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A survey on the dataset, techniques, and evaluation metric used for abstractive text summarization

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ABSTRACT

Whenever there is too much information out there, it is desirable to summarize. If humans are trying to create the summary, it will take lot of time. Now to make the problem of summarizing information easier and more effortless one can automate the summarization process which can reduce the time taken in creating summary. This is called as automatic summarization. The two ways of summarization are extractive summarization and abstractive summarization. Extractive summarization and its applications have been the subject of extensive research and have received state of art solution. But abstractive summarization still is a progressive field as it is difficult to create abstractive summary as humans do. Also, it is still a question i.e., how to evaluate the quality of a summary? Therefore, this paper is a comprehensive survey on the dataset used with its details and statistics, analysis of various abstractive summarization techniques and important parameters for evaluating the quality of summary. Deep leaning based models have given new direction in this field. The author also focuses on problems and challenges faced in the generation of summary which are opening the future research scope in this domain.

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1. INTRODUCTION

Massive amount of data is being produced and consumed every day, and the credit goes to cheap internet facility which gave rise to the excess use of social media. Everyone wants to pull out the important information from the large amount of data. As, no one wants to spend much time and efforts in reading lot of data and receive less information. So, to reduce the time and efforts it is necessary to consolidate textual information and organize the content into a summary. The lengthy data can be shrunk to small data. As, in today's scenario due to the busy schedule no one wants to spend lot of time on reading unnecessary data [1].

The objective of summarization is to condense large amounts of information into shorter, more concise versions while retaining the most important and relevant content. Summarization aims to provide a quick overview or understanding of a text, document, or piece of information, making it easier and faster for readers to grasp the main points without having to go through the entire original text. This process can be done manually by humans or automatically by algorithms, with the goal of saving time and effort in information processing and comprehension. Summarization serves various purposes, such as: i) optimize topic coverage: the summary must incorporates all the main topics from the original document, ii) optimize readability: the summary must have proper logical flow to understand the summary, iii) optimize coherence: summary must have connectivity among word sentences and paragraphs, iv) reduction of redundancy: the summary should not include repetition of sentences, and v) reducing the size of original text: the size of original document need to be compressed depending on the type of summary needed by the user.

Process of automatic text summarizer (ATS): the general ATS system comprises of the following steps. Firstly, by acquiring the required data. Passing it to the system where text pre-processing is initial step where the raw data is prepared for the next step then the processing is done with the help of certain model whichever is chosen according to the summarization approach. Finally, the last step includes the post processing in which few problems are addressed such as the reordering of the sentences is done. These steps in return gives the output as the summary. Further, categorization of the automatic summarization can be done on the basis of different factors. The Table 1 helps to understand the categorization based on various parameters clearly which are based on the input elements, approach and output elements.

Table 1. Different types of summarizations on the basis of various factors

Factors	Description
On the basis of input element	
Input size: single document	The output summary is produced from only one input document.
Input size: multi document	The output summary is produced using many input documents [2].
Input language: mono	The input text is in single language (i.e., either English, Hindi) out of which summary is generated.
Input language: multi	Summarizing documents in multiple languages with the intention of producing the summary.
Input language cross	Summaries generated in different language other than the source document [3].
Input medium: text	The input document comprises of text only. The summary is generated from text.
Input medium: multimedia	The Input document can be of audio or video out of which the summary is produced.
Purpose: generic	Model does not make any assumptions for any domain specific knowledge so as to understand which words or phrases are important for the summarizer. It includes normal understanding of the language to be used and the generic words.
Purpose: domain specific	The summary to be generated needs a domain specific knowledge so as to understand which words or phrases are important for the summarizer. e.g., bio science documents.
Purpose: query based	Summaries can be user focused means these are tailored according to the needs of a particular group of users or users who need to have answer for the query [4].
On the basis of approach	
Extractive approach	During the creation of a summary, extractive methods directly take sentences or phrases out of the source or input text [5]. It creates a summary by obtaining the important sentences from the input text and does not create its own sentences and hence it is easier to achieve.
Abstractive approach	Before using the algorithm of natural language generation (NLG) to create a brief summary using paraphrasing, sentence reduction, and substitution of synonyms, abstractive systems must first understand the text's semantics [5]. Therefore, here the summary is generated by picking up the important keywords and rephrasing the sentences and creating the short sentences out of lengthy ones. This same as we humans do.
Hybrid approach	The new trending approach is hybrid approach. As the name suggest it is the fusion of extractive and abstractive approach which has its own advantages [6].
On the basis of output	
Summary type: extractive	Extraction of only the important information of original text which is concise. Important information is extracted from the text.
Summary type: abstractive	Recreating the sentences with important keywords along with new words and phrases which are not present in the original summary and also reducing the size of original document. Its very similar way that we humans summarize. Human brain creates internal semantic representation of text that human read. Then it recreates the sentences with new words.
Summary content: indicative	An indicative summary does not include the substance of the input text, but rather indicates the basic subject matter or domain of the text [7]. It simply gives an idea of the source document whether to read the text or not. The document length is reduced to 5% of the input.
Summary content: informative	This type of summary includes all the important content from the source document [7]. The document is compressed 20% of the whole text length.

Research objectives: the goals of the research are to have detail survey on various datasets used for the ATS and analyze different techniques of abstractive summarization used so far. And also, understand how to assess the quality of produced summary through ATSs.

Structure of the paper: the manuscript's organization is: most commonly dataset used for summarization are discussed including the size, domain, language, and its type in section 2. Section 3 overviews the methods that are used for abstractive summarization process. The evaluation metric is explained in section 4. The result and analysis of the survey in terms of dataset and methods is in section 5. At the end, the complete work and analysis report is concluded in section 6.

2. DATASET USED FOR AUTOMATIC TEXT SUMMARIZATION

As dataset plays a crucial role in building any deep learning model the same is applied to summarization models it helps to prepare the model to learn the summary generation task. In our survey it is seen that the maximum dataset used for text summarization are related to news articles namely DUC 2001-2007, text analysis conference (TAC) 2008-2011, New York times (NYT) [8], CNN/daily mail [9], and Gigaword. Other datasets are LCTS which is of microblogging data, PubMedCite is of biomedical papers. The Table 2 is all about the dataset available for summarization with its statistics of the size, domain, language and type.

Table 2. Comparison of dataset on size, domain, language, and type

Dataset	Dataset size	Domain	Language	Type
DUC 2001-2003	60×10	News	English	Single and multi document
DUC 2004	100×10	News	English and Arabic	Single and multi document
DUC 2005	50×32	News	English	Multi document
DUC 2006	50×25	News	English	Multi document
DUC 2007	25×10	News	English	Multi document
TAC 2008	48×20	News	English	Multi document
TAC 2009	44×20	News	English	Multi document
TAC 2010	46×20	News	English	Multi document
TAC 2011	44×20	News	English	Multi document
CNN/daily mail	287,226	News	English	Single document
Newsroom [10]	995,041	News	English	Single document
Multinews		News	English	Multi document
SummBank	40×10	News	English	Single and multi document
CAST	147	News	English	Single document
NYT	589,284	News	English	Single document
XSUM	226,711	Headline generation	English	Single document
EASC	153	News and Wikipedia	Arabic	Single document
Gigaword	3,800,000	News	English	Single document
LCSTS	2,4000,591	Microblogging	English and Chinese	Single document
Opinions	51×100	Reviews	English	Multi document
PubMedCite	192 K	Biomedical papers	English	Single document
S2ORC	81.1 million	Acdemic papers	English	Single document

3. METHODS FOR ABSTRACTIVE SUMMARIZATION

Recreating the sentences with important keywords along with new and fresh vocabulary which are not present in the original summary. And also reducing the size of original document is what abstractive summarization is. There are different techniques and methods used in abstractive summarization which is broadly classified into three i.e., structure based, semantic based, and deep learning based as shown in Figure 1.

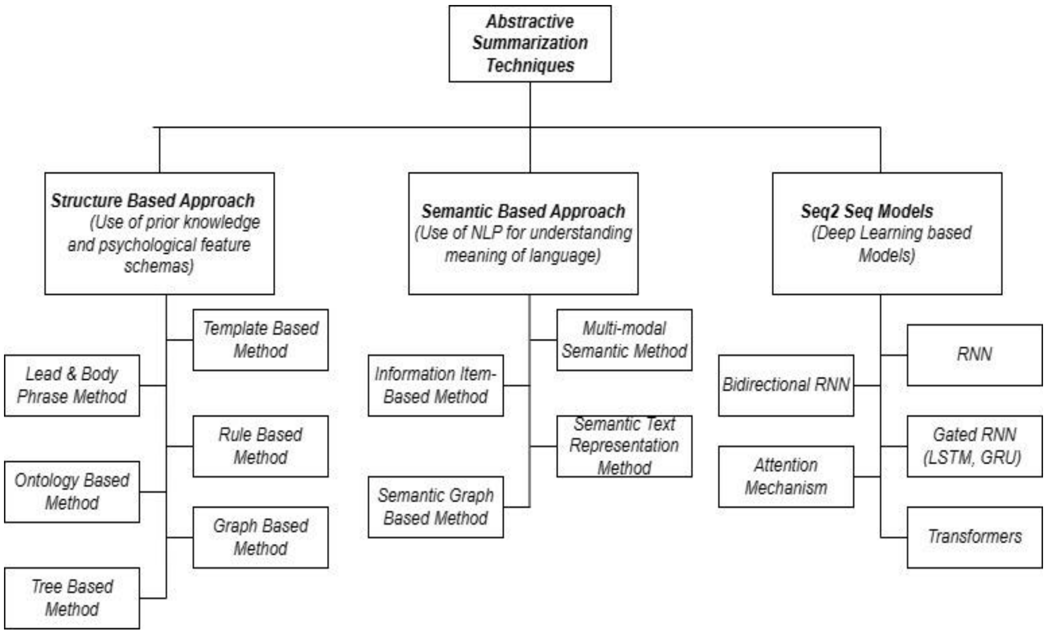

Figure 1. Various abstractive summarization techniques

3.1. Structural based approach

One of the traditional approaches is the structural based approach which presents the summary based on the previous knowledge. The fundamental idea behind structure-based solutions is to encode the most important data from the input document using previous knowledge, psychosocial feature schemas that include flexible alternative structures, and templates with extraction rules including graphs, ontologies, trees, lead, and body [11]. Lead and body phrase method: Tanaka *et al*. [12] proposed this method, which involves analyzing the syntactic structure of the lead and body sentences is used in order to summarize broadcast news. This technique, which took inspiration from the sentence fusion method, utilizes sentence revision to construct a summary by inserting and replacing identical phrases found in the lead and body chunks. The advantage of this approach is that it helped find adjustments to a lead sentence that were semantically appropriate [13]. While the problem with this approach is parsing mistakes reduce sentential completeness, including repetition and grammaticality.

Template based method: this approach uses a specific guide for describing a whole document. Text samples i.e., template that could be mapped into the text snippets are found by comparing language conventions or extraction rules (to form a database). These passages of text act as markers for the outline [14]. It creates thorough and logical summaries and may be applied to the summarizing of multiple documents. The disadvantage is it is necessary to manually design the language conventions, extraction rules for the template slots. It is impossible to handle similar information spread over several publications [15].

Rule based method: input documents are represented by classes and lists of aspects in rule-based approaches. Verbs and nouns with comparable meanings are found in order to generate extraction rules. A selection of potential rules is made before being forwarded to the summary creation module. The production of outline sentences is done using generation patterns. The strength of this method is its capacity to produce summaries with higher information density. The basic weakness of this approach is the painstaking and time-consuming hand writing of all the rules and patterns.

Ontology based method: Lee *et al*. [16] proposed "fuzzy ontology" method, which is used to describe uncertain information in Chinese news summaries, is one of the most important techniques that is an example this method. The advantage of this approach is the documents pertaining to a particular domain are the major focus. It can easily handle text uncertainty and delivers coherent summaries. It requires a solid ontology, but creating one takes a long time because it mainly relies on domain experts to develop the ontology.

Tree based method: when using tree-based approaches, prior to applying these sentence clusters for the abstractive summarization, it is required to group related sentences in the source that contain pertinent information. Dependency trees, a common tree-based representation made of related words, are created by parsers. Lastly, with a method similar to pruning linearization, some of the clusters of sentence are utilized to build trees in order to produce summary sentences [17]. Using language generators results in more fluent, less redundant summaries, which raises the quality of the created material. The downfall side of this method is many important sentences in the text are missed since it does not take context into account.

3.2. Sematic based approach

The second most common and traditional approach used for generating the summary is the semantic based approach which uses a completely different idea when compared to the structure based approach. The basic goal of semantic-based techniques is to identify noun and verb phrase by using linguistics representation of the document(s) as input into a NLG system [18]. Multimodal semantic model: the concepts that are represented by both images and text in multimodal documents are captured by the multimodal semantic model, which also establishes the relationships between these concepts. The process of creating a semantic model begins with object based knowledge representation. Representation of concepts is shown as nodes, and the connections between them show their relationships. In order to construct a summary, the selected concepts are finally turned into sentences.

Information item based method: instead of creating the abstract from the input file's phrases, this method creates it from the input file's abstract representation. The smallest cohesive informational unit found in a text, the abstract representation is an information item [19]. Framework was put forth at the TAC for news multi-document summarization. Subject-verb-object triples are created at the beginning of the information item (INIT) retrieval process through the use of a parser to analyze the text's grammatical structure. The majority of INIT do not result in complete sentences, so before creating a text, they must be combined into a sentence structure. With this approach, a summary that is concise, cohesive, information-rich, and less redundant is produced. But the lexical quality of the produced summary is nevertheless diminished by the fact that it excludes a lot of important information.

Semantic text representation model: instead of focusing on the syntax or structure of the text, this technique seeks to analyze the input text utilizing the word meanings semantic role labelling is recommended in order to retrieve the predicate of the argument structure from each of the phrases or sentences. The document set is divided into sentences and given document and position numbers. In order to assign the position number, the SENNA semantic role labeler application programming interface (API) is used. The matrix of similarity is produced by using semantic graph for semantic similarity scores. Following that, the predicate structure, similarity measure of semantic, and relationship between the document sets are determined using a enhanced graph-based ranking algorithm. In order to reduce or remove repetition for summarization, MMR is finally applied.

Semantic graph based model: by building a semantic graph known as the rich semantic graph (RSG). There are three phases to the strategy which are: input documents are initially expressed using a RSG. The RSG depicts the noun and verb in the original document as graph nodes, with the edges denoting their semantic and topological relationships. The syntactical and semantic links created in pre-processing module connect the various sentence concepts. The original graph is then condensed using heuristic methods into a smaller graph. Lastly, the reduced linguistics graph is used to produce the abstractive outline. This approach results in fewer repetitive and grammatically sound sentences. However, it’s only applicable to single document and doesn’t support the multi document [20].

3.3. Deep learning based model

Recurrent neural network (RNN) encoder decoder summarizer: is a Seq2Seq model which can be used for any sequential information challenge. To create a text summarizer that produces a brief summary from a lengthy list of words in the text’s body, which also functions as a sequence. This can therefore be modelled as a many-to-many Seqence2Seqence issue. A Seq2Seq model primarily consists of two elements: encoder\decoder. Hence, a deep learning model called as RNN works to analyze data in a sequential manner, with each state’s input reliant on the preceding state’s output. As it is unidirectional it only predicts from the past [21], [22].

Bidirectional RNN: represent a class of recurrent neural network architecture that performs forward and backward processing of input data. Because of its bidirectional processing, the network can gather data from both past and future contexts, which makes it particularly useful for jobs where comprehension of the complete sequence is essential [23]. The detailed description of the operation of a bidirectional RNN can be explained as the forward RNN receives the input sequence and proceeds to process it in a left-to-right manner. Further it generates a hidden state at each time step, which is a summary of the data up to that point in the sequence. The identical input sequence is supplied into the backward RNN simultaneously, and it processes the data from right to left. Like the forward RNN, the reverse RNN summarizes data from the right time step up to the present time step by creating a sequence of hidden states. At every time step, the concealed states from the forward and backward RNNs are combined. Concatenated hidden states provide a more complete picture by capturing data from both past and future contexts. But it suffers from the issue of vanishing gradient. Also, the computation complexity is increased as compared to the RNN.

Gated RNN: the two commonly used gated RNN are the long short term memory (LSTM) and gated recurrent unit (GRU) [24]. While training a long sequence with an RNN, the issue of vanishing gradients arises. This issue is resolved by adopting gated RNNs.

Attention mechanism: the idea of an attention mechanism is to anticipate a word by concentrating exclusively on a small subset of the sequence’s components instead of analyzing the complete sequence. This is how we can solve the issue of lengthy sequence [25]. One can emphasize particular words of the source sequence that lead to the target sequence rather than focusing on all the words in the source sequence.

Transformers have advantages over the earlier RNN which used to input token sequentially but the transformers process words all at once and are highly parallelizable [26]. The main building block of transformer is the self attention mechanism. There are three types; i) encoder decoder, ii) encoder only, and iii) decoder only. Examples of encoder only transformer is bidirectional encoder representations from transformers (BERT), developed by [27] is used for for a range of activities, including as linguistic inference and answering questions.

4. EVALUATION METRICS

Every process that gives outcome needs to have certain evaluation metric to judge the quality of the outcome. In the same way the summary needs to be evaluated for the quality. But evaluation of automated generated summary is a challenging task due to the following reasons: i) summary quality depends on the need of the user that means user requirement defines the information to be added in the summary. Two users may have different needs; ii) a summarization is the process of compressing the source document while keeping the important information intact. Therefore, it needs to be evaluated at different compression rate which makes the task more challenging; iii) manual evaluation is a tedious job. So, there is a need of effective evaluation measure; and iv) depending on the summary’s goal, the content varies, therefore it is challenging to automatically collect this information [28]. The summary can be evaluated on the basis of broadly two categories intrinsic and extrinsic method as shown in Figure 2.

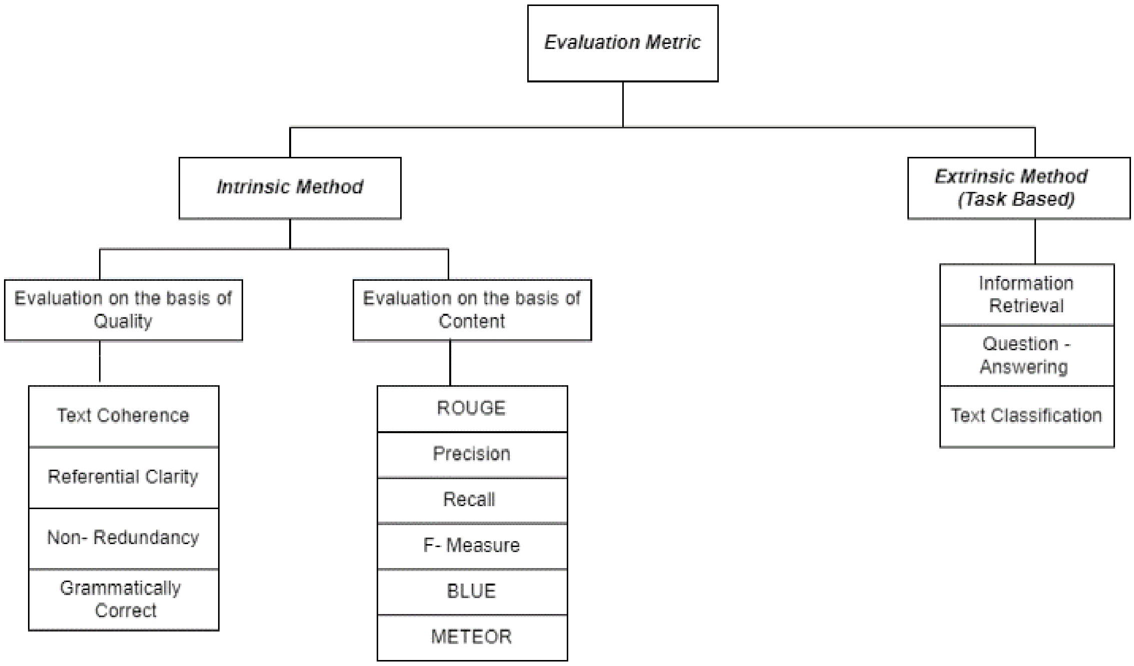

Figure 2. Various evaluation techniques

4.1. Intrinsic methods

In this method human judgement is used to assess summary quality. The intrinsic evaluation rates a summary on these parameters i.e. coherence, topic coverage, and information quality [29]. The quality of summary can be rated by comparing the summary generated by the human. The two most important criteria for evaluating a summary are its quality and its informational value. A summary's informativeness is typically judged by contrast to another summary created by a person, can be called as a reference summary.

Intrinsic evaluation on the basis of quality: how to know that our summaries are good enough in terms of (quality of summary). Evaluation of summary is done on the basis of various parameters [30]. As these parameters forms the characteristics of good summary. One can evaluate the summary considering the parameters i.e., coverage, informativeness, text coherence, and readability.

Intrinsic evaluation on the basis of content: recall-oriented understudy for gisting evaluation **(**ROUGE) was developed by [31] which has now become a standard metric to summary evaluation. It includes series of ROUGE. Deciding on number of grams one should select whether to calculate it on parameters:

a. $Precision = No. of\ n\ grams$ found in reference and model/No of n grams in reference.
b. $Recall = No. of\ n\ grams$ found in reference and model/ No of n grams in model.
c. $F1\ score = 2 \times ((precision \times Recall) \div (Precision + Recall))$.

Bilingual evaluation understudy (BLEU) [32] score compares a candidate sentence to one or more reference sentences to see how well it resembles the set of reference sentences. It assigns an output score ranging from 0 to 1. Metric for evaluation of translation with explicit ordering (METEOR): this metric is used to evaluate the machine generated text. It is not used by many but it gives better results with human judgement correlation as 0.964 as compared to BLEU as 0.817.

4.2. Extrinsic method

This approach uses an assignment-based performance indicator, like the information retrieving task, to assess the summary's quality [33]. These tasks can be text classification, questioning answering and information retrieval. In extrinsic method, the usefulness of summary is evaluated in relation to a particular application setting, such as relevancy assessment and reading comprehension.

5. RESULTS AND DISCUSSION

Dataset: according to our research we have considered the most widely used datasets for the automatic text summarization. Lot of news related datasets are available and work has been done on these. All the news and news article related datasets gives better results as the information in this is localized and hence easy to summarize. The chart in Figure 3 shows the comparison of statistics of available dataset on the basis of different domains which shows that the maximum available datasets are of the news domain which is 80% and then comes the other domains such as microblogging, reviews, scientific papers, and academic papers each of which are 4%. Hence, this shows the challenge of low domain specific resource availability which is related to the dataset that the available datasets are generic and not domain specific. Therefore, lot of work is done in those generic fields but not in domain specific context such as biomedical and medical related field where summarization can prove to be very beneficial.

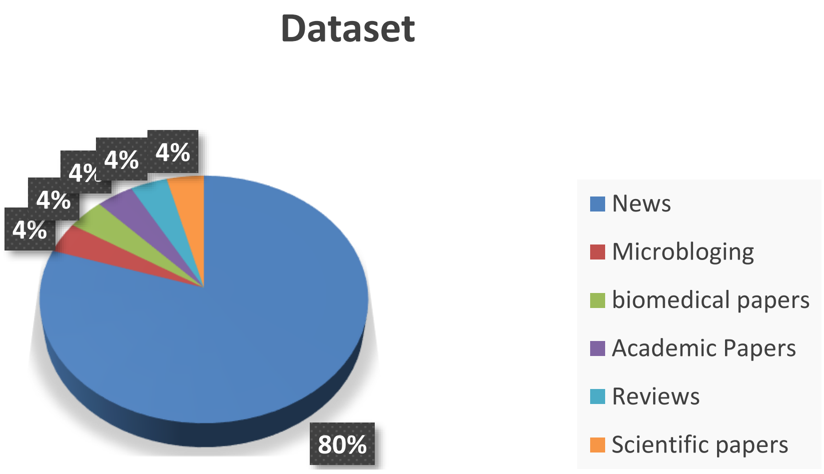

Figure 3. Statistics of summarization dataset on the basis of domain

Methods: various methods and approaches such as structural based, semantic based [34], and deep learning based [35] of abstractive summarization are discussed in our manuscript. These methods are analyzed on the basis of their strength and weakness. According to our analysis the method which can be chosen for better results are the deep learning based models. The transformers in combination with the attention mechanism which can present better summaries as compared to the earlier approaches focusing on the problem when lengthy summaries need to be generated. As, the traditional approaches are not capable enough to present informative summaries for articles which are lengthy with all its parameters. It is also difficult to produce the summaries for articles which are domain specific.

6. CONCLUSION

This article surveys relevant scientific literature to provide a review of different abstractive summarization methods highlighting its advantages and disadvantages. But still a lot of challenges and issues are there in abstractive summarization as it is more difficult to achieve when compared to extractive summarization. The deep learning models with attention mechanism can be more fruitful in creating summaries for lengthy articles. Our study also includes the dataset used with its details and statistics which shows that the maximum available datasets are of the news domain and then comes the other domains such as microblogging, reviews, scientific papers, and academic papers. Also, mainly they are generic and not domain specific. The research framework also focuses on the parameters involved in evaluation of summary including ROUGE, BLEU, and METEOR. As the proper evaluation and state of art solution cannot be declare only on the basis of one metrics. Therefore, in future work we can implement an abstractive summarization model which can be domain specific such as biomedical or health care domain and the summary can be evaluated and compared on more than one metric.

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