A Survey on Extractive Text Summarization

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***Abstract*—Text Summarization is the process of obtaining salient information from an authentic text document. In this technique, the extracted information is achieved as a summarized report and conferred as a concise summary to the user. It is very crucial for humans to understand and to describe the content of the text. Text Summarization techniques are classified into abstractive and extractive summarization. The extractive summarization technique focuses on choosing how paragraphs,important sentences, etc produces the original documents in precise form. The implication of sentences is determined based on linguistic and statistical features. In this work, a comprehensive review of extractive text summarization process methods has been ascertained. In this paper, the various techniques, populous benchmarking datasets and challenges of extractive summarization have been reviewed. This paper interprets extractive text summarization methods with a less redundant summary, highly adhesive, coherent and depth information.**

***Index Terms*—Text Summarization, Unsupervised Learning, Supervised Learning, Sentence Fusion, Extraction Scheme, Sentence Revision, Extractive Summary**

I. Introduction

In a recent advance, the significance of text summarization [1] accomplishes more attention due to data inundation on the web. Hence this information overwhelms yields in the big requirement for more reliable and capable progressive text summarizers. Text Summarization gains its importance due to its various types of applications just like the summaries of books, digest- (summary of stories), the stock market, news, Highlights- (meeting, event, sport), Abstract of scientific papers, newspaper articles, magazine etc. Due to its tremendous growth, many finest universities like Faculty of Informatics - Masaryk University, Czech Republic, Concordia University, Montreal, Canada- Semantic Software Lab, IHR Nexus Lab at Arizona State University, Arizona, USA and finally Lab of Topic Maps-Leipzig University, Germany has been persistently working on its rapid enhancements.

Text summarization has grown into a crucial and appropriate engine for supporting and illustrate text content in the latest speedy emergent information age. It's far very complex for humans to physically summarize oversized documents of text. There is a wealth of textual content available on the internet. But, usually, the internet contribute more data than is desired. Therefore, a twin problem is detected: Seeking for appropriate documents through an awe-inspiring number of reports offered, and fascinating a high volume of important information. The objective of automatic text summarization is to condense the origin text into a precise version preserves its report content and global denotation. The main advantage of a text summarization is reading time of the user can be reduced. A marvelous text summary system should reproduce the assorted theme of the document even as keeping repetition to a minimum. Text Summarization methods are publicly restricted into abstractive and extractive summarization.

An extractive summarization technique consists of selecting vital sentences, paragraphs, etc, from the original manuscript and concatenating them into a shorter form. The significance of sentences is strongly based on statistical and linguistic features of sentences. This paper generally summarizes the extensive methodologies fitted, issues launch, exploration and future directions in text summarization. This paper [1] is organized as follows. Section 2 depicts about the features for extractive text summarization, Section 3 describes extractive text summarization methods, Section 4 illustrate inferences made, Section 5 represent challenges and future research directions, Section 6 detail about evaluation metrics and the final sketch is the conclusion.

II. FEATURES FOR EXTRACTIVE TEXT SUMMARIZATION

Earlier techniques involve assigning a score to sentences based on a countenance that are predefined based on the methodology applied. Both word level and sentence level features are employed in text summarization literature. Certain features discussed are [2] [3] [4]used to exclusive sentences to be included in the summary are:

1. Word level features

1.1 Content Word feature

Keywords are essential in identifying the importance of the sentence. The sentence that consists of main keywords is most likely included in the final summary. The content (keyword) words are words that are nouns, verbs, adjectives and adverbs that are commonly determined based on tf x idf measure.

1.2 Title Word feature

The sentences in the original document which consists of words mentioned in the title have greater chances to contribute to the final summary since they serve as indicators of the theme of the document.

1.3 Cue phrase feature

Cue phrases are words and phrases that indicate the structure of the document flow and it is used as a feature in sentence selection. The sentence that contains cue phrases (e.g. "denouement", "because", "this information", "summary", "develop", "desire" etc.) are mostly to be included in the final summary.

1.4 Biased word feature

The sentences that consist of biased words are more likely important. The biased words are a list of the predefined set of words that may be domain specific. They are relatively important words that describe the theme of the document.

1.5 Upper case word feature

The words which are in uppercase such as "UNICEF" are considered to be important words and those sentences that consist of these words are termed important in the context of sentence selection for the final summary.

2. Sentence Level Features

2.1 Sentence location feature

The sentences that occur in the beginning and the conclusion part of the document are most likely important since most documents are hierarchically structured with important information in the beginning and the end of the paragraphs.

2.2 Sentence length feature

The sentence length plays an important role in identifying key sentences. Shorter texts do not convey essential information and very long sentences also need not be included in the summary. The normalized length of the sentence is calculated as the ratio between a number of words in the sentence to the number of words in the longest sentence in the document.

2.3 Paragraph location feature

Similar to sentence location, paragraph location also plays a crucial role in selecting key sentences. A Higher score is assigned to the paragraph in the peripheral sections (beginning and end paragraphs of the document).

2.4 Sentence-to-Sentence Cohesion

The cohesion between sentences for every sentence(s), the similarity between s and alternative sentences are calculated which are summed up and coarse value of the aspect is obtained for s. The feature values are normalized between [0, 1] where value closer to 1.0 indicates a higher degree of cohesion between sentences.

III. EXTRACTIVE TEXT SUMMARIZATION METHODS

Extractive Text Summarization methods can be broadly classified as Unsupervised Learning and Supervised learning methods. Recent works rely on Unsupervised Learning methods for text summarization.

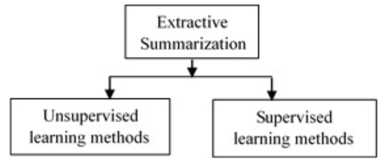

Fig. 1. Overview of Extractive Summarization

A. UNSUPERVISED LEARNING METHODS

In this section, unsupervised techniques for sentence extraction task is discussed. The unsupervised approaches do not need human summaries (user input) in deciding the important features of the document, it requires the most sophisticated algorithm to provide compensation for the lack of human knowledge. Unsupervised summaries provide a higher level of automation compared to supervised model and are more suitable for processing Big Data. Unsupervised learning models have proved successful in text summarization task.

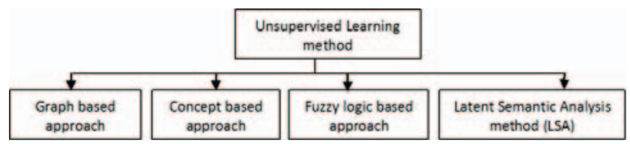

Fig. 2. Overview of Unsupervised Learning Methods

1. Graph based approach

Graph-based models are extensively used in document summarization since graphs can efficiently represent the document structure. Extractive text summarization using external knowledge from Wikipedia incorporating bipartite graph framework [4]has been used. They have proposed an iterative ranking algorithm (variation of HITS algorithm [5]) which is efficient in selecting important sentences and also ensures coherency in the final summary. The uniqueness of this paper is that it combines both graph based and concept based approach towards summarization task. Another graph based approach LexRank [6], where the salience of the sentence is determined by the concept of Eigen vector centrality. The sentences in the document are represented as a graph and the edges between the sentences represents weighted cosine similarity values. The sentences are clustered into groups based on their similarity measures and then the sentences are ranked based on their LexRank scores similar to PageRank algorithm [7]except that the similarity graph is undirected in LexRank method. The method outperforms earlier versions of lead and centroid based approaches.The performance of the system is evaluated with DUC dataset [8].

2. Fuzzy logic based approach

The fuzzy logic approach mainly contains four components: defuzzifier, fuzzifier, fuzzy knowledge base and inference engine. The textual characteristics input of Fuzzy logic approach are sentenced length, sentence similarity etc which is later given to the fuzzy system [9] [10].

TABLE I
SUPERVISED AND UNSUPERVISED LEARNING METHODS FOR TEXT SUMMARIZATION

Categories	**Methodology**	**Concept**	**Advantages**	**Limitations**
SUPERVISED LEARNING APPROACHES	Machine Learning approach Bayes rule	Summarization task modelled as classification problem	Large set of training data improves the sentence selection for summary	Human interruption required for generating manual summaries
SUPERVISED LEARNING APPROACHES	Artificial Neural Network	Trainable summarization - neural network is trained , pruned and generalized to filter sentences and classify them as "summary" or "non-summary sentence"	The network can be trained according to the style of human reader. The set of features can be altered to reflect user's need and requirements	1)Neural Network is slow in training phase and also in application phase. 2) It is difficult to determine how the net makes decision. 3) Requires human interruption for training data
SUPERVISED LEARNING APPROACHES	Conditional Random Fields (CRF)	Statistical modelling approach which uses CRF as a sequence labelling problem	Identifies correct features and provides better representation of sentences and groups terms appropriately into its segments	1) focuses on domain specific which requires an external domain specific corpus for training step. 2) Limitation is that linguistic features are not considered
UNSUPERVISED LEARNING APPROACHES	Graph based Approach	Construction of graph to capture relationship between sentences	1) Captures redundant information 2)Improves coherency	Doesn't focus on issues such as dangling anaphora problem
UNSUPERVISED LEARNING APPROACHES	Concept oriented approach	Importance of sentences calculated based on the concepts retrieved from external knowledge base(wikipedia, HowNet)	incorporation of similarity measures to reduce redundancy	Dangling anaphora and verb referents not considered
UNSUPERVISED LEARNING APPROACHES	Fuzzy Logic based approach	Summarization based on fuzzy rule using various sets of features	improved quality in summary by maintaining coherency	membership functions and work of the fuzzy logic system

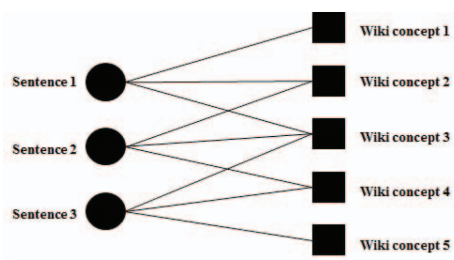

Fig. 3. Example of Sentence concept bipartite graph proposed in [4]

Ladda Suanmali et al [11] proposed fuzzy logic approach is used for automatic text summarization which is the initial step , the text document is pre-processed followed by feature extraction(Title features, Sentence length, Sentence position, Sentence-sentence similarity, term weight, Proper noun and Numerical data. The summary is generated by ordering the ranked sentences in the order they occur in the original document to maintain coherency. The proposed method shows improvement in the quality of summarization but issues such as dangling anaphora are not handled.

3. Concept-based approach

In concept-based approach, the concepts are extracted from a piece of text from external knowledge base such HowNet [12]and Wikipedia [4]. In the methodology proposed [12], the importance of sentences is calculated based on the concepts retrieved from HowNet instead of words. A conceptual vector model is built to obtain a rough summarization and similarity measures are calculated between the sentences to reduce redundancy in the final summary. A good summarizer focuses on higher coverage and lower redundancy. Ramanathan

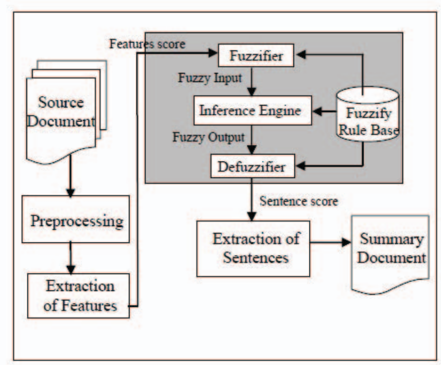

Fig. 4. Overall architecture of text summarization based on fuzzy logic approach proposed in [10]

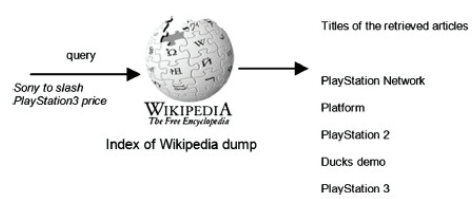

Fig. 5. Example of concepts retrieved for sentence from Wikipedia as proposed in [4]

et al [4] proposed a Wikipedia-based summarization which utilizes graph structure to produce summaries. The method uses Wikipedia to obtain concept for each sentence and builds a sentence-concept bipartite graph as already mentioned in Graph-based summarization. The basic steps in concept based summarization are: i) Retrieve concepts of a text from external knowledge base(HowNet, WordNet, Wikipedia) ii) Build a conceptual vector or graph model to depict relationship between concept and sentences iii) Apply ranking algorithm to score sentences iv) Generate summaries based on the ranking scores of sentences

4. Latent Semantic Analysis Method(LSA)

Latent Semantic Analysis(LSA) [13] [14] is a method which excerpt hidden semantic structures of sentences and words that are popularly used in text summarization task. It is an unsupervised learning approach that does not demand any sort of external or training knowledge. LSA captures the text of the input document and excerpt information such as words that frequently occur together and words that are commonly seen in different sentences. A high number of common words amongst the sentences illustrate that the sentences are semantically related. Singular Value Decomposition(SVD) [13], is a method used to find out the interrelations between words and sentences which also has the competence of noise reduction that helps to improve accuracy. SVD, [15] when enforced to document word matrices, can group documents that are semantically associated to one other despite them sharing no common words. The set of words that ensue in connected text is also connected within the same peculiar dimensional space. LSA technique is applied to excerpt the subject-related words and important content conveying sentences from report. The advantage of adopting LSA vectors for summarization over word vectors is that conceptual relations as represented in the human brain are naturally captured in the LSA. Choice of the representative sentence from every scale of the capacity ensures relevancy of sentence to the document and ensures non-redundancy. LS works with text data and the principal ambit due to the collection of topics can be located.

Considering an example to depict LSA representatieach otheron, Example 1: Consider following 3 sentences given to LSA based system. d0: 'The man was walked the dog. d1: 'The man took the dog to the park in the evening. d2: 'The dog went to the park in the evening. From Fig6 [13] it is to be noted in order that d1 is associated to d2 than d0 and the conversation 'walked' is linked to the talk 'man' but it is not significant to the word 'park'. These kind of interpretations can be built by using input data and LSA, beyond need for any extraneous awareness.

B. SUPERVISED LEARNING METHODS

Supervised extractive summarizationrelated techniques are based on a classification approach at sentence level where the system learns by examples to classify between summary and non-summary sentences. The major drawback with the supervised approach is that it requires known manually created summaries by a human to label the sentences in the original training document enclosed with "summary sentence" or "non-summary sentence" and it also requires more labeled training data for classification.

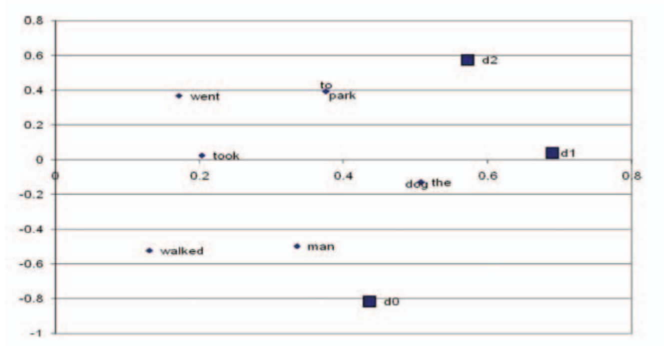

Fig. 6. Representation of LSA for Example [13]

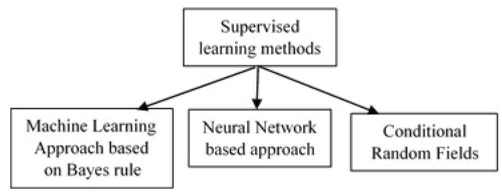

Fig. 7. Overview of Supervised Learning Methods

1. Machine Learning Approach based on Bayes rule

A set of training documents along with its extractive summaries is fed as input to the training stage. The machine learning approach views classification problem in text summarization. The sentences are restricted as a non-summary and summary sentence based on the feature possessed by the sentence. The probability of classification are learned from the training data by the following Bayes rule [16]: where s represents the set of sentences in the document and fi represents the features used in classification stage and S represents the set of sentences in the summary. P $(s \in < S|f_1, f_2, f_3, ...f_n)$ represents the probability of the sentences to be included in the summary based on the given features possessed by the sentence.

2. Neural Network based approach

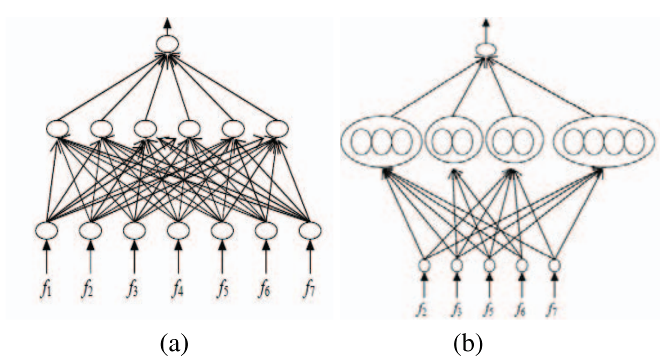

Fig. 8. Neural network after training (a) and after pruning (b) [17]

In the approach proposed in [18], RankNet algorautomaticallyithm using neural nets to identify the important sentences in the document. It uses a two-layer neural network with back propagation trained using RankNet algorithm. The first step involves labeling the training data using a machine-learning approach and then extract features of the sentences in both test set and train sets which is then inputted to the neural network system to rank the sentences in the document. Another approach [17]uses a three layered feed-forward neural network which learns in the training stage the characteristics of summary and non-summary sentences. The major phase is the feature fusion phase where the relationship between the features are identified through two stages 1) eliminating infrequent features 2) collapsing frequent features after which sentence ranking is done to identify the important summary sentences.Neural Network [17]after feature fusion is depicted in Fig 8. Dharmendra Hingu, Deep Shah and Sandeep S.Udmale proposed an extractive approach [19]for summarizing the Wikipedia articles by identifying the text features and scoring the sentences by incorporating neural network model [5]. This system gets the Wikipedia articles as input followed by tokenisation and stemming. The pre-processed passage is sent to the feature extraction steps, which is based on multiple features of sentences and words. The scores obtained after the feature extraction are fed to the neural network, which produces a single value as output score, signifying the importance of the sentences. Usage of the words and sentences is not considered while assigning the weights which results in less accuracy.

3. Conditional Random Fields

Conditional Random Fields are a statistical modeling approach that focuses on machine leaning to provide a structured prediction. The proposed system overcomes the issues faced by non-negative matrix Factorization (NMF) methods by incorporating conditional random fields (CRF) to identify and extract correct features to determine the important sentence of the given text. The main advantage of the method is that it is able to identify correct features and provides a better representation of sentences and groups terms appropriately into its segments. The major drawback of the method is that it focuses on domain-specific which requires an external domain specific corpus for training step, thus this method cannot be applied generically to any document without building a domain corpus which is a time-consuming task. The approach specified in [20]uses CRF as a sequence labelling problem and also captures interaction between sentences through the features extracted for each sentence and it also incorporates complex features such as LSA_scores [21] and HITS_score [22] but the limitation is that linguistic features are not considered.

IV. INFERENCES MADE

- Abounding variations of the extractive path [15] have been focused in the prior ten years. However, it is difficult to say how analytical improvement (sentence or text level) devote to work.
- Beyond NLP, the achieved summary might endure a lack of semantics and cohesion. In texts consist of numerous topics, the provoked summary may not be fair. Conclusive proper weights for respective features is vital to the quality of concluding summary depends on it.
- Feature weights should be given more importance because it plays a major role in choosing key sentences. In text Summarization, the most challenging task is to summarize the contented from a number of semi-structured sources and textual, which includes web pages and databases, in the proper way (size, format, time, language,) for an explicit user.
- Text summary software should crop effective summary within a fewer amount of redundancy and time. Summarization appraise using extrinsic or intrinsic part.
- Intrinsic parts pursuit to measure summary nature adopting human evaluation whereas, extrinsic parts measure the same over a effort-based work measure being the information rehabilitation-oriented task.

V. EVALUATION METRICS

Numerous benchmarking datasets [1] are used for experimental evaluation of extractive summarization. Document Understanding Conferences (DUC) is the most common benchmarking datasets used for text summarization. There are a number of datasets like TIPSTER, TREC , TAC , DUC, CNN. It contains documents along with their summaries that are created automatically, manually and submitted summaries[20]. From papers surveyed within the previous sections et al in literature, it's been found that agreement between human summarizers is sort of low, each for evaluating and generating summaries quite the shape of the outline, it is tough to judge the outline content.

i) Human Evaluation

Human judgment usually has wide variance on what's thought-about a "good" outline, which implies that creating the analysis method automatic is especially tough. Manual analysis is used, however, this can be each time and labor-intensive because it needs humans to browse not solely the summaries however conjointly the supply documents. Other issues are those regarding coherence and coverage.

ii) Rouge

Formally, ROUGE-N is an n-gram recall between a candidate summary and a set of reference summaries. ROUGE-N is computed as follows:

$$\text{ROUGE-N} = \frac{\sum_{S\in\text{reference\_summaries}} \sum_{\text{N-grams}} \text{Count}_{\text{match}}(\text{N-gram})}{\sum_{S\in\text{reference\_summaries}} \sum_{\text{N-grams}} \text{Count}(\text{N-gram})}$$

where, n stands for the length of the n-gram $\text{Count}_{\text{match}}$(N-gram) is the maximum number of n-grams co-occurring in a candidate summary and a set of reference summaries. Count(N-gram) is the number of N-grams in the set of reference summaries.

iii) Recall $R = \frac{|S_{\text{ref}} \cap S_{\text{cand}}|}{|S_{\text{ref}}|}$

where $S_{\text{ref}} \cap S_{\text{cand}}$ indicates the number of sentences that co-occur in both reference and candidate summaries.

iv) Precision (P) $P = \frac{|S_{\text{ref}} \cap S_{\text{cand}}|}{|S_{\text{cand}}|}$

v) F -measure $F = \frac{2(\text{Precision})(\text{Recall})}{\text{Precision} + \text{Recall}}$

vi) Compression Ratio $C_r = S_{\text{len}} \cdot T_{\text{len}}$

where, S_{len} and T_{len} are the length of summary and source text respectively.

VI. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Evaluating summaries (either automatically or manually) is a difficult task. The main problem in evaluation comes from the impossibility of building a standard against which the results of the systems that have to be compared. Further, it is very hard to find out what a correct summary is because there is a chance of the system to generate a better summary that is different from any human summary which is used as an approximation to correct output. Content choice [23] is not a settled problem. People are completely different and subjective authors would possibly select completely different sentences. Two distinct sentences expressed in disparate words will specific a similar can explicit the same meaning also known as paraphrasing. There exists an approach to automatically evaluate summaries using paraphrases (ParaEval). Most text summarization systems perform extractive summarization approach (selecting and photocopying extensive sentences from the professional documents). Though humans can cut and paste relevant data from a text, most of the times they rephrase sentences whenever necessary, or they may join different related data into one sentence. The low inter-annotator agreement figures observed during manual evaluations suggest that the future of this research area massively depends on the capacity to find efficient ways of automatically evaluating the systems.

VII. CONCLUSION

This review has shown assorted mechanism of extractive text summarization process. Extractive summarization process is highly coherent, less redundant and cohesive (summary and information rich). The aim is to give a comprehensive review and comparison of distinctive approaches and techniques of extractive text summarization process. Although research on summarization started way long back, there is still a long way to go. Over the time, focused has drifted from summarizing scientific articles to advertisements, blogs, electronic mail messages and news articles. Simple eradication of sentences has composed satisfactory results in massive applications. Some trends in automatic evaluation of summary system have been focused. However, the work has not focused the different challenges of extractive text summarization process to its full intensity in premises of time and space complication.

REFERENCES

[1] N. Moratanch and S. Chitrakala, "A survey on abstractive text summarization," in *Circuit, Power and Computing Technologies (ICCPCT), 2016 International Conference on*. IEEE, 2016, pp. 1–7.

[2] F. Kiyomarsi and F. R. Esfahani, "Optimizing persian text summarization based on fuzzy logic approach," in *2011 International Conference on Intelligent Building and Management*, 2011.

[3] F. Chen, K. Han, and G. Chen, "An approach to sentence-selection-based text summarization," in *TENCON'02. Proceedings. 2002 IEEE Region 10 Conference on Computers, Communications, Control and Power Engineering*, vol. 1. IEEE, 2002, pp. 489–493.

[4] Y. Sankarasubramaniam, K. Ramanathan, and S. Ghosh, "Text summarization using wikipedia," *Information Processing & Management*, vol. 50, no. 3, pp. 443–461, 2014.

[5] J. M. Kleinberg, "Authoritative sources in a hyperlinked environment," *Journal of the ACM (JACM)*, vol. 46, no. 5, pp. 604–632, 1999.

[6] G. Erkan and D. R. Radev, "Lexrank: Graph-based lexical centrality as salience in text summarization," *Journal of Artificial Intelligence Research*, pp. 457–479, 2004.

[7] S. M. R . W. T. L., Brin, "The pagerank citation ranking: Bringing order to the web," Technical report, Stanford University, Stanford, CA., Tech. Rep., (1998).

[8] (2004) Document understanding conferences dataset. Online. [Online]. Available: http://duc.nist.gov/data.html.

[9] F. Kyoomarsi, H. Khosravi, E. Eslami, P. K. Dehkordy, and A. Tajoddin, "Optimizing text summarization based on fuzzy logic," in *Seventh IEEE/ACIS International Conference on Computer and Information Science*. IEEE, 2008, pp. 347–352.

[10] L. Suanmali, M. S. Binwahlan, and N. Salim, "Sentence features fusion for text summarization using fuzzy logic," in *Hybrid Intelligent Systems, 2009. HIS'09. Ninth International Conference on*, vol. 1. IEEE, 2009, pp. 142–146.

[11] L. Suanmali, N. Salim, and M. S. Binwahlan, "Fuzzy logic based method for improving text summarization," *arXiv preprint arXiv:0906.4690*, 2009.

[12] X. W. Meng Wang and C. Xu, "An approach to concept oriented text summarization," in *in Proceedings of ISCITŠ05, IEEE international conference, China,1290-1293,*, 2005.

[13] M. G. Ozsoy, F. N. Alpaslan, and I. Cicekli, "Text summarization using latent semantic analysis," *Journal of Information Science*, vol. 37, no. 4, pp. 405–417, 2011.

[14] I. Mashechkin, M. Petrovskiy, D. Popov, and D. V. Tsarev, "Automatic text summarization using latent semantic analysis," *Programming and Computer Software*, vol. 37, no. 6, pp. 299–305, 2011.

[15] V. Gupta and G. S. Lehal, "A survey of text summarization extractive techniques," *Journal of emerging technologies in web intelligence*, vol. 2, no. 3, pp. 258–268, 2010.

[16] J. L. Neto, A. A. Freitas, and C. A. Kaestner, "Automatic text summarization using a machine learning approach," in *Advances in Artificial Intelligence*. Springer, 2002, pp. 205–215.

[17] K. Kaikhah, "Automatic text summarization with neural networks," 2004.

[18] K. M. Svore, L. Vanderwende, and C. J. Burges, "Enhancing single-document summarization by combining ranknet and third-party sources." in *EMNLP-CoNLL*, 2007, pp. 448–457.

[19] D. Hingu, D. Shah, and S. S. Udmale, "Automatic text summarization of wikipedia articles," in *Communication, Information & Computing Technology (ICCICT), 2015 International Conference on*. IEEE, 2015, pp. 1–4.

[20] D. Shen, J.-T. Sun, H. Li, Q. Yang, and Z. Chen, "Document summarization using conditional random fields." in *IJCAI*, vol. 7, 2007, pp. 2862–2867.

[21] Y. Gong and X. Liu, "Generic text summarization using relevance measure and latent semantic analysis," in *Proceedings of the 24th annual international ACM SIGIR conference on Research and development in information retrieval*. ACM, 2001, pp. 19–25.

[22] R. Mihalcea, "Language independent extractive summarization," in *Proceedings of the ACL 2005 on Interactive poster and demonstration sessions*. Association for Computational Linguistics, 2005, pp. 49–52.

[23] N. Lalithamani, R. Sukumaran, K. Alagammai, K. K. Sowmya, V. Divyalakshmi, and S. Shanmugapriya, "A mixed-initiative approach for summarizing discussions coupled with sentimental analysis," in *Proceedings of the 2014 International Conference on Interdisciplinary Advances in Applied Computing*. ACM, 2014, p. 5.

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