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Abstractive Text Summarization Models Using Machine Learning Algorithms

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***Abstract*— In today's era of cyberspace and intermedia, the number of e-documents have been enlarged enormously. The speedy growth of large data and documents in the field of Data Mining and emerging domain such as Information Retrieval (IR) and the demanding area of Natural Language Processing (NLP) needs Automated Text Summarization. Text Summarization is a process that decreases size of the source document while keeping its important information with actual meaning. It is burdensome and laborious for Homo sapiens to physically do the summarization of huge documents of text. Thus it is necessary to revise old methods and techniques of abstractive text summarization models and modernize them to be efficient and fulfill the requirements of users as per the need by resolving issues of continuously increased data. Now this paper presents a survey of the current futuristic models and the various algorithms and techniques used in Abstractive Text Summarization systems liable to be subjected to an Encoder-Decoder framework. This research can help to gain the overall concepts of recent machine learning algorithms and encoder-decoder architecture resting on abstractive text summarization prototypes with a review of the challenges, issues, and future scope of these models. This research can help solve the research community's problems, newsletters, email overload, and media monitoring.**

Keywords—Abstractive Text Summarization, Machine Learning encoder-decoder, Natural Language Processing, Evaluation Parameters

I. INTRODUCTION

The amount of text data is tremendously increasing daily on cyberspace and other libraries. Text summarization is extracting the important details contained in large volumes of text and presenting them in a brief, representative, and consistent summary. Text summarization gains popularity over the periods. Physical summary generation is currently the best task for small documents. Since there has been an increase in available literal data, physical summary generation cannot satisfy the need anymore. Text summarization plays a crucial part in the area of Natural Language Processing (NLP), Data Mining, Information Retrieval (IR), Multimedia, Computer Science, and statistics. Abstractive and Extractive summarizations are the two ways of generating summaries from text documents. The extractive summarization technique picks major sentences or identifies major texts from the original text, and the abstractive summarization technique generates new texts or creates newer speech that is semantically correct. Single-Document and Multi-Document are mainly two types of documents that are currently in existence. Since the max boundary of the summary, a Single-Document text summarization process picks the major sentences from the source document. More than one document can be given as input in the multiple documents summarization method to generate a summary. The purpose of summarization is of three types 1. Generic, 2. Domain-Specific and 3. Query-based. Generic-summaries are not related to any particular group of users, they are broadly used for the public, while domain specific summaries are useful for the particular need of an individual or specific group of users. Query-based summaries are creating a summary of longer text documents that specifically answer a user's query. This query-based approach is generally used for search engines and chatbots.

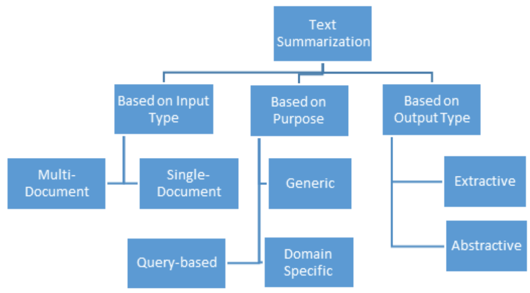

Fig. 1. Classification of Text Summarization

Conventional text summarization methods need a better understanding of the document to identify the important words. Improved text summarization methods follow a quality structure. Text summarization turns out to be more precise, errorless, accurate, reduced text, and less redundant with adequate design and implementation [1]. Advanced Natural Language Processing (NLP) techniques like neural word embedding [2], Bag of Word (BoW) [3], word2vec [4], and modern deep learning technologies like a recurrent neural network (RNN) [5] and long-short-term-memory [6] have been progressed in automatic text generation [1]. Most of the existing text summarization methods are built on the encoder-decoder mechanism. However, the max amount of information lost in the encoding and decoding stages results in more diverse rephrased answers with more processing power for long articles.

II. LITERATURE SURVEY

The method of generating a small and concise summary which apprehends the notable ideas of the source text is known as Abstractive Text Summarization. These produced summaries possibly contain new clauses and sentences that might not occur in source text. The objective of the Abstractive Text Summarization Model is to find new techniques and methods to pick the utmost valuable information from the source text. It then successively shortens and makes it effortless for the users.

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Researchers have investigated the existing survey of the automatic text summarization domain. They have presented the former methods and proved the importance of the research. However, recent trends, applications, limitations, challenges, and effects of the automatic text summarization methods were not present. The applications of Natural Language Processing (NLP) using neural network has been growing attractive nowadays. The main idea is training the neural network model which generates a human-readable summary that is semantic to the original text remains a challenging task. The very first system was developed by RUSH *et al*. [7] to generate a summary from the short input text by using attentional neural networks. The improved results were achieved on DUC 2004 and Gigaword datasets.

Zhuang *et al*. [5] has proposed a model of generative adversarial networks that contains three elements generator and two different discriminators. At first, generator encodes the comparatively lengthy text into a small one. The first discriminator demonstrates the generator that creates human-interpretable summaries and the second discriminator restricts the outcome of the generator to replicate the input text. The policy gradient method is used in [5] will optimize the generator for solving the differentiable problem. The 'state of art result' is achieved on remarkable News data

The two-stage hybrid model of extractive and then abstractive is depicted by Liu *et al*. [8]. In first phase of the hybrid model Neural Network attention mechanism is used to extract a definite number of important sentences from the input dataset. In the second stage, the Beam-Search algorithm rearranges and rephrases the syntactic chunks of extracted sentences from the first stage. The beam search method can discover the ideal solution to reduce time cost and searching space. Laith *et al*. [9] has described Methods, Processes, Primary structure, strategies Multi-Document Abstractive Text Summarization Using Optimization Methods and Machine Learning Algorithms, and datasets measurements of ATS. Text summarization is important because of the increase in digital data these days. Researchers gather the most appropriate and recent research of text summarization for study and analysis for forthcoming research. The idea and classification of features, similarity scores, and sentence extraction are not clearly specified. It may be remarkable by providing a new path to investigators interested in this area in the future. The divide-and-conquer approach for long documents was presented by Gidiotis *et al.* [10]. The proposed method divides long documents and their summaries into multiple pairs used for training the models. The final summary is formed by synthesizing the partial summaries. The model reduces the computational complexity by decomposing the long document into smaller ones by using seq-to-seq RNNs and Transformers [10]. This summarization is performed on academic articles arXiv and PubMed datasets and state-of-art results are achieved.

Li. *et al*. [11] examine the role of the Semantic-Link-Network (SLN) in Abstractive Text Summarization models. The presented framework uses Semantic Link Network to transform documents into Events and Concepts and again transform Semantic Link Network into a final Summary. The framework is useful for news Documents, the important information of the document can be successfully selected. Co-referent concepts and events be able to easily detected (Avoid redundancy, Aggregated). Concepts and events bring useful syntactic knowledge that can help to convert them into proper sentences. The performance is significantly improved over the benchmark. RNN-based sequence-to-sequence attention model is very effective in abstractive text summarization. Yao *et al*. [12] presented the dual encoding model including primary and secondary encoders. To resolve the semantic inaccuracy repetition that appeared in deep learning-based abstractive summarization, Guo *et.al.* [13] has presented the Encoder-Decoder model which is the basic Multi-Head Self-Attention technique called an MS-Pointer Network. The proposed MS-Pointer Network solved the issues of Out-Of-Vocabulary (OOV) which is presented in the encoder-decoder and has closer meanings to the original sentences. The Rouge score is improved and greater than that of the futuristic model.

The researcher Jang *et.al.* [14] has proposed a model based on reinforcement learning that solved the problem of optimized metrics. The presented ROUGE-SIM [14] and ROUGE-WMD [14] metrics are the revised ROUGE metric that is derived from the n-gram language model. The generated models are robust because repetitions are reduced and few grammatical errors. The model uses LSTM sequence-to-sequence attention encoder-decoder.

Tinghuai *et al*. [15] presented a T-BERTSum technique a modified version of Bidirectional Encoder Representations from Transformers (BERT). It is also called a Topic-Aware Abstractive and Extractive Summarization tool to handle lengthy text dependence and apply Latent Topic Mapping [15]. This T-BERTSum tool emphasizes pre-trained topic mining and external information to extract a precise appropriate representation of the text. The presented model takes more processing power for lengthy articles containing multiple topics.

According to research carried out by previous researchers, some challenges are identified in the process of text summarization. More powerful models, which are capable of generating cohesive, concise, and salient text summaries, are needed that improves the performance of text summarization models.

Table 1 presents the algorithms and methods used for abstractive text summarization in reviewed research papers. This paper highlights key methods, issues addressed, datasets used, evaluation parameters used, and achieved accuracy. Most of the research papers utilize standard news datasets that are depicted in above table 1.

Evaluation metrics shown in the above table were computed for summary evaluation. The accuracy is calculated with regard to the 'rouge score' and 'state-of-the-art-result'. Accuracy is equated with previous methods. The researcher has proved their model consistently outperforms the baseline datasets.

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TABLE I. THIS TABLE PRESENTS THE METHODS USED IN ABSTRACTIVE TEXT SUMMARIZATION MODELS

Reference	Algorithms	Key points/Method Used	Issues and Challenges	Dataset	Evaluation Parameter	Score
[5]	1. Generative Adversarial Network (GAN) 2, Policy Gradient Algorithm	1. Generator Two Discriminators- 1. Readability Discriminator 2. Similarity Discriminator	Difficult to generate long sequences	CNN/ Dailymail	1.ROUGE 1 2.ROUGE 2 3.ROUGE L	41.11 16.23 37.18
[8]	Beam Search	1. Hybrid model 2. Unsupervised approach	Does not involve multi-document	DUC2004 Chinese Data	1.ROUGE 1 2.ROUGE 2 3.ROUGE L	36.06 13.61 29.21
[10]	Divide and Conquer DANCER	Encoder-decoder 1. DANCER LSTM 2. DANCER RUM 3. DANCER PEGASUS	Combine DANCER with a more complex summarization model that improves quality work on other domain	arXiv PubMed	1.ROUGE 1 2.ROUGE 2 3.ROUGE L	46.34 17.69 42.42
[11]	Semantic Link Network	1. FrameNet-Based Event Extraction	Few sentences have syntax errors.	DUC2005 DUC2006 DUC2007	1.ROUGE 1 2.ROUGE 2 3.ROUGE-SU4 Pyramid	42.76 14.17 17.48 83.80
[12]	Dual Encoding Model DEATS	1. Primary encoder 2, Secondary encoder 3. decoder	Need to balance recall and precision	CNN/ Dailymail and DUC2004	1.ROUGE 1 2.ROUGE 2 3.ROUGE L	40.85 18.18 37.37
[16]	Attention-based bidirectional LSTM	1. Seq2seq structure 2. Enhanced Semantic Network (ESN) 3. Pointer_Network 4. mixed learning objective (MLO) function	Semantic similarity feature, a small number of network layers. and simple reward function	LCSTS TTNews	1.ROUGE 1 2.ROUGE 2 3.ROUGE L	33.75 14.09 32.69
[13]	MS-Pointer Network	encoder-decoder	-	CNN/ Dailymail and Gigaword	1.ROUGE 1 2.ROUGE 2 3.ROUGE L	40.21 19.37 39.29
[14]	1. Reinforcement Learning 2. LSTM 3. ROUGE-SIM (meaningfully similar words) 4. ROUGE-WMD (Word Movers Distance)	Function adding semantic similarity	Only Single layer LSTM is used.	Gigaword	1.ROUGE 1 2.ROUGE 2 3.ROUGE L	ROUGE-SIM 45.50 23.60 41.80 ROUGE-WMD 42.20 23.30 40.60

TABLE II. THIS TABLE PRESENTS THE METHODS USED IN ABSTRACTIVE TEXT SUMMARIZATION MODELS

Reference	Method Used	Methodology	Advantages
[11]	Semantic Link network	Saliency Score = w1 * Degree Centrality + w2 * Semantic Relevance Degree Centrality: Number of connected nodes Semantic Relevance: Semantic similarity measure w1 and w2:Weight	1. Co-referent concepts and events are easily identified. (Avoid redundancy, Aggregated) 2. Increased consistency and informative of produced summary
[14]	1. ROUGE-SIM 2. ROUGE-WMD	S: Set of words in a generated summaries R: Set of words in reference summaries 1. ROUGE-SIM: V: Set of unique words in both S and R x and y be the vectors representing the word frequencies of S and R, respectively, in V The ROUGE-SIM score is given by: ROUGE-SIM = (x * y) / (||x|| * ||y||) 2. ROUGE-WMD: Let D be the pre-trained word embedding model, which maps words to vector representations Let WMD(S, R) be the Word Mover's Distance between S and R, calculated as follows: WMD(S, R) = min(∑d(s_i, t_j) * f(i, j)) / ∑f(i, j)) d (s_i, t_j): Distance among the vector representations of words s_i in S and t_j in R. f(i, j): Flow among the words s_i and t_j. The ROUGE-WMD score is given by: ROUGE-WMD = exp(-α * WMD(S, R)) where α is a scaling factor that controls the impact of the WMD distance on the ROUGE-WMD score	1. Semantic similarity 2. Relevance to the Task 3. Robust and flexible to variations in sentence structure and order

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[6]	FrameNet-Based Event Extraction	Salience(e) = α * ∑(Relevance(s) * Weight(s)) + β * ∑(Importance(a) * Weight(a)) where α and β are scaling factors, and Weight(s) and Weight(a) are the weights assigned to each sentence and argument, respectively, based on their position and importance.	1. Accurate identification of salient events 2. Improved coherence 3. Flexibility and Robust 4. Improved summarization quality
[7]	Dual Encoding Model DEATS	1. Encoder For each sentence, X_i, the Encoder computes the unseen states h_i using a bidirectional GRU: h_i = BiGRU(X_i) where BiGRU is the bidirectional GRU function that takes an input sentence and returns its hidden states. 2. Decoder The Decoder creates the output summary Y depending on the h_i (hidden states) and the previously generated tokens. Unidirectional GRU (with attention mechanism) computes the probability distribution over the terminology at each time step t. p(y_t | Y_1 : t-1 , X) = softmax(W_s * s_t) s_t: decoder state at time step t. 3. Objective function The objective function training the dual encoding model is the cross-entropy loss among the predicted-summary Y and the real summary Y*: L = - ∑(log p(y_t | Y_1 : t-1 , X , Y*))	1. Efficient training 2. Better modeling of long-term dependencies 3. Attention mechanism 4. Dual encoding 5. Good Performance

Table 2 depicts the methodology used in reviewed papers. The saliency score is calculated in the semantic link network [11] and FrameNet-based event extraction [6] method using Semantic similarity measure.

III. SUMMARIZATION DATASETS

Abstractive text summarization has a primary source of newspapers, articles, blogs, reviews, emails, and message datasets based on type. DUC (Document Understanding Conference) 2004, CNN, and Dailymail are newspaper datasets and have been used as benchmark datasets. LCSTS, Gigaword, and Wikihow are the blogs and article types of datasets. The arXiv dataset is an electronic preprint of scientific papers from various domains. The PubMed dataset is biomedical literature, including articles from journals, books, and conference proceedings. All these popular datasets are used for evaluating the performance of various automatic summarization systems, including both Abstractive and Extractive summarization models.

TABLE III. THIS TABLE PRESENTS THE ACCEPTED DATASETS USED IN ABSTRACTIVE TEXT SUMMARIZATION MODELS

Datasets	**Documents /Sentences**	**Language used**	**Reference**
DUC 2004	1000 Sentences	Arabic and English	[8],[12],[3]
DUC 2005	1600 Sentences	English	[11]
DUC 2006	1250 Sentences	English	[11]
DUC 2007	250 Sentences	English	[11]
CNN/Dailymail	One Million news	English	[5],[12],[1], [7],[13],[4]
Gigaword	3.8M Text	English, Chinese	[7]-[14]
Wikihow	200K	English	[18]
LCSTS	2400591 News Text	Chinese	[6],[3],[4], [16]
BBC New Summary	2225 Documents	English	[18]
arXiv	215 K Documents	English	[10]
PubMed	133K Documents	English	[10]
Chinese Data	1200 News Text	Chinese	[8]
BBC XSUM	204K Document	English	[1]
SOGOU	1359956 News Text	English	[6]

A. Evaluation Parameters

ROUGE (Recall-Oriented Understudy for Gisting Evaluation) is a standard measure in the assessment of Text Summarization. It evaluates machine-generated-summary in opposition to the reference standard summary. The reference standard summary also called as gold standard summary used in summarization created by human assessors. The Rouge score is calculated by the intersection of these two standard summaries are taking into account. There are five types of ROUGE evaluated in reviewed papers that depend on 1. N-gram overlapping, 2. Skip-bigram, 3. Longest common subsequence (LCS), 4. Weighted longest subsequence, and 5. Pairwise co-occurrence.

ROUGE matches the N-grams of the reference summary with the N-grams of the generated summary. There are three types of Rouge metrics exist that are ROUGE1, ROUGE2, ROUGEL, etc.

1) *Rouge1:* This measures the overlap among unigram (single word) sequences in the machine-created-summary and the human-written-reference-summary. It calculates the three measures F1-score, Precision and Recall that are depend on the amount of unigrams match among the generated-summary and the human-written referred reference-summary. Highest score of Rouge1 predicts that the generated-summary is more similar to the referred reference-summary

2) *Rouge2:* This measures the overlap between bigram (pair of an adjacent word) sequences in the machine-

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generated-summary and human-written-reference-summary. It calculates Recall, Precision with F1-score depend on the number of bigrams that match among the machine- generated-summary and the human-written referred reference- summary. Highest score of the Rouge-2 indicated that the generated-summary is more like to the reference-summary. It is useful when evaluating longer summaries, and the reference summary uses phrases and expressions that the summarization system may not capture with single words.

3) RougL: Longest Common Subsequence (LCS) is another evaluation metric for text summarization systems. It's an additional comprehensive metric than Rouge-1 and Rouge-2. It takes Longest Common Subsequence (LCS) of words in the machine created summary and the reference-summary. RougeL measures the ratio of length of the LCS to the length of the reference-summary, which gives an indication of how well the generated-summary captures the important details in the reference-summary. This metric is more robust than Rouge1 and Rouge-2 as it takes into account the differences in length of the sentence, word order, and word choice. It captures the meaning and context of the summary more accurately

4) RougeSU4: It is an improved of the ROUGE metric that assess the overlap among N-gram (4 grams) in generated summary and reference summary. The “SU” stands for “skip-gram with unigram”. It takes into account both unigram (individual words) and skip-gram (non-contiguous words). Rouge-SU4 is useful for capturing the coherence and fluency of the generated summary.

5) F1-Score: This measure is the performance metric that uses performance metrics precision and recall. Precision means true positives between all the predicted positives and recall means true positives between all the actual positives. F1-score is calculated by 2 multiply by the dot product of Precision and Recall divided by the addition of Precision and Recall.

F1-Score falls in 0 to 1 range. The highest 1 score is the finest possible value of the score. The highest F1-Score means that the used model has the highest precision and highest recall score, meaning that it can correctly identify relevant examples and filter out irrelevant ones.

B. Issues, Challenges, and Future Scope

Though these systems pretence some issues and challenges, there are several improvements in abstractive text summarization with machine learning and encoder-decoder framework over the years. That may result in a more efficient and robust summarization system. The researchers have addressed the challenges and mentioned the future scope for further improvement.

TABLE IV. ISSUES AND CHALLENGES IN ABSTRACTIVE MODELS

Issues and challenges	References	Future scope
Difficult to generate long sequences	[5]	May use pre-trained models like BERT
Involve only a single document	[8]	Multi-document and cross-document text summarization.
More complex summarization model	[10]	Work on more fine-tuning and hyper-parameter tuning models
Syntax errors.	[11]	More effective approaches.
Need to balance recall and precision	[12]	Work on dynamic decoding length using reinforcement learning.
Semantic similarity feature, a small number of network layers. and simple reward function	[16]	Optimization of the evaluation indexes

IV. CONCLUSION

Here’s the conclusion of the paper that presents an overview of abstractive text summarization by reviewing related scientific literature. The research work has presented the algorithms and methods, datasets used, and evaluation metrics for abstractive text summarization models in current years. The review provides the various types of encoder-decoder mechanisms in abstractive models, languages for which these models are designed, issues, and challenges that have been associated with this model. Few of these have been labeled by the researchers whereas some still have to pay attention. The research gap and future scope are highlighted. In the upcoming future, this research can be modified with more research on this subject. An abstractive text summarization model may be implemented by using the study of recognized elements in the research.

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