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Recent Trends in Deep Learning Based Abstractive Text Summarization

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***Abstract:** With the rapid growth of cyberspace and the appearance of knowledge exploration era, good text summarization method is vital to reduce the large data. Text summarization is the mechanism of extracting the important information which gives us an overall abstract or summary of the entire document and also reduces the size of the document. It is open problem in Natural Language Processing (NLP) and a difficult work for humans to understand and generate an abstract manually while it have need of a accurate analysis of the document. Text Summarization has become an important and timely tool for assisting and interpreting text information. It is generally distinguished into: Extractive and Abstractive. The first method directly chooses and outputs the relevant sentences in the original document; on the other hand, the latter rewrites the original document into summary using NLP techniques. From these two methods, abstractive text summarization is laborious task to realize as it needs correct understanding and sentence amalgamation. This paper gives a brief survey of the distinct attempts undertaken in the field of abstractive summarization. It collectively summarizes the numerous technologies, difficulties and problem of abstractive summarization.*

***Keywords:** Abstractive summary, Deep learning, Structure based approach, Semantic based approach, Text Summarization,*

I. INTRODUCTION

There is no denying the fact that data on the internet is flourishing in an alarmingly speed. Currently, public avail the internet to search the data using Google, Yahoo, Bing etc which are Information Retrieval (IR) engine. Information conciseness or outline of the fetched result is eventually a necessity for the users. In the present time of information pile, Text Summarization has transformed into a necessity to promptly apprehend the large amount of the information. The motivation behind the automatic text summarization is compressing a document into a shorter version and yet preserving most of the important contents (if not all).

A summary helps the user with the overview of the whole document. For humans, reading the whole document and writing a summary is a very time consuming process despite of a straightforward process. Therefore, the need for an automated summary generation is becoming more and more obvious to realize the familiar concept of document.

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Text summarization can be defined as a mechanism which generates representations of primitive document which includes concise and important sentences plucked out from one document or several documents. An approach to automated text summarization consists of:

A. ***Eliminating repetition of words or phrases***
The sentences in the document which reveal the look-alike content are said to be redundant and it can be deleted straightaway.

B. ***Recognition of significant sentences***
Summarizing shorter text representations would only require the inclusion of the original sentence from the source document.

C. ***Production of understandable summaries***
The selected sentence should be ordered and grouped in such a way as to maintain consistency and readability.

D. ***Metrics to evaluate these summaries***
The quality of the summary is judged by humans, but it needs to unanimous across for all methodology and hence a technique for measuring the summaries is a desirable feature.

Several methodologies such as statistics and semantics have emerged to solve this problem. The approach for text summarization is generally categorized as Extractive and Abstractive.

In Extractive summarization methods, summaries are generated by repeating few sentence of the original document by priority ranking based on linguistic and statistical features and later on incorporate the above mentioned parts or sentences together. The aim is to choose relevant sentences to a certain extent from the source document and to keep the generated summary free from redundant data. Earlier text summarization methodologies did not consider the redundancy, but recent studies in this field explain it in their unique manner. The crucial belief of this approach depends upon a review of man-made summaries, and identifies features likely to be in naturally achieved summary. Numerical methods or equations are devised to gain and select sentences from the source document which correlate with human created summaries. Recognizing the sentences to be extracted is an important task in extractive methods. Essential sections of document (phrases, sentences, paragraphs) are considered significant. These significant phrases or sentence from different documents may be mixed and re-arranged using identical methods which right about reduce repetition of sentences. At the end, policies are enforced to generate summary. Some of the methodologies to realize extractive summaries are Classical method (High frequency word, cue word), Term frequency-Inverse document frequency (TF-IDF), Cluster based methods (similarity measures), Graph theoretic, and Rhetorical structure theory.

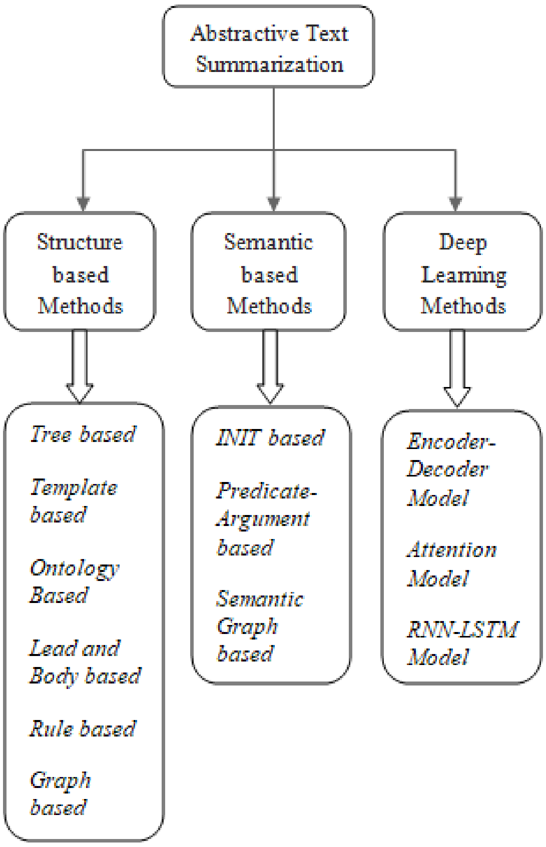

Fig. 1 Various Abstractive Summarization Approaches

Abstractive summarization method extracts phrases and lexical chains from the documents by using language understanding tools to generate a summary. Abstractive Summarization involves process such as derivation of essential features, recognizing the pertinent information, and clarifying and compressing information. Abstractive summarization is complicated as it cannot be mathematically or logically devised. The quality of summaries generated by abstractive summarization techniques rely on the profound linguistic expertise. These techniques are basically divided in two groups.

A. *Structured based approaches*

It encodes crucial data from the document based on its logical compositions such as scripts, and templates. The template, for example, is a predefined structure with space. This space is filled with fragments which are obtained with clue or any keywords from the document.

B. *Semantic based approaches*

Here, Natural Language Generation (NLG) system takes input the semantic or linguistic depiction of sentences. The aim of this approach is to identify the noun phrases and verb phrases to deal with linguistic data. The outputted sentences are connected with its idea, aspect and relations of a domain-particular ontology. The crucial part in a document (sentences, paragraphs) is chosen by ontology-based annotations and clustering methods. This acquired data is used to convert the part of document into semantic representation.

A large number of works has already been accomplished on extractive approaches as it is easy to specify rules to rank significant part from the whole document instead of understanding the document and generating new summaries. Due to the intricacy of NLP, abstractive summarization is a very difficult task. But it produces summaries with immense quality (such as accurate, comprehensible and informative). This paper discusses the recent research activities in the field of abstractive summarization. It gives outline of distinct available techniques and specifies the challenges in the area of abstractive summarization.

II. SINGLE-DOCUMENT SUMMARIZATION

Text summarization is a sentence minimization concept but without loss of meaning from document. Because the summary is short and to the point, it becomes more and more important to not lose the documents original meaning. A document can consist of several small or sub-documents. The content described in each document emphasizes different aspects, although these documents are surrounded by same subject. The process of summarization identifies words and phrases from a document. When this group has only one document, then it is termed as single-document summarization; or else it is termed as multi-document summarization. Single document summarization method produces summary out of one document. A single document can consist of several sub-documents with several paragraphs. The content expressed in these documents emphasizes the various concepts that are relevant to identical subject. In general, single document consist of various lateral information which are relevant with the topic of the document. Regarding logical structure, a unique set of document can also be treated as a group of subjects. Some paragraphs include similar sentences, and each semantic sentence is also a local subject in itself. This section explains some single document abstractive text summarization methods.

Le and Le [1] proposed an abstractive text summarization method with syntactic constraints, word graph, and discourse rules. Once the keyword is captured by discourse rules and syntactic constraints, they are used for generating sentences. With the help of word graph, generated sentences are combined. These graphs are used to represent relation among the word and to combine more sentences into one. The method of creating phrases from the essential part of document is divided into two phase where the first phase is about examining the initial part of a sentence and second phase is about examining the end of a sentence. Sentence combination is achieved by considering and following several syntactical and linguistic options.

Generating abstract templates or frameworks by using fusion based technique was proposed [2]. Templates are created based on the noun phrases as well as POS tagging (Parts of Speech) and hyponyms. Once the framework is ready, they combine it by deriving root verbs from the sentences. Final Summary is generated by these word graph and the templates created.

Table 1: Literature Survey

Sr. No.	Year	Approaches	Language	Dataset used	Method of Evaluation	Single (SD) / Multi-Document (MD)
1	2005	Tree Based [13]	English	DUC 2002	Manual Evaluation based on Human	MD
2	2008	Tree-Based Compression [3]	English	Opiniosis	Semi-manual based on Human feedback and Compression Rate	SD
3	2010	Graph Based [4]	English	Opiniosis	ROUGE-1, 2, & SU4	SD
4	2011	Information Item based [17]	English	-	Based on pyramid score, linguistic quality as well as overall responsiveness score	MD
5	2012	Rich Semantic Graph [8]	English	Graduate student details	Compression rate	SD
6	2013	Syntactical and Discourse Rules [1]	Veitnamese	Veitnamese Newspapers	ROUGE-1 & 2	SD
7	2014	Template Based [2]	English	AMI Corpus	ROUGE-1, 2, & SU4	SD
8	2014	Template Based and Discourse Structure [15]	English	Reviews (Amazon.com & Cnet.com)	Human Based Evaluation	MD
9	2015	AMR Graph [5]	English	AMR Bank	ROUGE-1	SD
10	2015	Deep Learning using Attention Model	English	DUC 2003 & 2004, English Gigaword	ROUGE-1, 2, & L	SD
11	2016	Concept Fusion and Generalization [7]	English	-	-	SD
12	2016	Semantic Graph [20]	English	-	F-score	MD
13	2016	Convolutional + RNN [10]	English	English Gigawords and DUC 2004	ROUGE-1, 2, & L	SD
14	2017	Tree Based, Predicate Argument Structure	English	DUC 2004 & 2007, TAC 2011	Based on both Human Evaluation as well as ROUGE Metrics	MD
15	2017	Graph Based and Integer Linear Programming	English	DUC 2004 & 2005	ROUGE-2, L, & SU4 and Human Evaluation	MD
16	2017	Semantic Analysis and Discourse [9]	English	DUC 2002	F-1 Score and ROUGE-1	SD
17	2017	PAS [21]	English	DUC 2002	Pyramid Score	MD
18	2017	Graph based [22]	English	DUC 2004	ROUGE-2 and SU4	MD
19	2018	Rule Based [6]	English	DUC 2002	ROUGE-1, 2, Average of all Precision, Recall & F-Score	SD
20	2018	Semantic Graph [18]	English	DUC 2002	ROUGE-1, 2 and Pyramid Scores	MD
21	2018	Deep Learning [12]	English	News bits from CNN and DailyMail	ROUGE-N	SD
22	2018	Relevance Sensitive Attention Model [23]	English	Debatepedia, DUC 2005, 2006 & 2007	ROUGE-1, 2, & L	MD Query-Specific
23	2018	Diversity Driven Attention Model [24]	English	Debatepedia	ROUGE-1, 2, & L	MD Query Specific

Dependency tree is the utmost preferred template or architecture used for representing the data (in this case, its text) in a hierarchical format. Yousfi-Monod and Prince [3] refined a methodology named as CoLIN. It depends on dependency tree pruning and linearization whilst preserving the semantic clue, knowledge content, linguistic precision, and rationality in the summary. In their work, they achieved the semantic evaluation of the document and fixated on probing of semantics.

Ganesan [4] proposed a framework which is graph-based, termed as Opinosis that generates short abstractive summaries from superfluous opinions out of documents. The generated summaries are fluent, balanced and descriptive to conclude about the whole document. This approach uses shallow NLP instead of domain knowledge. The opiniosis-graph eliminates repetition and assists to come upon new phrases by recognizing the lingual relations among them.

Liu [5] presents a different framework that uses tree structures for the Abstract Meaning Representation (AMR). Here, the text from the source was mapped to an AMR graphs, further these graphs are constructed to a summary graph which in return generates the text from it.

Bhoib, A., & Balabantaray[6] proposed a hybrid approach was presented. This approach generates summary by clustering the sentences using sentence level relationships (SLA) among sentences along with Markov clustering principle. Later on ranking of the sentences is done in each and every cluster. Then highest ranked sentences from each cluster are shortened and combined using classification algorithm to produce the abstractive summary.

Belkebir et al., [7] uses the technique of concepts fusion and generalization. Concept fusion means when one concept which encompasses the whole meaning of the document is used instead of different concepts involved in a sentence. Here, they have used a novel approach that allows the usage of any one sentence instead of many sentences using its semantic resources. This work by itself may not generate an excellent summary because the identification of the prevalent factor is an immense requirement; therefore, adopting the fusion network to form the well-formed sentence is a complicated issue.

Moawad, I. F., & Aref, M [8] presented an approach which uses reduction technique on Rich Semantic Graph (RSG) to create an abstractive summary of a document. The approach maps the whole document into a Rich Semantic Graph. Once the mapping is done, then some heuristic rules are applied on these graphs which reduce this graph by merging or deleting some nodes by analyzing. After the reduction phase, a summary is generated out of the reduced graph using Natural Language Generation (NLG) system.

Vilca et al., [9] proposes an analysis of abstractive summarization technique by integrating semantic analysis and discourse information. By using lexical resources and Abstract Meaning Representation (AMR) they designed a conceptual graph. Later they tested PageRank algorithm to obtain the most relevant concepts. PageRank works by counting the words in a sentence to determine a rough estimate of how important the sentence is. The underlying assumption is that more important words are likely to be used in other sentence in the document. Also, it incorporated discursive information of Rhetorical Structure Theory (RST) into the PageRank to improve the identification of the relevant concepts. Finally, SimpleNLG are applied to create the summaries.

Chopra et al., [10] introduced a method by conditioning of recurrent neural network (RNN) that summarizes the content of source document. The objective is achieved by using a convolution attention-based encoder-decoder model which makes sure that input words at each phase of the generation is scrutinized by decoder itself.

Li et al., [11] adopted the sequence-to-sequence encoder-decoder model to create abstractive summaries. They treated the latent semantic analysis, generative latent variables and the discriminative deterministic states of the text to enhance the nature of summaries. Recurrent generative decoder was utilized to render the source code as hidden layer and again to previous words to reproduce the summary.

Song et al., [12] proposes an ATS framework (ATSDL) based on LSTM-CNN capable of constructing revised statements by analyzing smaller section than the whole sentences or semantic sentences. Unlike current abstraction based methods, this framework comprises of 2 phases. The first phase chooses phrases from source documents and the second phase generates text summaries using deep learning.

III. MULTI-DOCUMENT SUMMARIZATION

Multi-document summarization is the technique of managing a huge extent of knowledge in multiple source documents which are related to each other in terms of subject or topic, including only the essential or main ideas in a document in less space. Extraction technique based multi-document summarization is identical to single-document summarization, with a difference that it is necessary to acknowledge few features as point of repetition, temporal dimension, compression ratio and co-reference problem in single document summarization. It can be considered as a broadening of concept of single document summarization, where a group of documents comprising the identical subject, or data acquired from different documents are input. Managing these concepts or factors from single document to multi-document is the ultimate objective for researchers. Multi-document summarization is an automated process to extract the data or knowledge from more than one document having similar topics included. The summary eventually generated let individual users to easily become familiar with the knowledge contained in a more than one documents. In this manner, multi-document summarization systems are addressing the issue of overburden of knowledge or data. An optimal approach for multi-document summarization is to presents knowledge acquired from the key aspects apart from shortening the source texts to illustrate broad area of opinion related to the subject. This section explains some multiple document abstractive text summarization methods.

Barzilay [13] adopted text-to-text generation method to generate the informational summaries. They defined phrases with dependency trees and were able to find most relevant data amid phrases by refining the trees. Fusion lattice was calculated by discovering the relation among sub-trees and by applying tree traversals to construct the final sentence. This method fails to seize the relation among the sentences by not searching the intersected phrase in it.

Kurisinkel et al., [14] proposed a novel method for generating abstractive multi-document summarization. They utilized partial dependency tree extraction, recombination and then linearization to create rational structures which are relevant with the topic of document for effective reception of data.

Gerani et al., [15] propose a novel abstractive summarization method which assists for generating reviews of product using their discourse structure. Firstly, Discourse tree representation for every review is obtained by applying a discourse parser to each review, and then updates the discourse trees with aspect words from sentences as leaf node. Secondly, combine the aspect discourse trees and create a graph which in return represents the crucial aspects and the rhetorical relations among them by PageRank algorithm. And then transform the selected sub-graph into an aspect tree. Subsequently, it generates a summary by a template-based NLG framework.

Banerjee et al., [16] develop an abstractive summarizer using ILP (integer linear programming) based multi-sentence compression. This approach first recognizes the crucial document from the set of multi-document. The sentences in the identified document are aligned in the same way with the sentences in other documents to generate group of similar sentences. Later with the help of word-graph structure, it generates K-shortest paths from the sentences of each group. Here, Integer Linear Programming (ILP) is used to select sentences from the set of shortest paths generated from all the clusters for increasing content of information and understandability of the final summary.

A new, ambitious framework for abstractive summarization was proposed in [17]. This method generates summary from an abstract representation of the original document and not by the actual sentences. This abstract representation is obtained by defining the smallest element of coherent information in a text or a sentence. They have incorporated the Information Items (INIT) algorithm. Basically INIT based methods consist of four factor i.e. information items retrieval, language generator, sentence selector which selects the best rated sentences assuming the parameters such as document frequency [18].

Khan et al., [19] introduced a semantic graph approach clubbed with an efficient sentence ranking algorithm for abstractive summarization of multi-documents. The semantic graph is built from the source documents. Each node of the graph denotes the predicate argument structures (PASs) and Edges of the graph represent similarity weight. Here, PASs is the semantic structure of sentence, which is automatically identified by semantic role labeling. The similarity weight is calculated from PASs semantic similarity. The edge of semantic graph is further augmented with PAS-to-document and PAS-to-document set relationships to represent the influence of both document and its set on PASs. They suggested the way to decrease the redundant PASs by adopting maximal marginal relevance for re-ranking the PASs. Thereafter, summaries are generated from the highest ranked PASs using natural language generation (NLG) system.

Bartakke et. al [20] developed an approach to create multi-document abstractive summary by using a RSG (Rich Semantic Graph) reduction method. The approach takes the document and summarizes it by building an RSG. This generated graph is later on reduced with the reduction and optimization techniques, which in turn the abstractive summary from the reduced graph.

Extending the work of [20], Alshaina et al., [21] developed an approach which uses the semantic relationship among the input documents. The approach works to generate multi-document summaries which comprise of following phases; firstly, to represent text semantically, predicate argument structure of the sentences is extracted. Next, semantically similar predicate argument structure are clustered together by hybrid approach of K-mean and agglomerative hierarchical clustering. K-mean is selected due to its run time efficiency and agglomerative hierarchical clustering is selected due to its quality. Selection and Extraction of features from the predicate argument is achieved arbitrarily in the optimization stage. Later, natural language generation (NLG) system is inputted a highest ranked predicate argument structure which is outputted from the optimization phase to generate a summary.

Chen [22] recommended a methodology for multi-document abstractive summarization which depends on chunk-graph (CG) and recurrent neural network language model (RNNLM). In this approach, A Chunk-Graph which is basically a word-graph is designed to integrate all information in a sentence cluster. On the other hand, Chunk-Graph can reduce the graph size and assign more semantic information than word-graph. They uses beam search and character-level RNNLM to generate readable and information-oriented summaries from the Chunk-Graph for each sentence cluster, RNNLM is comparatively a better model to evaluate sentence linguistic quality than the existing n-gram language model.

Baumel et al., [23] devised a method which generates abstractive summaries from the multi-document which are query specific by using Relevance Sensitive Attention-based model.

Nema et al., [24] introduced a framework for the query-based summarization task by using encode-attention-decode technique. This paradigm has two critical enhancement of a query based attention model apart from the document based attention model that adapts itself to spot a chunk of the query at distinct timing rather than using a static model for the query and a revised assorted attention model which eliminate the issue of redundant parts or section in the summary.

IV. INFLUENCE OF DEEP LEARNING IN ABSTRACTIVE TEXT SUMMARIZATION

Deep Learning is a subfield of machine learning concerned with algorithms inspired by the structure and function of the brain called artificial neural networks. It has many levels of non-linear methods to obtain text functionality. Basically, learning is categorized into two types namely supervised or unsupervised, which has been effectively applied to different NLP activities.

Abstractive summarization system, produce more meaningful summaries which are well-formed, accurate and logical. The advent of deep neural networks has driven the success of useful abstractive summarizer systems. Recently, quite an effort has been made for modeling the abstractive summarization task using deep neural network architectures. The neural abstractive summarization system uses encoder-decoder architecture. The encoder captures the thought of the source sequence (text) into a continuous vector from which the decoder generates the target summary. Rush et al.

[25] proposed a Neural Network Language Model (NNLM) called ABS (Attention Based Summarization) for generating English abstractive summaries from longer sentences. Chopra et al. [10] extended this work by using a Recurrent Neural Network (RNN) for the decoder in place of feed forward neural network. Unlike these existing works our neural network methods extracts semantic and compositional features for abstractive summarization.

Rush et al. [25] proposed a neural network based model with local attention modeling which uses a large training corpus. They linked a neural language model with a contextual input encoder. The encoder uses a latent soft alignment over the input text to create the summary. Basically, the encoder and the summary generation model are trained together. In case of decoder, it incorporates a beam-search decoder as well as additional features to model extractive elements.

Gu et al., [26] integrated a copying mechanism into a seq2seq framework to improve the quality of the generated summaries.

Chen et al., [27] proposed a new attention mechanism. In this mechanism, it generates the summary from the inputted document which encompasses the overall meaning of the source by considering the most relevant source segments and also distracts them in the decoding step. A new framework for abstractive text summarization was proposed in [11] based on a sequence-to-sequence oriented encoder-decoder model equipped with a deep re-current generative decoder (DRGD). Abstractive summaries are generated based on both the latent variables and the deterministic states.

Though deep learning approaches are been explored recently, it has got its own pros and cons related to abstractive text summarization.

Pros:

1. Role of each word and its semantic as well as syntactic structure is well captured by Deep learning networks.
2. Both the intrinsic and high level representations of data are efficiently extracted by Deep learning networks.
3. Grammatical errors are taken care of.

Cons:

1. Differences among the original data and training data cause the alignment problem which makes abstractive summarization difficult.
2. It relies on number of occurrence of words together that might lead to grammatical and semantic structure problems.
3. Large datasets required for training to capture better representation of words in sentences.
4. According to [12], summaries generated by deep learning networks possess repetition problems and if document for which the summary is to be generated is long enough, it suffers from gradual encoding.

Our literature review clearly states that various deep learning methods are already used for the single-document non-specific summarization systems.

Nema et al., 2018 in their paper [24] used the attention model which is diversity-driven for solving the same old problem. They have tried to resolve the replicated sentence generation problem by sequence-to-sequence model along with an attention model, which assisted them to bring about an improvement of 28% with ROUGE-L Score.

Lin et al., 2018 in their paper [11] benefitted from the sequence to sequence based model called as Seq2Seq which is sequence to sequence along with the attention model to clarify the issue of above mentioned redundancy. They adopted convolutional gated units with the encoder-decoder model to generate the abstractive summaries of a document where encoder is global encoding and decoder is unidirectional LSTM.

Below in Table 1, we have enlisted the ROUGE Scores obtained by abstractive summarization methods. These scores are based on the DUC 2001 dataset.

Table 1: Evaluation Metrics on DUC Datasets

Methodologies	ROUGE Score
Tree-based	0.3 – 0.4
Template Based [2]	0.21-0.35
Lead and Body Phrase [12]	0.2-0.3
Graph Based	0.31
Semantic Graph Based [19]	0.3-0.4
Predicate-Argument Based	0.3-0.4
Discourse-Based	0.2-0.35
Deep Learning [29]	0.28-0.47

V. CONCLUSION & FUTURE SCOPE

Summarization is not yet an advanced area, therefore automatically generated summaries would result in illogical meaning even though they belong to the sentence. Considering extractive summarization methods, border of any sentences may suffer from the problem of incoherency whereas abstractive summarization techniques are strenuous, as they profoundly depend on the compliance of systems to process information extraction and language generation. De facto, extractive approaches are more appealing when sophisticated NLP tools are not available as they are easy to realize from scratch.

On the other hand, abstraction summarization approaches are challenging and difficult to implement as it depend upon semantic insight of text. There is no de facto framework for summarization, hence parsing and alignment of these parse trees is a challenging task at hand. Generating a good and efficient summary is a world-wide problem which needs selecting the important sentences and then ordering it so it should be in the proper order as in the original source document. Summarization involving substitutions of lexical terms, paraphrase and reformulation is arduous with abstractive summarization. The potential of the system is restricted by the representation abundance and their approach towards creating structure is the biggest task for abstractive summary. Still abstractive text summarization does not completely take care of information diffusion.

Automatic text summarization is an age-old issue though the research outlook is gradually turning from extractive summarization to abstractive summarization one. Because of the complexity of natural language processing, abstractive text summarization is a demanded area. This paper put forth a survey that embodied different approaches of abstractive summarization. Abstractive summarization approaches generates highly cohesive, coherent, less redundant summary which are also abundant with information or knowledge.

The motivation behind writing this paper is to bestow a comprehensive survey and contrast various approaches of abstractive summarization. This paper mainly focuses on single and multiple documents abstractive summarization. Generating abstract using abstractive summarization methods is a difficult task since it requires more semantic and linguistic analysis. Difficulties related to the abstractive summarization techniques can be overcome by recent emerging technologies such as semantic analysis, discourse analysis and neural networks.
Summarization is one of the application of Natural Language Processing (NLP). So generating abstractive summaries also poses lots of complexity as well. Based on our survey, few of the open issues in this field are enlisted below:

A. ***The concern of Unique Words in Neural Networks***
To resolve this, efforts such as combining the syntactic structure with the semantic of the text has to be explored with the use of Deep Learning.

B. ***Non-availability of Datasets for efficient Deep learning approaches***
Even though there is availability of data with the recent years. The unavailability of substantial datasets such as structured data is lacking in this domain. From the literature review, it can be concluded that nearly all abstractive text summarization systems make use of DUC 32 and TAC 33 dataset. Additional research on building better corpus is necessary for the research sector.

C. ***Scalability Issues***
In abstractive summarization, many works have been achieved on clean and complex sentences.

D. ***The need for Cross-Lingual Based Abstractive Summarization Systems***
From literature survey, it can be observed that there was moderate progress in the creation of abstractive summaries for cross-lingual documents. There is an additional complexity on abstractive summarization techniques in terms of cross-language as it requires simple, descriptive and stability, but the translation excellency is a crucial feature that determines the worth of the summary.

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