summarization is a unique method that selects essential sentences without using labelled summaries and does not require user feedback or human overviews. It is more efficient and better suited for lengthy text summaries than supervised methods. Various unsupervised techniques or methods for summarizing texts or documents are discussed below:

1. **Fuzzy-Logic-Based Methods**- A fuzzy logic-based approach for text summarization involves selecting fuzzy rules and membership functions, and has four components: a fuzzifier, inference engine, demulsifier, and knowledge base. This approach is used for selecting important sentences from the source document but requires redundancy removal for better results. Some research has focused on this method for ATS.
2. **Concept-Based Methods** - The concept-based method extracts and scores concepts to reduce redundancy in the original document, but it has limitations. Ramanathan et al. proposed a method that employs a sentence concept bipartite graph structure to generate summaries.
3. **Latent Semantic Analysis (LSA) Method**- LSA is an unsupervised method that extracts hidden semantic structures from input documents, without the need for outside training. However, it has limitations such as not analyzing word order or relying solely on input document information. It works well for semantic text summarization tasks and has been used in various studies.

B. <u>Supervised Learning Methods-</u> Supervised learning methods classify sentences as summarized or not based on human-generated summaries, but they require manual context summaries and a lot of labelled training data.

1. **Machine Learning (ML) Method**- Machine learning methods are used for sentence-level classification in summarization by learning to distinguish between summarized and non-summarized sentences. They require a trained dataset of documents and summaries and commonly use algorithms like C4.5 or naive Bayes. They also use pre-processing algorithms like stop-word removal and stemming and can be implemented with neural network models.

2. **Neural Network (NN) Based Method**- Neural network methods are used for summarization, with a three-layered feedforward network being used to learn sentence features during training. The neural network-based method removes infrequent features and combines frequent ones, followed by sentence ranking to define meaningful sentences. RankNet is a technique that uses a two-layer neural network with backpropagation for sentence classification. Several studies have proposed using neural networks for summarizing source documents.
3. **Conditional Random Fields (CRFs) Method**- Various text summarization methods include machine learning, neural networks, conditional random fields, optimization-based, statistical-based, topic-based, sentence centrality, and clustering-based methods. Abstractive summarization requires language generation and compression strategies and can be structured or semantic.

C. **<u>Structure-Based Methods</u>**- In the abstractive summary, the source document requires newly constructed sentences to summarize. In the structure-based method, phrases from source documents are interpreted in a specified structure without losing their meaning. Structure-based approaches mainly rely on preset forms and spatial reasoning schemas, such as templates, tree-based, ontology-based, and rule-based structures.:

1. **Tree-Based Methods -** The tree-based method uses a tree-like structure to recognize shared knowledge and facts between sentences for abstractive summarization. It produces less redundancy but overlooks significant phrases and focuses too much on syntax. However, it is still effective in structured-based methods.
2. **Template-Based Methods** - Template-based method uses predefined guidelines or templates to extract the content and construct informative and coherent summaries. It is useful when a document requires a specific structure. However, it lacks variety and may not produce fluent summaries.
3. **Rule-Based Methods**- Rule-based approach uses questioning to extract essential information and generate summaries. It is less efficient than other methods and requires time-consuming manual rule preparation. BERTSUM is a transformer-based model used in this approach.
4. **Ontology-Based Methods**- Ontology is a knowledge-based approach that formalizes entity types in a domain. It works best for domain-specific documents, generating coherent summaries. However, preparing a suitable ontology is a time-consuming process and not generalizable to other domains.

D. **<u>Semantic-Based Methods</u>**- Semantic-based methods analyze a document's text using natural language generation systems, focusing on noun and verb phrase identification for less redundant and grammatically correct sentences. However, they may ignore critical information.

1. **Multimodal Semantic Method**- The multimodal-based method summarizes both text and image concepts by representing them as nodes and connections. SimpleNLG is an example of a system that translates selected ideas into sentences for summarization.
2. **Semantic Graph-Based Method**- The semantic graph-based approach creates a rich semantic graph and reduces it to generate brief, cohesive, and grammatically correct sentences. It assigns weights to nodes and edges to extract semantic information but

requires a semantic representation of the text. Several studies have proposed semantic graph-based methods for text summarization.

3. **Information Item Method**- This method summarizes a text file based on its abstract, using an abstract representation of the source material. It retrieves information based on a logical flow of information in the text, resulting in concise and fewer redundant summaries.

E. <u>Extractive + Abstractive Methods</u>

1. **<u>Graph-Based</u>:** The graph-based method can be applied to both extractive and abstractive text summarization. This approach is an unsupervised learning method that rates the required sentences or terms using a graph. The purpose of the graphical process is to extract the most relevant sentences from a single text.
   Some popular methods are
   - LexRank
   - Weighted or Undirected Graphs
   - Graph-Based Attention
   - PageRank
   - TextRank
   - Positional Power Function
   - Hyperlink Induced Topic Search (HITS)
2. **<u>Deep Learning Algorithms</u>**: Deep learning models are beneficial for information-driven ATS, as they aim to imitate the human brain's functions and make ATS more efficient, accessible, and user-friendly. Deep neural networks are often used in NLP tasks because their design aligns with the complexity of language, with each layer capable of performing a specific task before passing on the output to the next layer.
   Some popular algorithms are
   - RNN Encoder-Decoder
   - Gated Recurrent Unit (GNU)
   - Long Short-Term Memory (LSTM)
   - Restricted Boltzmann Machine (RBM)
   - Naive Bayesian Classification
   - Query Based
   - Generic Summarization
   - Q-Network

Several pre-trained language models like **BERT**, **GPT-2**, **TransformerXL**, and **XLnet** have made significant improvements in various NLP tasks, such as sentiment analysis, question answering, natural language inference, named entity recognition, textual similarity, and paraphrasing. These models are trained on vast amounts of text data and fine-tuned with different task-specific objectives. They are primarily used as encoders for natural language understanding tasks, including sentence and paragraph classification. The unsupervised goal of masked language modelling and next-sentence prediction makes these models highly effective.

Lately, there has been a growing interest among researchers in exploring the ATS domain, particularly in finding better text summarization methods. This section will first review the significant research on ATS and then delve into its sub-domains, highlighting their respective state-of-the-art accuracy.

Inference from Research:

We went through a number of papers in order to find the trends in the research. The entire process has been summarised in the following table.

Task	Method	Dataset	Feature Extract	Accuracy	Limitation & Future Work
Text summarization by sentence selection [212]	Fuzzy logic	DUC 2002	Tif, SL, TW, SP, TW, etc.	F-measure: 0.498, recall: 0.457 and precision: 0.471 respectively	- Fuzzy logic did not produce promising results - Authors would like to use other learning with fuzzy logic in thei future work
Sentence similarity measure [101]	TF-IDF, Word2vec, Sectence2vec	SKE for English and Arabic	AE, VAE, ELM-AE	ROUGE-1: 0.6043 and ROUGE-2: 0.5771	- Arabic abstractive summarization was not possible - Authors would like to use auto encoders or attention encoders in their future work
Sequence labeling [235]	Conditional Random Fields (CRF)	DUC 2001	SP, SL, Log-likelihood, TW, Indicator words etc.	ROUGE-2 :0.245, F1 Measure: 0.202 of	- Linguistic features were not used - Authors would like to use rhetorical structures for robustness in their future work
Short representation from a long document [316]	Latent Semantic Analysis (LSA)	Corpus of Contemporary Arabic (CCA)	Euclidean Distance, Cosine Similarity, Jaccard Coefficient etc.	Entropy 0.1275(approx.), Purity 0.385(approx.) and	- NA
Query-based single-document summarization [99]	Restricted Boltzmann Machine (RBM)	SKE, BC3, TAC	Key phrase oriented, Subject oriented summarization	Precision: 0.1694, Recall: 0.2115 and F-score of AE: 0.1816	- Did not cover multi-documents summarization into this system - Authors would like to extend generic summarization by clustering

Task	Method	Dataset	Feature Extract	Accuracy	Limitation & Future Work
Two-stage extractive and abstractive framework [37]	Highlighting the relevant information	WikiSum (self-generated)	TF-IDF, TextRank, SumBasic, T-D, T-DMACA etc.	ROUGE-L: 38.8	- Required performance measurement improvement - Authors would like to conduct further research to improve performance
Decrease summarization redundancy with DISCOBERT [322]	BanditSum, NeuSum, JECS, BertSum, PNBert, HiBert	New York Times (NYT), CNN, and Daily mail (CNNDM)	EDU	ROUGE-1: 50.00, ROUGE-2: 30.38 and ROUGE-L: 42.70	- Did not apply different task on long document encoding - Authors would like to explore better encoding methods in their further research
To find Solution to information overload [323]	Sentence clustering	DUC 2001, 2002	Stop words, Stemming	ROUGE-1: 0.47856, ROUGE-2: 0.18528 and F1 measure: 0.48324	- Author tested one method only - Authors would like to explore more datasets to evaluate the model
Enhancing criterion and objective functions [324]	Discrete differential evolution algorithm	DUC 2001, 2002	Sentence similarity, Sentence clustering	ROUGE-1: 0.45412, ROUGE-2: 0.18982	- NA
Quantitative and qualitative assessment of 15 algorithms [325]	Word scoring, Sentence scoring and graph scoring	CNN Dataset, Blog summarization dataset, SUMMAC dataset	Word Frequency, TF/IDF, Lexical Similarity, SL, SP, Text rank etc.	Average Recall: 0.47, Precision: 0.19, and F-measure is: 0.26	- Authors would like to compare with other algorithms in their future work
[Do not touch I am working from 6.30pm again] Word-sentence co-ranking model [326]	CoRank model	DUC 2002	Redundancy removal strategies	F-measure: 0.59, ROUGE-1: 0.69 and ROUGE-2: 0.60	- Did not conduct query-oriented and event-driven summarization tasks - Authors would like to extend co-rank model multi-document summarization
Joint Extractive and Compressive Summarizer (JECS) [327]	Neural Network model	CNN/Daily Mail, New York Times	Sentence and Document Encoder, Compression Encoder, Compression	ROUGE-1: 45.5, ROUGE-2: 25.3	- NA

Challenges of Summarization:

The ultimate goal of any ATS system should be able to summarise texts as closely as possible to a human-generated summary. However, to reach this goal, existing ATS systems still have significant important challenges.

1. **Evaluation**: The challenges in automatic text summarization are commonly encountered, and different datasets and metrics can produce different results. Datasets and metrics can be biased towards certain summarization techniques. Using a common dataset and metric can produce good results, but automatic evaluation techniques have several issues that need to be addressed. Precision and recall analysis may be misleading to researchers and not lead to desired conclusions. While scoring, metrics typically overlook sentences that are semantically or syntactically incorrect. This can be a problem because some metrics may give high scores to unimportant sentences while failing to properly evaluate those that contain grammatical errors.
2. **Important Sentence Selection**: ATS systems usually select the most relevant sentences from the original text and mark them as essential. However, determining which sentences are most significant can be subjective. Selective sentences or words need to be standardized according to the benchmark, and this can make a difference in the resulting summary. User-specific data can help solve this problem in professional summarization. Despite attempts to use vector representation and similarity matrices to find word correlations, there is no reliable way to identify the most important sentences.
3. **Anaphora Problem**: Anaphora problem is a prevalent difficulty in text summarization. During the discussion, humans, frequently substitute the subject with synonyms or pronouns. The `anaphora problem' determines which pronoun complements which word.
4. **Predefined Template**: Recently, natural language processing has made an incredible amount of progress in ATS. But these methods cannot generate new sentences on their own. Therefore, the template-based algorithm was introduced, where a specific template needs to be predefined for a particular summarization task.
5. **Long Sentences and Jargon**: Current learning methods for text summarization are typically limited to summarizing short sentences and may struggle to interpret longer sentences or jargon. To address this issue, researchers should identify the problem and develop a new architecture that can effectively summarize longer sentences and handle jargon to reduce or eliminate this problem.
6. **Interpretability**: Abstractive models offer a concise representation of the essential concepts in the source content. However, machines have difficulty with the complexities of human language and the expression of emotions in written materials. Thus, ensuring the interpretability of source content through abstractive models is a challenging task.
7. **Cataphora Problem**: The presence of ambiguity in words can impact the accuracy of sentence summarization. This ambiguity may arise due to multiple meanings of abbreviations or the use of a word in different contexts. To ensure that the summary conveys the intended sense, the acronym used must match the topic. This problem is called the Cataphora problem and can be addressed using disambiguation algorithms.

Some other challenges can be that the summary sentences should be meaningful and impactful to the users, and the representation should be robust in all areas where the system encounters difficulties. One of the ongoing research topics in text summarization is achieving a higher level of abstraction. This presents numerous possibilities for researchers and linguists to explore in order to find a solution to this problem.

In addition to the above-mentioned general challenges we also present a few limitations of the current algorithms used in the ATS domain.

		Algorithm	Limitations
Extractive	Unsupervised	Fuzzy logic	It requires a redundancy removal technique in the post-processing phase to improvise the summarization quality.
		Concept-based	It needs to utilize similarity measures for reducing redundancy which can affect the quality of the summary.
		Latent-Semantic	The LSA generated summary required a large amount of time.
	Supervised	Machine Learning	It needs a large set of data for training and improving the sentence selection for making a good summary.
		Neural Network	It is quite slow in training phase and application phase. Also requires human interruption for training data.
		Conditional Random Fields	In CRF linguistic features are not considered. It also requires external domain specific corpus.
Abstractive	Structure-based	Tree based	It ignores the context and significant phrases in the text, eventually failing to detect the relation between sentences. Another drawback is that it continuously focuses on syntax, not semantics.
		Template based	The templates are pre-defined in this method that creates a lack of diversity in the summaries.
		Rule-based	The requirement to prepare the rules is a time-wasting process. Another challenge is that the rules needed to be written manually.
		Ontology-based	A suitable ontology preparation is a very time-consuming process and cannot be generalized to other domains.
	Semantic-based	Multi-modal semantic	An automatic evaluation of the framework is required as it is manually evaluated by humans.
		Information item	Difficulties of creating meaningful and grammatical sentences from text. Also linguistic quality of summaries is very low due to incorrect parses.
		Semantic graph	This method is limited to single document abstractive summarization.
		Deep learning	It need human effort for building big training data manually.
		Graph-based	It does not consider importance of words and does not consider dangling anaphora problem.

Performance of a Summarizer:

The performance of a summarizer is judged based on some conventionally approves metrics which are discussed below.

1. **Precision Metric**: The precision metric evaluates whether the percentage of sentences chosen by humans and the computer is correct.

$$\text{Precision} = \frac{S_{\text{ref}} \cap S_{\text{cand}}}{S_{\text{cand}}}$$

2. **Recall Metric:** The recall metric determines the system recognizes how many sentences are selected by humans.

$$\text{Recall} = \frac{S_{\text{ref}} \cap S_{\text{cand}}}{S_{\text{ref}}}$$

3. **F-Measure Metric:** The F-measure metric incorporates recall and precision metrics.

$$\text{F-Measure} = \frac{2\,(\text{Precision})\,(\text{Recall})}{\text{Precision} + \text{Recall}}$$

4. **ROUGE Metric**: Recall-Oriented Understudy for Gisting Evaluation (ROUGE) is a series of evaluations ATS and machine translation. It compares an automatically generated summary or translation to a set of predetermined summaries such as human-generated summaries. ROUGE consists of ve measures: ROUGEN, ROUGE-L, ROUGE-W, ROUGE-S, and ROUGE-SU.
5. **Pyramid Method**: The pyramid technique is used because there is no best comparison summary among the human-created model summaries. A good summary has more SCUs from higher pyramid levels than lower levels, whereas a poor summary has more SCUs from lower tiers than higher tiers.
6. **Relative Utility**: This measurement assigns a score between 0 and 10 to each sentence in the input document based on relevance. The highest-scored sentence is thought to be more appropriate for a summary.
7. **Factoid Score:** Factoid score is the evaluation of computerized summaries in terms of factoids which are atomic units of information. Different pre-defined summaries are utilized, and shared knowledge is evaluated among these.
8. **BLEU:** The Bilingual Evaluation Understudy (BLEU) evaluation metrics assess the output quality of machine translation systems in terms of reference translation. The BLEU method is computed as

$$\text{BLE}U = \min\left(1, \frac{\text{output length}}{\text{reference length}}\right)\left(\prod_{i=1}^{4} \text{precision}_{\,i}\right)^{\frac{1}{4}}$$

9. **CHRF:** Character n-gram F-score (CHRF) generates a simple F-score by combining the recall and precision of character n-grams of maximum length 6 with several parameter values (= 1, 2, or 3).

$$CHRF = \left(1 + \beta^2 \frac{ChrP \cdot ChrR}{\beta^2 \cdot ChrP + ChrR}\right)$$

Conclusion:

Despite being an old topic, text summarization continues to attract the attention of researchers. However, the overall performance of text summarization is considered average, and the generated summaries are not always ideal. To address this, researchers are working to improve existing methods and develop new approaches that can produce high-quality, human-like summaries. One way to achieve this is by enhancing Automatic Text Summarization (ATS) with other integrated systems to perform better. ATS is a critical area of research that is widely used and integrated into various applications to summarize and reduce text volume.

In this paper, we present a systematic survey of the broad ATS domain, covering fundamental theories, previous research backgrounds, dataset inspections, feature extraction architectures, influential text summarization algorithms, performance measurement matrices, and challenges of current architectures. We also highlight the current limitations and challenges of ATS methods and algorithms, which researchers can address to overcome new challenges and enhance the quality of ATS summaries.

Link to presentation:

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