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A Survey on Automatic Text Summarization and its Techniques

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Abstract: In a world with an ever-growing amount of data available on both offline and online sources, the task of extracting the key information from the documents and summarizing the content creates the need for automatic text summarization. In this paper, we will look into the types of automatic text summarization and how it has been helpful in various fields like social media marketing, legal contract analysis, video scripting, etc. Further, this paper conducts a methodical study on abstractive text summarization and highlights the approach which mimics the human cognitive method of summarizing text. The paper aims to analyze the numerous techniques, difficulties, opportunities, and current state of art of abstractive summarization. A detailed survey of research papers/articles was conducted based on the technologies used to make this task quicker and more accurate in recent years.

Keywords: *Abstractive Text Summarization, Seq2Seq, Pointer Generator Network, Text Categorization.*

1. Introduction

Nowadays, there is a lot of information available from both online and offline sources. There are so many websites that provide us with a vast amount of information about a single topic. Consider the internet, which is made up of websites, media publications, social media, blog posts, and much more. There is a massive amount of written texts, and it is only getting bigger with each day. There is a strong need to condense much of this text data into shorter, concentrated summaries that capture the key details, so we can access it more effectively and determine whether the larger documents contain enough information we seek. Because the data is unstructured, the best way to navigate it would be to look up and scrape the results. Manually going through all of those articles to get the key information is a really difficult task. To make this task easier and quicker, automatic text summarization came into existence in the 1950s. Summarization can be classified on the basis of scale and approach. (Fig 1)

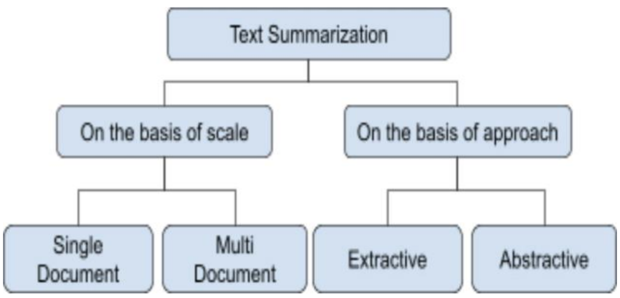

Fig.1 Types of Text Summarization

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A. On the basis of scale:

● Single Document SummarySingle-document summarization converts a source text into a concentrated, shorter text that retains the necessary information.

● Multi-Document Summary

Multi-document summarization is an automatic process for extracting information from multiple texts on the same topic. The summary allows individuals and organizations to quickly acquaint themselves with information found in a huge number of documents. In this way, multi-document summarization systems complement news aggregators, which are using the technique to cope with information overload.

B. On the basis of approach:

● Extractive Text Summarization

The extractive approach focuses on extracting phrases and lines from the documents. The summary is then created by combining all of the important lines. So, in this case, every line and word of the summary is taken from the original document that is being summarized.

● Abstractive Text Summarization

The abstractive approach is based on deep learning summarization. As a result, it employs new phrases and terms that differ from those found in the original document while keeping the points consistent, much like how humans summarize. Thus, it is more complex than extractive summarization.

In this survey paper, we will look into various techniques of text summarization and the steps involved in it. The focus of this paper is abstractive text summarization. A lot of research had been done and developments were made to understand or interpret the importance of sentences and relationships between words in the given text. Also, we will look into how automatic text summarization is being implemented in fields like finance, social media, contracts, etc.

Motivation

Summaries are beneficial as they reduce reading time and give us important information about the matter. Due to the immense amount of data available today, going through all those related documents and deciphering has become a tedious task for humans. To tackle this issue, automatic text summarization was introduced with the objective to generate the most relevant and meaningful summaries that imitate those generated by humans. There are numerous benefits of automatic text summarization which increase the demand for such systems.

Specifically, human cognition reading is composed of three primary stages which are rough reading, active reading, and post-editing. Researches are being done to create a model which can mimic the above process and produce summaries equivalent to humans. Despite the fact that this field has been studied since its inception, it cannot be claimed that summaries produced by the implemented techniques were as good as summaries written by humans.

2. Applications of Text Summarization

I. Search Engines

Nowadays with the more usage of the Internet, the quantity of data and documents is increasing exponentially. Creating any kind of copies of the document is being permitted for personal work or classroom use without any fee charged, provided that those copies had full citation of the notice at the beginning of the document regarding the profit or commercial advantage. The legal rights of the external components of this work should be respected. The abundant quantity of documents needs to be managed properly and for that research is going on regarding the automation of the text summarization.

According to *Radef et al. [1]*, a summary is defined as "the summarized content which is derived from the original content contains important text to convey and it is lesser than the half of the original text". Text Summarization means to summarize the text into smaller paragraphs by retaining its important meaning and terms. In recent times, multiple attempts and implementation is going on in the Automated Text Summarization and its application has been helpful in various fields. Search engines, for example, provide a glimpse of the phrase being searched [2]. Automatic text summarizing is difficult because, when we humans summarize a piece of text, we normally read it completely to have a thorough comprehension of it before writing a narrative emphasizing its important points. Because computers lack human understanding and linguistic skills, automatic text summarization is a tough and time-consuming operation. These days, important research involves summarizing scientific documents. *Luhn et al. [3]* proposed a method for extracting important sentences from text based on factors like terms and sentence recurrence. They advocated weighting an article's phrases associated with high terms while avoiding very strong common terms. Edmundson et al. [4] proposed a model based on important words that employed the three following ways to assess phrase strength in combination with standard frequency based on weights:

(1) Cue Method: The existence or missing of particular prompts in the prompt dictionary is used to determine the significance of a phrase.

(2) Title Method: The total of all substantive terms occurring in a text's title and headings is used to calculate a sentence's value.

(3) Location Method: This approach implies that phrases near the start of a text, and also the start of particular sections, are more likely to be useful.

II. Financial Reports

Quoted firms are required to submit accounting statements in textual form on a regular basis. Annual accounting records usually feature thorough finance and commercial information, providing useful insight into the company's prospects. Manual examination of these financial reports, on the other hand, could be time-consuming because most of the info provided may be regarded as non-informative or repetitive by experienced readers. As a result, there is a growing interest in automating the extraction of domain-specific briefs that contain only the most necessary data. The most well-established method of assessing the health of a corporation is to examine its annual financial statements. Rating agencies, banks, and hedge funds, for example, use data from domain-specific reports to give evaluations, provide lending, and guide investment strategies (Piotroski, 2000). Sadly, the content of the.However, the financial statements' information is often duplicated, as it usually includes contextual and technical info that is only occasionally useful to domain experts. When a portion of the document content has already been marked by human experts as relevant or not, the summary process can be supervised, or unsupervised if no prior information is provided. The FNS shared task encourages the research, implementation, and deployment of automated phrase summarizing approaches that are specifically targeted to the financial sector. It supplies academics with a big quantity of human-annotated data to extract relevant lines from annual financial statements.

III. Email Overloading

Information overload motivates the automatic summary of e-mail messages. E-mail inboxes have become overburdened as personal information management devices, according to *Whittaker and Sidner [5] and Ducheneaut and Bellotti [6]*. According to research conducted by the Center for the Future [7], more than 95 % of workers use email every day or many times a week. A normal user receives 24 messages every 24 hours, with "high-volume" users receiving hundreds [8]. Users are also under pressure to respond fast to emails, with 27% of messages requiring rapid response [9].The purpose of this program is to enhance users' email interactions by assisting them in better prioritizing new unseen emails and recalling previous read messages with more accuracy. To achieve the above mentioned task, our system makes use of e-mail threads and other regularly used elements to produce a summary which is more relevant. Email threads give useful information for summarizing emails, and they permit summary systems to take advantage of the framework of e-mail that isn't present in different texts. E-mail threads are sets of replies to an initiating e-mail message, either explicitly or implicitly. Threads are important because it enables you to organize a collection of texts together around a common theme. Theoretically, e-mail threads can decrease the number of mail-in users' inboxes, promote awareness of others' comments on a subject, and lessen the number of mail-in users' inboxes. Individuals and activities are frequently mentioned in e-mail exchanges, particularly in the workplace. Frequently encountered capabilities give the consumer hints regarding the selected topic of e-mail messages. The designated identities of persons and firms, as well as dates, are stated in e-mail conversations because much of professional e-mail is about teamwork. The purpose of reporting common features is to be the 1st estimate of a more broad goal of providing crucial parts discussed in e-mail exchanges. E-mail messages, unlike archival documents, are frequently brief, informal, and poorly written. We've discovered that modifying the feed, understanding we're working with email conversations can lead to a much more readable overview of technologies that weren't meant for this purpose. Each time a new message in a thread is retrieved**.**There are many more applications on Text Summarization like Summary of Medical cases, video scripting, patent research, automated content creation, etc.

3. Text Summarization Over the Years

Automatic text summarization is a method for extracting the key information from single or multiple documents and comes under natural language processing. Machine Translation is the origin of Natural language processing, as it existed in the 1940s during world war 2 to translate Russian into English and vice versa using a computer which was not well efficient. With progress in the Artificial intelligence field, NLP also started gaining interest in the 1980s.

In the early days, text summarization was done using rule-based methods. Then, the TF-IDF algorithm was introduced by Edmundson which is based on term frequency and weightage.

As the research in the field of NLP progressed, neural networks came into the picture and many researchers used this technology for automatic text summarization along with machine learning algorithms like k-means, graph-based algorithms, fuzzy logic, etc.

Later in 2016, researchers started using sequence-to-sequence models using Recurrent Neural Networks for the purpose of text summarization which consists of LSTM encoder-decoder attention modules as shown in fig. There are some known algorithms BERT and Pointer generator networks that are used in integration with seq2seq models for automatic text summarization. We will briefly look into the work done in the field using above mentioned techniques in recent years.

ML/ Deep learning Algorithm for Text summarization

Latent Semantic Analysis

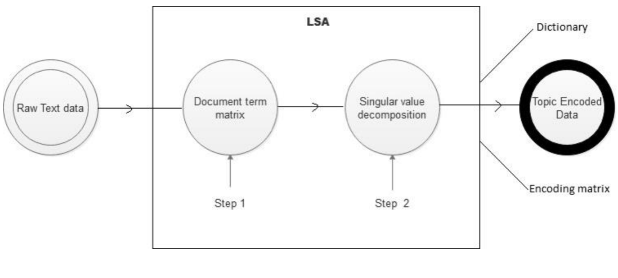

Fig. 2 Latent Semantic Analysis

Latent Semantic Analysis is a powerful Algebraic-Statistical method for extracting hidden semantic relationships of words and sentences, — in other words features that cannot be noted directly. These characteristics are essential for data, but they are not original to the dataset. It is an unsupervised technique that employs Natural Language Processing.(Fig 2)

LexRank

LexRank is an unsupervised text summarization method based on computing sentence importance using the concept of eigenvector centrality in a sentence graph representation.. The key idea is that phrases “recommend" other phrases that are similar to the reader. As a result, if one phrase is quite similar to many others, it is quite probable that it is a very important phrase. The significance of this phrase is also derived from the significance of the phrase "recommending" it. Thus, in order to be ranked highly and included in a summary, a phrase must be similar to many other phrases, which are also similar to many other phrases.

TextRank

TextRank is a graph-based unsupervised ranking model in natural language processing that is inspired by the PageRank Algorithm and can be used to identify the relevant phrases in text as well as keywords. The edges between phrases are found on the basis of some kind of similarity function. TextRank uses a similarity measure based on the number of words two sentences have in common.

Table 1 shows many different algorithms used by some of the researchers over time for automatic text summarisation.

Massih-Reza Amini et al.[10] implemented semi-supervised algorithms for summarization which use few labeled data along with a larger set of unlabeled data and proposed semi-supervised algorithms for training classification models for text summarization.

Rafael Ferreira et al.[11] conducted an experiment using the TextRank algorithm with the graph-based model which turned out to be effective in the case of text summarization.

Akshi Kumar et al.[12] introduced a hybrid model using fuzzy logic along with one semantic-based approach called LSA. and two graph-based approaches, TextRank and LexRank.

Shashi Pal Singh et al.[13] presented Bilingual unsupervised automatic text summarization using deep learning in combination with Boltzmann machine to give out the summary of the document.

Min Yang et al.[14] proposed an innovative Hierarchical deep neural network for the purpose of abstractive text summarization which is aimed to mimic how humans process the document and give out the summary.

Romain Paulus et al.[15] introduced a deep neural network model with a novel intra-attention that takes in the input and keeps generating a summary with a new training approach standard supervised word prediction with reinforcement learning.

Muhammad Yahya Saeed et al.[16] gave an approach that analyzes a group of multiple unstructured documents and generates a linked set of multiple weighted nodes by applying multistage Clustering.

4. Hierarchical Text Summarization

The idea of hierarchical abstractive text summarization is based upon human reading cognition which involves three primary steps.

● a knowledge-aware hierarchical attention module (rough reading): This module consists of three levels of the attention phase i.e. word, phrase, and document as shown in fig 2.

● a multitask learning module (active reading): This module has three tasks to do. First is text categorization, then text summarization, and the last one is syntax annotation.

● generative adversarial network (post-editing): This module verifies the accuracy of the summary generated by the model using a discriminator for improving the performance of the model and to produce more human-like summaries.

A. Network Structures

Sequence-to-sequence Models

These are encoder-decoder models based on deep neural networks. Seq2Seq models are proven to gain an upper hand in various automatic tasks like machine translation, text summarization and image captioning (Table 2 shows an implementation of the seq2seq model for different tasks). A Seq2Seq model is built such that it takes a sequence/series of

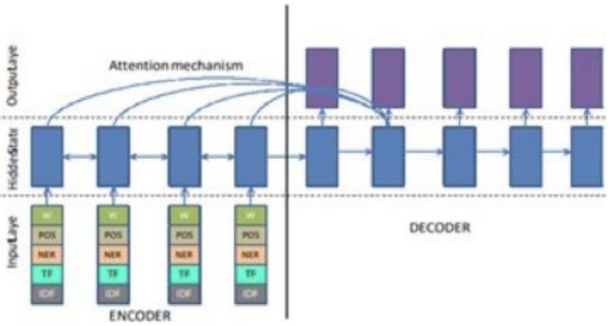

Fig. 3 Seq2Seq model basic Architecture

summarization and image captioning (Table 2 shows an implementation of the seq2seq model for different tasks). A Seq2Seq model is built such that it takes a sequence/series of data (words, letters, time series, etc) as input and gives out a corresponding sequence of data.

Authors	Learning Technique	Model/ Algorithm	Dataset	Type ofSummarization
Massih-Reza Amini	Semi-SupervisedLearning	ClassificationExpectationMaximisation (CEM), Naive Bayes	Reuters, Sumac cmp_lg collection	Extractive
Rafael Ferreira	UnsupervisedLearning	TextRank	CNN	Extractive
Akshi Kumar	UnsupervisedLearning	TextRank, LexRank,LSA	Opinosis dataset	Extractive
Shashi Pal Singh	Unsupervised Deep learning	Deep Learning Restricted BoltzmannMachine(RBM)	Hindi and EnglishDocuments	Extractive
Min Yang	Supervised Learning	Beam Search, Policygradient	CNN/DailyMail	Abstractive
Romain Paulus	Hybrid (Supervised - Reinforced)	Neural Encoder-Decodermodel	CNN/DailyMail andNew York Times	Abstractive
Muhammad YahyaSaeed	Semi-SupervisedLearning	K-means Clustering	News Articles -kaggle	Both Extractive andAbstractive

Table 1. Text Summarization Approaches based on ML/Deep Learning Techniques

Seq2Seq model for machine translation

Jiun Oh et al.[17] performed an experiment to pretrain models on a monolingual set of text documents for machine translation using seq2seq technique. The benefit of these already trained models is that two models that are pre-trained on two different languages can be put together and the resulting model will behave as a multilingual model. The only drawback of these models is size and number of languages are restricted.

Zaixiang Zheng et al.[18] proposed REDER, the reversible duplex Transformer for the reversible sequence-to-sequence problem, and applied it to machine translation for the first time and showed the feasibility of a reversible machine translation system.

Seq2Seq model for Image captioning

Luowei Zhou et al.[19] presented a model which is pre-trained on loads of unstructured pairs of image-text data with two objectives. First is bidirectionality and the second being vision-language prediction.

Chun pu Xu et al.[20] proposed a novel technique for training image paragraph captioning models which is built upon the LSTM seq2seq model. With the help of seq2seq model it retrieves the best captions for candidate sets and dynamically updates the attention modules.

Seq2Seq model for text summarization

Rush et al.[21] introduced neural sequence to sequence encoder-decoder models with an attention based process for abstractive sentence summarization, which significantly outperformed the traditional methods.

Chujie Zheng et al.[22] came up with a contrastive approach for training in integration with the seq2seq model which is proven to enhance the accuracy of abstractive text summarization.

Li Wang et al.[23] came up with a topic-aware Convolutional Seq2Seq model with reinforcement learning for abstractive text summarization. It has been proved that this model gives out some high-level contextual information for summarization.

Junyang Lin et al.[24] showed that The convolutional gated unit performs global encoding on the source side information in order to reserve the core information and filter the secondary information.

Author	Application	Dataset used	Advantage	Limitations
Jiun Oh	LanguageTranslation	Pre-training-WMT17, ParaCrawlFine Tuning-IWSLT14, IWSLT17	Translation performance is improved significantly by the cross-connection method used here.	The number of languages is limited due to computational resources.
Zaixiang Zheng	LanguageTranslation	WMT14 (EN) ↔ (DE) WMT16 (EN) ↔(RO)	REDER can translate both directions in one model	REDER requires to re-train the whole system which increases the difficulty and cost to train.
Luowei Zhou	Image Captioning	Conceptual Captionsdatasets(2018)	The VLP model makes use of bidirectional functionality for vision language prediction.	–
Chunpu Xu	Image Captioning	Stanford datasets	Seq2Seq Dynamic memory-augmented attention model for image paragraph captioning which retrieves best captions for candidate sets and eliminate the problem of repetitive and incomplete captioning	_
Alexander M.Rush	Text Summarization	DUC-2004, Gigaword	Accurate abstract summaries are produced with the probabilistic model using a generation algorithm	Grammatically correct paragraph-level summaries are not yet achieved.
Chujie Zheng	Text Summarization	CNN/DailyMail	ESACL, an enhanced seq2seq model,improves the performance of ATS.	The optimal number of augmentation operation has not been answered yet.
Li Wang	Text Summarization	Gigaword,DUZ2004, LCSTS dataset	ConvS2S model with reinforcement learning for ATS produces better summaries with more relevance, information,and variety.	Based on the SentenceSummarization, multi-document summarization is yet to be achieved.

Table 2. Seq2Seq Model Implementation for Different Application

BERT algorithm

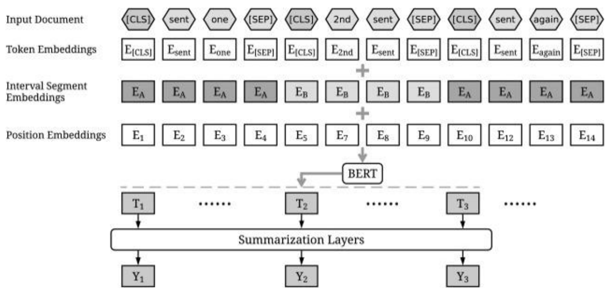

Fig. 4 BERT Algorithm

It stands for Bidirectional Encoder Representations from Transformers. It is a technique built upon neural networks used for pre-training NLP models.

Yuuki Iwasaki et al[25] used BERT to demonstrate Japanese abstractive text summarization with a neural network model. Using BERT, the encoder is fed with a feature-based input vector of sentences.

Anirudh Srikanth et al.[26] used the BERT model for extractive text summarization using k-means clustering for sentence embeddings and introduced a dynamic method to find out the appropriate number of sentences to select from clusters.

Hritvik Gupta et al.[27] presented using truncated SVD, which retrieves all important material from the document, as well as Term frequency - inverse document keyword extractor for each sentence in a written text, along with BERT encoder model for encoding the sentences from the text document in order to fetch the positional embedding of topics word vectors.

Pointer - Generator Network

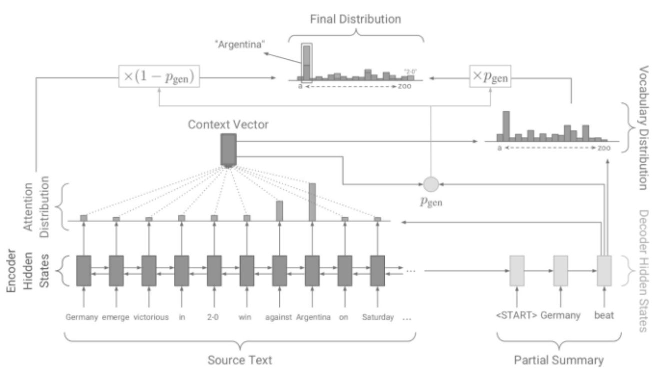

Fig. 5. Pointer-Generator Network

The pointer-generator network, as a cutting-edge method for abstractive summarization, generates more proficient summaries and addresses two limitations: incorrectly replicating specific information and phrase repetition.

Abigail See et al.[28] demonstrated a hybrid pointer generator framework with coverage mechanism that enhances accuracy and reduces redundancy.

Zhixin Li et al.[29]implemented a dual-attention pointer with the self-attention framework which is used to retrieve relevant information from the original document, and the gate system is integrated to govern information selection and added truncation parameters towards the established coverage technique to avoid disrupting with the other targets.

Sebastian Gehrmann et al.[30] presented a straightforward but precise information selection model for text summarization that recognises phrases in a document that are supposed to be included in the summary.

B. Attention Modules in Seq2Seq model

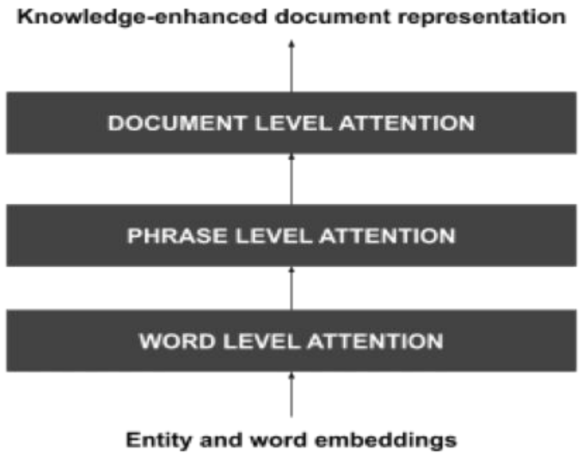

Fig 6. Attention Modules

The knowledge-aware hierarchical attention module makes use of prior knowledge present in Knowledge Base as common sense and builds candidate entity embeddings facilitated by context representation. Given the word vector from the source text, the context representation is obtained in the form of word embeddings. Both of the embeddings then help the attention module to produce knowledge-enhanced document representation at different levels as shown in fig 6.

Jianpeng Cheng et al.[31] showed a data-driven summarization approach that is based on an encoder-extractor structure, as well as two classes of models based on phrase and word retrieval.

Baihan Kang[32] proposed a CNN model with an attention mechanism that gives important words more attention weights through concatenation. Thus, it is more accurate in text classification tasks.

Lijun Wu et al.[33] proposed a two-component model to compute attention weights by making use of clean source word-level information and contextual gates to dynamically find the hidden states of words which are proven to improve the semantic representation of the source text.

Wei Wu et al.[34] developed a Phrase-level Self-Attention Networks which conduct self-attention throughout all words within a phrase to encapsulate context dependencies at the phrase level, then using the gated memory updating mechanism to extract each word's representation hierarchically with longer-term context dependencies discovered in a relatively large phrase.

Fagui Liu et al.[35] proposed a novel neural network model that is divided into two parts. To obtain the compositional semantics of the document, the first part employs a two-layer compositional bidirectional Gated Recurrent Unit . To capture more dependencies between multiple sentences, the other part employs a two-dimensional convolution operation and two-dimensional max pooling.

Authors	Modified Techniques	Dataset	Metric	Accuracy Score
Zhixin Li	Dual Pointer-Generator Network	CNN/Daily Mail	Rouge-1, Rouge-2,Rouge-L	36.86, 16.01, 33.66
Abigail See	Hybrid Pointer-Generator Network	CNN/LCSTS	Rouge-1, Rouge-2,Rouge-L	40.34, 17.70, 36.57
Sebastian Gehrmann	Pointer- GeneratorNetwork	CNN/DailyMail/NYT	Rouge-1, Rouge-2,Rouge-L	39.1, 17.40, 36.1
Hritvik Gupta	BERT algorithm	News dataset - kaggle	Rouge-1, Rouge-2,Rouge-L	45, - , 44
Yuuki Iwasaki	BERT algorithm	Livedoor newsDataset	Rouge-1, Rouge-2,Rouge-L	_
Anirudh Srikanth	BERT algorithm	CNN/DailyMail	Rouge-1, Rouge-2,Rouge-L	41.4, 17.9, 37.9

Table 3. Modifications made in seq2seq Model for Text Summarization

C. Text Categorization

One of the important aspects of summarising a document is to categorize the content of the text into fields. For example, a news article can be categorized into fields like sports, politics, the stock market, etc. The automatic text categorization/classification approaches fall into three types:

- Rule-based systems
- Machine learning-based systems
- Hybrid systems

Rule-Based Text Categorization

Asmaa M. Aubaid et al.[36] came up with the rule-based method for converting document files to vector files that used the embedding technique.

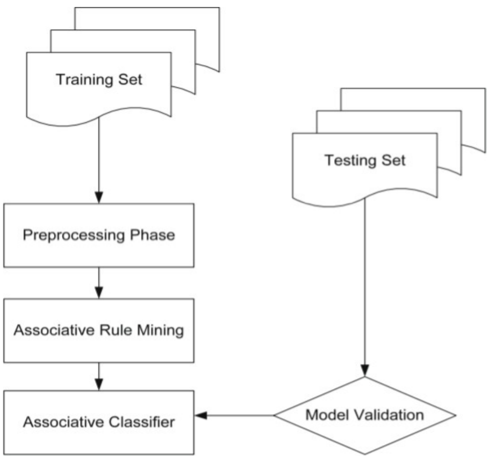

Fig 7. Rule-based Architecture

Hui Han et al.[37] introduced a rule-based, context - dependent word clustering technique based on rules derived from different field records and the alphabetic properties of the word text.

Machine learning-Based Text Categorization

Wang Heyong et al.[38] used a supervised feature selection method, Hebb rule-based feature selection. The method is based on a neural synapse model and identifies discriminative terms by the Hebb rule which states that “when a cell persistently activates another nearby cell, the connection between the two cells becomes stronger”.

Zhuo Chen et al.[39] proposed a KNN-based classification method of Lao news text which showed a significant improvement in classification.

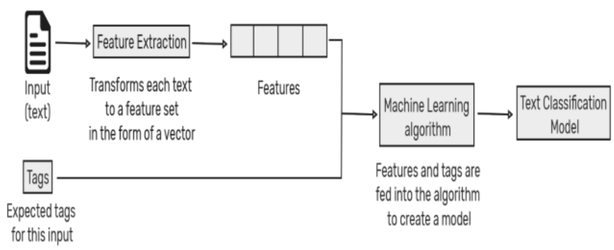

Fig 8. ML-based Architecture

Authors	Approach	Algorithm/Technique	Dataset	Performance Metric	Year
Liang Yao	Hybrid systems	CNN	Obesity Challenge data	Macro F1, MicroF1	2018
Zhuo Chen	Machine learning-based systems	KNN	Lao news text dataset	AccuracyPrecision,recall, F1-Score	2020
WangHeyong	Machine learning-based systems	CNN & RNN	CarF, CarR,CNAE,IMDB, KDC,TTC	F-measure, ROC area	2019
JulioVillena-Roman	Hybrid systems	KNN	Reuters-21578	Precision, Recall	2011
Asmaa M.Aubaid	Rule-BasedSystems	Document embedding	Reuters-21578 Dataset, 20 Newsgroup Dataset	F-measure,Accuracy, Precision, Recall,error-rate	2020
Hui Han	Rule-BasedSystems	Word clustering	CMU dataset	F-measure	2003

Table 4. Comparative Analysis of Text Categorization Models based on Approach

Hybrid System for Text Categorization

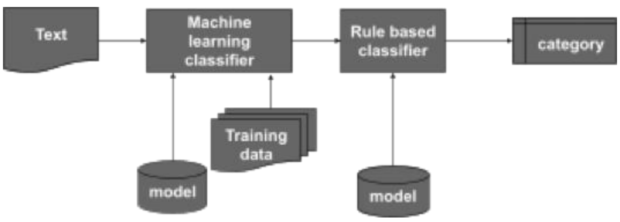

Fig *9*. Hybrid Architecture

Julio Villena-Román et al.[40] A hybrid approach to text categorization that combines a machine learning algorithm with a rule-based expert system was presented. The model achieved accuracy comparable to top methods, with the added benefit of requiring less human expert workload.

Liang Yao et al.[41] presented a novel clinical text classification method that combines rule-based feature engineering and knowledge-guided deep learning. They demonstrated that the CNN model is effective for learning hidden features and CUIs embeddings can be used to develop clinical text representations.

5. Conclusion

In this paper we have seen various Text summarization techniques based on network structures, attention modules, machine learning, and deep learning algorithms used by the researchers in recent years. We have found that the process of Automatic text summarization includes tokenization of data, word embeddings, LSTM layer, Attention mechanism, text categorization and adversarial Training. The common challenges faced in this field are generating more accurate and human-like summary, second one is repetition of words and the coverage which is tackled using pointer generator networks. Most Researchers used graph-based methods for context vector generation which are quite effective with respect to abstractive text summarization implemented along with various supervised/unsupervised/hybrid learning models. The performance metrics used by the most are ROUGE 1, ROUGE 2, ROUGE L.

References

[1] Dragomir R Radev et al.. Introduction to the special issue on summarization. Computational linguistics 28, 4 (2002).

[2] Andrew Turpin, Yohannes Tsegay, David Hawking, and Hugh E Williams. Fast generation of result snippets in web search.In Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval. (2007).

[3] Hans Peter Luhn. 1958. The automatic creation of literature abstracts. IBM Journal of research and development 2, 2 (1958).

[4] Harold P Edmundson. 1969. New methods in automatic extracting. Journal of the ACM (JACM) 16, 2 (1969).

[5] S. Whittaker and C. Sidner. Email overload: exploring personal information management of email. In Conference proceedings on Human factors in computing systems, pages 276–283, New York, NY, USA, 1996. ACM Press.

[6] N. Ducheneaut and V. Bellotti. E-mail as habitat: An exploration of embedded personal information

management. ACM Interactions, 8(1):30–38, September-October 2001.
[7] "Pitney Bowes study reveals increased use of electronic communications tools among North American and European workers". Pitney Bowes press release, August 7, 2000.
[8] M. Levitt. Email usage forecast and analysis, 2000-2005. IDC Report 23011, IDC, September 2000.
[9] "The Spam Within Gartner says one-third of business email is 'occupational spam' ". Gartner, Inc. press release, April 19, 2001.
[10] Massih-Reza Amini, Patrick Gallinari, The Use of Unlabeled Data to Improve Supervised Learning for Text Summarization, 2002
[11] Rafael Ferreira, Frederico Freitas, Luciano de Souza Cabral, Rafael Dueire Lins, Rinaldo Lima, Gabriel Franca, Steven J. Simske, Luciano Favaro, A Four Dimension Graph Model for Automatic Text Summarization, 2013.
[12] Akshi Kumar, Aditi Sharma, Anand Nayyar, Fuzzy Logic based Hybrid Model for Automatic Extractive Text Summarization, 2020
[13] Shashi Pal Singh, Ajai Kumar, Abhilasha Mangal, Shikha Singhal, Bilingual Automatic Text Summarization Using Unsupervised Deep Learning, 2016
[14] Romain Paulus, Caiming Xiong & Richard Socher, A DEEP REINFORCED MODEL FOR ABSTRACTIVE SUMMARIZATION, 2017
[15] Banafsheh Rekabdar, Christos Mousas, Bidyut Gupta, Generative Adversarial Network with Policy Gradient for Text Summarization, 2019
[16] Muhammad Yahya Saeed, Muhammad Awais, Ramzan Talib, Muhammad Younas, Unstructured Text Documents Summarization With Multi-Stage Clustering, 2020
[17] Juin Oh, Young-Sulk Choi, Reusing Monolingual Pre-Trained Models by Cross-Connecting Seq2seq Models for Machine Translation, 2021
[18] Zaixiang Zheng, Hao Zhou, Shujian Huang, Jiajun Chen, Jingjing Xu, Lei Li, Duplex Sequence-to-Sequence Learning for Reversible Machine Translation, 2021
[19] Luowei Zhou, Hamid Palangi, Lei Zhang, Houdong Hu, Jason J. Corso, Jianfeng Gao, Unified Vision-Language Pre-Training for Image Captioning and VQA
[20] Chunpu Xua, MinYanga, Xiang Aob, Ying Shenc, Ruifeng Xud, Jinwen Tiane, Retrieval-enhanced adversarial training with dynamic memory-augmented attention for image paragraph captioning, 2021
[21] Alexander M. Rush, Sumit Chopra, and Jason Weston. 2015. A neural attention model for abstractive sentence summarization. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing.
[22] Chujie Zheng, Kunpeng Zhang, Harry Jiannan Wang, Ling Fan, Zhe Wang, Enhanced Seq2Seq Autoencoder via Contrastive Learning for Abstractive Text Summarization,2021
[23] Li Wang, Junlin Yao, Yunzhe Tao, Li Zhong, Wei Liu, Qiang Du, A Reinforced Topic-Aware Convolutional Sequence-to-Sequence Model for Abstractive Text Summarization, 2018
[24] Junyang Lin, Xu Sun, Shuming Ma, Qi Su, Global Encoding for Abstractive Summarization,2018
[25] Yuuki Iwasaki, Akihiro Yamashita,Yoko Konno, Katsushi Matsubayashi, Japanese abstractive text summarization using BERT, 2019
[26] Anirudh Srikanth, Saravanan Thanu, Ashwin Shankar Umasankar, S Jaya Nirmala, Extractive Text Summarization using Dynamic Clustering and Co-Reference on BERT, 2020 Hritvik Gupta, Mayank Patel, METHOD OF TEXT SUMMARIZATION USING LSA AND SENTENCE BASED TOPIC MODELING WITH BERT, 2021
[27] Abigail See, Peter J. Liu, Christopher D. Manning, Get To The Point: Summarization with Pointer-Generator Networks, 2017
[28] ZHIXIN LI, ZHI PENG SUQIN TANG, CANLONG ZHANG, HUIFANG MA,Text Summarization Method Based on Double Attention Pointer Network, 2020
[29] Sebastian Gehrmann, Yuntian Deng, Alexander M. Rush, Bottom-Up Abstractive Summarization, 2018.
[30] Jianpeng Cheng, Mirella Lapata, Neural Summarization by Extracting Sentences and Words,2016
[31] Baihan Kang, A Convolutional Neural Network with Word-level Attention for Text Classification,2020
[32] Lijun Wu, Fei Tian, Li Zhao, Jianhuang Lai, Tie-Yan Liu, Word Attention for Sequence to Sequence Text Understanding, 2018
[33] Wei Wu, Houfeng Wang, Tianyu Liu, Shuming Ma, Phrase-level Self-Attention Networks for Universal Sentence Encoding, 2018
[34] Fagui Liu, Jingzhong Zheng, Lailei Zheng, Cheng Chen,Combining attention-based bidirectional gated recurrent neural network and two-dimensional convolutional neural network for document-level sentiment classification, 2019
[35] Asmaa M. Aubaid, Alok Mishra, A Rule-Based Approach to Embedding Techniques for Text Document Classification, 2020
[36] Hui Han, Eren Manavoglu, C. Lee Giles, Hongyuan Zha, Rule-based Word Clustering for Text Classification, 2003
[37] Wang Heyong, Hong Ming, Supervised Hebb rule based feature selection for text classification, 2019
[38] Zhuo Chen, Lan Jiang Zhou, Xuan Da Li, Jia Nan Zhang, Wen Jie Huo, The Lao Text Classification Method Based on KNN, 2020
[39] Julio Villena-Román, Sonia Collada-Pérez, Sara Lana-Serrano, José C. González-Cristóbal, Hybrid Approach Combining Machine Learning and a Rule-Based Expert System for Text Categorization , 2011
[40] Liang Yao, Chengsheng Mao and Yuan Luo, Clinical text classification with rule-based features and knowledge-guided convolutional neural networks, 2018.