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Review of automatic text summarization techniques & methods

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A B S T R A C T

Text summarization automatically produces a summary containing important sentences and includes all relevant important information from the original document. One of the main approaches, when viewed from the summary results, are extractive and abstractive. An extractive summary is heading towards maturity and now research has shifted towards abstractive summation and real-time summarization. Although there have been so many achievements in the acquisition of datasets, methods, and techniques published, there are not many papers that can provide a broad picture of the current state of research in this field. This paper provides a broad and systematic review of research in the field of text summarization published from 2008 to 2019. There are 85 journal and conference publications which are the results of the extraction of selected studies for identification and analysis to describe research topics/trends, datasets, preprocessing, features, techniques, methods, evaluations, and problems in this field of research. The results of the analysis provide an in-depth explanation of the topics/trends that are the focus of their research in the field of text summarization; provide references to public datasets, preprocessing and features that have been used; describes the techniques and methods that are often used by researchers as a comparison and means for developing methods. At the end of this paper, several recommendations for opportunities and challenges related to text summarization research are mentioned.

Contents

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1. Introduction

Along with the growth of the internet and big data, making people overwhelmed by the large information and documents on the internet. This triggers the desire of many researchers to develop a technological approach that can summarize texts automatically. Automatic text summarization generates summaries containing important sentences and includes all important relevant information from the original document (Allahyari et al., 2017; Gambhir and Gupta, 2017). So the information quickly arrives and does not lose the original intent of the document (Murad and Martin, 2007). The area of text summarization research has been studied since the mid-20th century, which was first discussed openly by Lun (1958) with a statistical technique namely word frequency diagrams. Many different approaches have been created to date. Based on the number of the document, there is single and multi-document summarization. Meanwhile, based on the summary results there are the extractive and abstractive results.

A single document produces a summary that is sourced from one source document (Radev et al., 2001) and the content described is around the same topic. While the multi-document summarization is taken from various sources or documents that discuss the same topic (Qiang et al., 2016; Ansamma et al., 2017; Widjanarko et al., 2018). (Christian et al., 2016) made text summarizing in a single document using TF-IDF and (Sarkar, 2013) designed automatic text summarizing in a single document using the Main Concepts. (Qiang et al., 2016) summarized multiple documents by the pattern-based summarization (Patsum) method on the 2004 DUC dataset and showed that the results outperformed not only the term-based method but also the ontology-based method. Ansamma et al. (2017) summarized multiple documents using Latent Semantic Analysis (LSA) and Non-Negative Matrix Factorization (NMF) and the results outperformed the state of the art in precision and recall. Qaroush et al. (2019) proposes the summarization of the Arabic single document which produces a fairly informative extractive summary combining machine learning and score-based approaches that evaluate each sentence based on a combination of semantics and statistics. The results are superior in terms of precision metrics, memory, and F-scores, the disadvantage is that it has not optimized the weight of the features. Verma and Om (2019) minimized redundancy in multi-document summarizing by the Shark Smell Optimization (SSO) method and the performance results were far better than the previous summary method.

Extractive summarization is a summary that summaries consist entirely of extracted content so that the results of summary sentences are sentences or words obtained from the original text (Khan and Salim, 2014). The usual problem raised from the extractive summarization research at first was determining the position of the sentence (Khan and Salim, 2014) and the frequency of words in the text (Baxendale, 1958). The next experiment raised the extraction problem which is known as the Information Extraction (IE) technique to produce a summary with more specific results and to increase accuracy. One example of an automatic summarizing system that has been developed by adopting IE techniques is RIPTIDES, which functions to summarize news based on scenarios chosen by the user (White et al., 2001). Research by Naik and Gaonkar (2017) using a rule base produces the best average precision, f-measure, and recall values for Rule-Based Summarizers but has not yet been tried on broader data. Furthermore, there are extractive summarizing studies using neural networks, which in recent years have achieved greater popularity than conventional approaches, some of these studies are (Mohsen et al., 2020; Anand and Wagh, 2019; Xu and Durrett, 2019; Chen et al., 2018a,b; Alami et al., 2019). Research conducted by Anand and Wagh (2019) used a deep learning technique namely Feed Forward Neural Network (FFNN) to summarize a single document in a legal document that has the advantage of producing an extractive summary without the need to create features or domain knowledge and perform well as measured by the Rouge score and produces a coherent summary, will but weak in terms of simplifying complex and long sentences.

In contrast to extractive summarization, sentences generated by abstractive summaries are new sentences or commonly called paraphrases which produce summaries using words that are not in the text. Abstractive summaries are very complex and relatively more difficult than extractive summaries because producing abstractive summaries requires extensive natural language processing (Gambhir and Gupta, 2017). Approach techniques in abstractive summary are generally grouped into two categories namely the linguistic approach and the semantic approach. Examples of methods that use linguistic approaches such as information-based methods (Genest and Lapalme, 2012) and tree-based methods (Barzilay et al., 1999; Tanaka et al., 2009). While examples of methods that use semantic approaches such as template-based methods (Genest and Lapalme, 2011) and ontology-based methods (Chang-Shing et al., 2005). More recently research on abstractive summarizing has been inspired by the encoder-decoder framework, as in research conducted by Xu et al. (2020); Lee et al. (2020); Yao et al. (2018a); Iwasaki et al. (2019). Besides being believed that this model is smoother, the encoder-decoder framework is also convenient in adjusting parameters automatically (Xu et al., 2020).

In the 2000s, there was a renewed trend in the field of text summarizing research. Summaries are not only generated once but are also able to summarize events in real-time or update summaries when new information appears called real-time summarization (Ekstrand-abueg et al., 2016; Lou and Man, 2012; H, A.S.S., K, M. M.C., 2016; Maio et al., 2015; Rodríguez-Vidal et al., 2019; Kacprzyk et al., 2008; Fu et al., 2015; Wu et al., 2015a,b; Wang et al., 2014). Approach techniques that have been used in real-time summarization are fuzzy-based and machine learning. An example of a method that uses a fuzzy-based approach is the fuzzy logic with classic Zadeh's calculus of linguistically quantified propositions (Kacprzyk et al., 2008) which addresses trend extraction and real-time problems where the results are superior in t-norm evaluation, but weak in semantic problems because the semantic results of other t-norms are unclear and unclear can be understood. Fuzzy Formal Concept Analysis (Fuzzy FCA) (Maio et al., 2015) which addresses semantic and real time problems where the results excel at evaluations in f-measures with optimal recall and comparable precision. An example of a method that uses a machine learning approach is Incremental Short Text Summarization (IncreSTS) by Liu et al. (2015a,b) which has better outlier handling, high efficiency, and scalability on target problems. Rank-biased precision-summarization (RBP-SUM) by Rodríguez-Vidal et al. (2019) which has advantages in overcoming redundancy by evaluating using rouge, but this method can only produce extractive summaries.

Text summarization is a formidable challenge in the field of Natural Language Processing (NLP) (Rane and Govilkar, 2019; Shabbir Moiyadi et al., 2016) because it requires precise text analysis such as semantic analysis and lexical analysis to produce a good summary. A good summary, in addition, must contain important information and must be concise but also must consider aspects such as non-redundancy, relevance, coverage, coherence, and readability (Verma et al., 2019). Where to get all these aspects in a summary is a great challenge.

The review of papers on text summarization is important because summarizing extractive techniques has become a very broad research topic and is heading towards maturity (Gupta and Gupta, 2019). Now research has shifted towards abstractive summarization (Gupta and Gupta, 2019) and real-time summarization. This is because abstractive summaries are more complex and complicated than extractive summaries. So extractive summaries are easier to give expected and better results than abstractive summaries (Elrefaiy et al., 2018; Allahyari et al., 2017; Mishra and Gayen, 2018). However, extractive summarization is also still in great demand as evident extractive research still exists in the last two years (Ren et al., 2018; Sanchez-gomez et al., 2018; Yao et al., 2018b; Khan et al., 2019; Qaroush et al., 2019; Anand and Wagh, 2019; Lierde and Chow, 2019). This indicates the possibility that there are still opportunities or loopholes to improve.

A clear literature study is demanded as a means for the advancement of research in the field of text summarization. Where literature studies are generally contained, analyzed, and compared in a review or survey paper. Review paper made by Gupta and Gupta (2019) discusses popular components specifically about abstractive summarizing, such as research trends in the field of abstractive summarization, general description of existing abstractive summarizing techniques, tools, and evaluations. Other reviews were conducted by Abualigah et al. (2020) gave a brief survey of the techniques of text summarization and specifically in Arabic. A survey conducted by Nazari and Mahdavi (2018) discussing text summarization focuses on the approach techniques and methods used in text summarization. Nazari and Mahdavi (2018) grouped approaches to statistics, machine learning, semantic-based, and swarm intelligence. Another survey was conducted by Elrefaiy et al. (2018) which is about summarizing extractive texts that focus on unattended techniques, presents a list of strengths and weaknesses in a comparison table, alluding to a little about evaluations and future trends.

Some other review articles only cover smaller sections, for example only about approach techniques (Allahyari et al., 2017; Nazari and Mahdavi, 2018), the methods used (Rajasekaran et al., 2018), evaluations technique (Saziyabegum and Sajja, 2017), or discuss the topic of extractive or abstractive text summarization (Abualigah et al., 2020). So that will make researchers, especially those who are new studying this field, need to work hard and may have difficulty doing a thorough review. Therefore the objectives of this study are as follows: a) to identify and analyze research topics/trends in the field of summarizing texts and to classify them; b) to provide an overview of the various approaches to summarizing texts (where the strengths and limitations of the commonly used approach are also highlighted); c) to briefly explain the methods that already exist in this field, both frequently used and the latest methods; d) to explain the preprocessing stages that already exist and what features have been used; e) to discuss what problems have been the challenges in the field of text summarization so far and what problems have been solved or have not been resolved properly; f) to briefly discuss existing evaluation techniques in summarizing text, as well as the data sets that have been used; g) to present recommendations for future development of text summarization research.

To explore more opportunities in research in this field, this research using techniques Systematic Literature Review (SLR) to get the results of the exploration of a more systematic, measurable, and the diversity of topics that reviews more diverse and wider (Wahono, 2015). The advantages of SLR over traditional review techniques are the use of scientific methods and their systematic workmanship (Okoli and Schabram, 2010). To minimize bias and the results are clear and can be accounted for. Because of its definite method of operation, SLR can confidently provide input to policymakers. The categorized various researches from 2008 to the end of 2019 into the research question (RQ) group. The activities carried out are as follows: the research methodology in the review paper is explained in Section 2, the results and answers to the questions presented in Section 2 are explained in Section 3, the conclusion, and future work in Section 4.

2. Method

2.1. Review method

This review research on text summarization was conducted with Systematic Literature Review (SLR). SLR is a way to identify, evaluate, and interpret research results that have been carried out as a whole relevant to the topic field or research questions that aim to provide answers to research questions (Okoli and Schabram, n.d.), namely research on text summarization. In general, there are three parts (Wahono, 2015) that are carried out in the SLR, i.e.: the first part is the planning phase, the second part is the implementation phase, and the third part is the reporting phase, to see more detail can see Fig. 1.

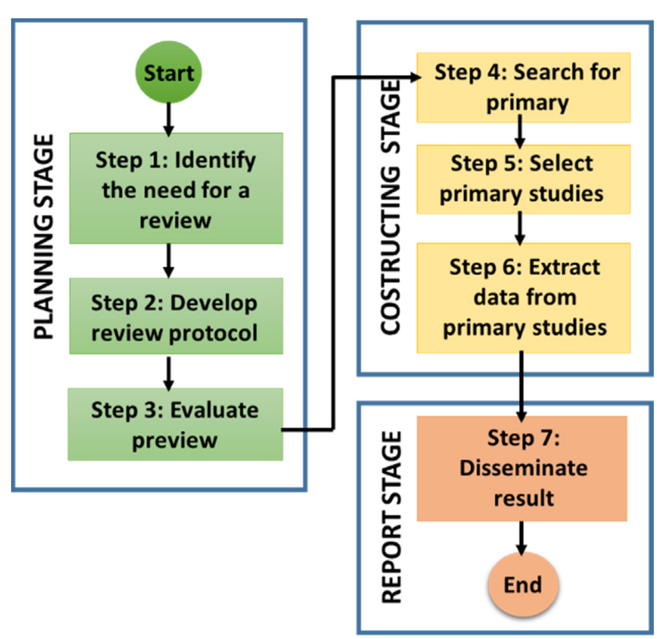

Fig. 1. Systematic Literature Review (Okoli and Schabram, n.d.)

Table 1
PICOC Criteria.

Population	Text summarization
Intervention	The method in text summarization
Comparison	–
Outcomes	Automatic text summarization performance
Context	Study in computer laboratories with small and large datasets

Table 2
Research Question and Motivation.

ID	Research question	Motivation
RQ1	What journal/conference paper about text summarization?	Identify the most significant journal/conference papers in the text summarization
RQ2	What dataset is used in text summarization?	Identify datasets commonly used in text summarization
RQ3	What journal/conference paper about text summarization?	Identify the research topic/trend of text summarization
RQ4	What preprocessing methods are used in text summarization?	Identify preprocessing used in text summarization research
RQ5	What features are used in text summarization?	Identify what features in text summarization
RQ6	What approach techniques are used in text summarization?	identify approaches that are often used in text summarization
RQ7	What is currently the problem in a document summarizing?	Identify problems are in the text summarization
RQ8	What method is used in text summarization?	Identify the method used in text summarization
RQ9	What evaluation techniques are used in text summarization?	Identify what evaluations are carried out in the text summarization

2.2. Research question (RQ)

RQ is prepared to facilitate the review process to be more focused and consistent. In general, research questions are prepared using PICOC meaningful criteria (Population, Intervention, Comparison, Results, and Context) (Kitchenham and Charters, 2007) which are displayed as the following Table 1.

The research question and motivation in this literature review are explained in Table 2.

RQ2 and RQ4 through RQ9 are the main study research questions, while RQ1 and RQ3 are assigned to help evaluate the context of the main study. RQ2 shows the dataset and RQ4 to RQ9, namely preprocessing, features used, approach techniques, problems, methods, and evaluations. RQ1 and RQ 3 provide a synopsis of certain areas of research in summarizing texts. To understand research questions more easily about summaries of text summaries, illustrated by the mind map in Fig. 2.

2.3. Search strategy

Data sources used in this review of text summarization are papers available on the sciencedirect.com site, ieeexplore.ieee.org and dl.acm.org. The webpage is a leading paper journal and conferencing site suitable for reviewing this text summarization research. To get papers that fit the topic is to enter the following keywords or synonyms of the keywords determined from the research topic being conducted. Here is a search string used for the paper search process: (text summarization OR abstractive summarization OR extractive summarization OR real-time text summarization) AND (approach OR technique OR method).

Adjustment of the search string is conducted to significantly reduce the list of irrelevant studies. To meet each specific requirement from the database on each site, search adjustments are needed. Specific requirements for database searches are based on title, abstract, and keywords. Limited searches for publication year: 2008–2019. Publications included are journaled papers and conferences or proceedings with an initial determination of 80% of journals and 20% of conferences or proceedings. Conference papers or proceedings are given in part for this review paper because it does not rule out the possibility of bright ideas coming from conferences or continuing paper articles. The paper articles included are limited to paper articles in English.

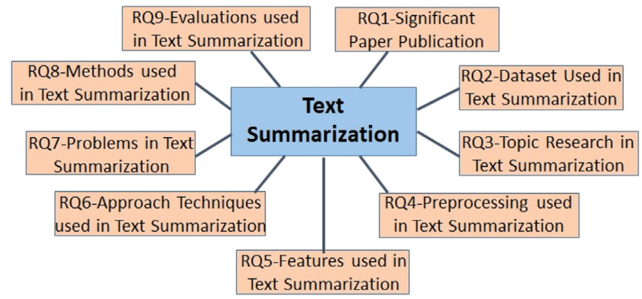

Fig. 2. Mind Map of Review Text Summarization.

Table 3
Inclusion and Exclusion Criteria.

Inclusion criteria	Studies that summarize texts include topics, problems, datasets, techniques and methods used This research consisted of journals and papers from the conference that specifically discussed the summation of texts The publications taken were studies from 2008 to 2019
Exclusion criteria	Studies that do not have experimental results and use a dataset are unclear Studies that discuss topics beyond summarizing texts Studies not written in English

Table 4
Data Extraction.

Property	Research question
Publication	RQ1
Text summarization dataset	RQ2
Research topic or trend	RQ3
Text summarization preprocessing	RQ4
Text summarization feature	RQ5
Text summarization technique	RQ6
Text summarization problem	RQ7
Text summarization method	RQ8
Text summarization evaluation	RQ9

2.4. Study selection

When the paper article search stage is carried out it will filter out very many articles that fit the criteria when making the search adjustment process. The determination of paper criteria included in the main study was obtained from the inclusion and exclusion process described in Table 3. Besides, to produce limited paper articles that fit the research topic for later review, we need a method that is described in Fig. 3.

The initial paper article that was obtained when conducting an initial search by automatically filtering titles, abstracts, and keywords was 1338 studies. Then choose the main paper article that matches the complete contents of the entire text so that there are 85 papers. The final results of the 85 papers will be summa-

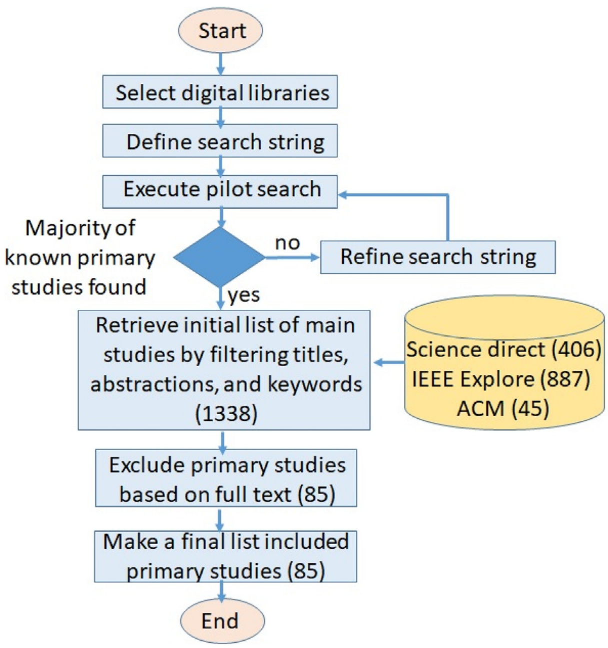

Fig. 3. Search and Selection.

rized and reviewed for later analysis. Mendeley's software is used in managing search results so that it will be easier to group based on the specified topics.

2.5. Data extraction

The data extraction stage is a process that functions in gathering data from the main study to answer research questions. Table 4 The following is the data extraction table used.

3. Result

3.1. Paper studies publication

From the results of the filtering process, it was found that the papers which had discussed the research about text summarization. 85 papers discuss text summarization from 2008 to 2019. Fig. 4 shows a graph of the development of the number of paper publications from year to year for ten years, from the graph it appears that research on text summarization is still relevant.

The most research on text summarization is in 2018 with 18 publications. This study's research experienced a significant increase in 2015, with 15 publications out of 85 selected publication studies. From the graph, it can be seen that from 2008 to 2012 research on this study was of little interest, namely only 1 or 2 publications. This research began quite a lot in 2013 until now, namely, in 2019 there were 15 publications.

Publication Journal papers or important conferences based on literature studies are shown in Fig. 5. As explained in the background that in this review paper, researchers took 80% of journal papers and 20% of conferences. From the analysis of journal sources and conferences that publish publications in the field of text summarization research, Expert System with the Application journal is the most journal source that publishes research topics on summarizing text.

3.2. Dataset

In research, a dataset is needed to test the performance of a proposed method. In the text summarization study, various datasets have been used which are divided into two groups of datasets, private and public. To see a comparison of private and public datasets that have been used for the past ten years can be seen in Fig. 6.

The public dataset is more widely used than private datasets. Of the 85 studies chosen on text summarization research, 55 studies used public datasets and 30 studies that used private datasets. The most favorite public dataset in this research is 70% DUC. Then tweet 11%, news 9%, multilingual 5%, and TAC2011 5%.

There are several types of DUC dataset used in the last ten years. DUC 2002 there were 21 studies, DUC 2003 only 1 study, DUC 2004 there were 11 studies, DUC 2005 and 2006 only 1 study, and DUC 2007 3 studies were using the dataset. DUC dataset is a public dataset published by the National Institute of Standards and Technology (NIST) is an agency of the U.S. Commerce Department. There are eight types of DUC datasets published by NIST to date, namely DUC 2000 to DUC 2007. DUC datasets are widely used by researchers for information retrieval research, especially Text summarization. Based on the past ten years of literature, DUC datasets that are often used in this field are DUC 2002 and DUC 2004. The DUC 2002 and 2004 datasets are well suited to be used or devel-

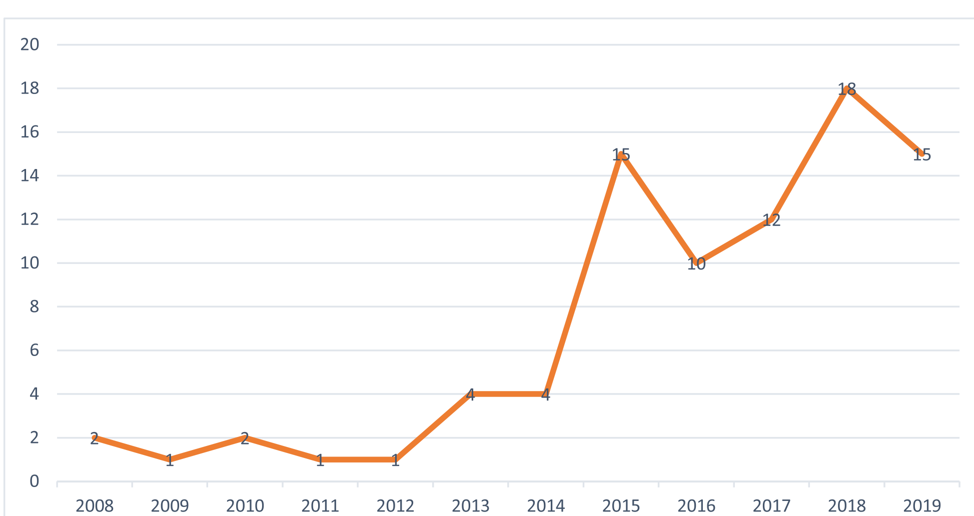

Fig. 4. Distribution over the past ten years for selected studies.

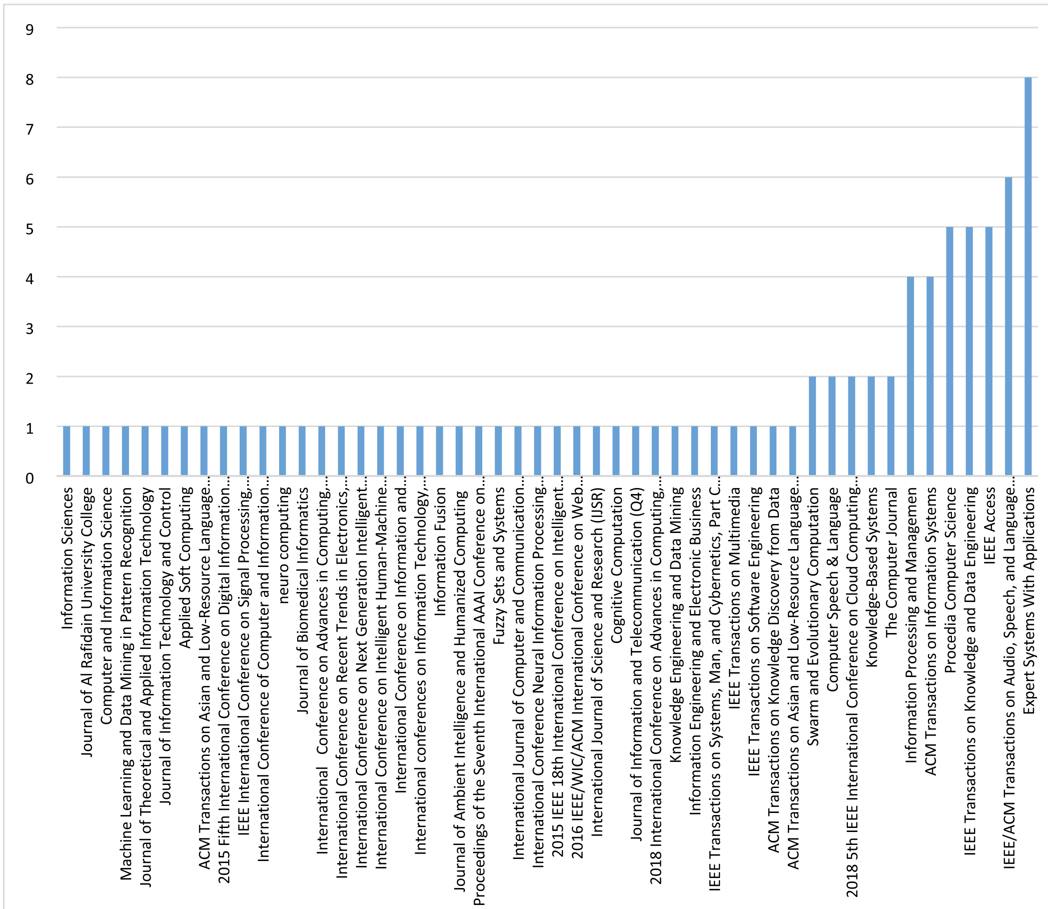

Fig. 5. Journal and Conference/Prosiding Publications and Distribution of Selected Studies.

oped for several research trends/topics such as extractive (Song et al., 2011; Yao et al., 2018b; Yadav and Meena, 2016; Fang et al., 2016; Ansamma et al., 2017; Chen et al., 2018a,b; Al-sabahi et al., 2018), abstractive (Fuad et al., 2019; Sahoo et al., 2018; Bhargava et al., 2016; Khan et al., 2015a; S et al., 2017), single-document (Cagliero et al., 2019; Goyal et al., 2013; Patel and Chhinkaniwala, 2018) or multi-document (Padmapriya and Duraiswamy, 2014; Patel et al., 2019; Malallah and Ali, 2017; Fuad et al., 2019; Khan et al., 2015a; S et al., 2017). Because DUC 2002 and 2004 contain more than one document containing news in the U.S. and every single news document is cut into sentences. So it can help researchers to create sentence segmentation in documents. However, DUC 2002 and DUC 2004 are not suitable for the topic of real-time summarization, because news data is not sequential and does not continue. The positive thing if using a DUC public dataset is that it can compare the performance of the proposed method with the many different methods that have been developed previously.

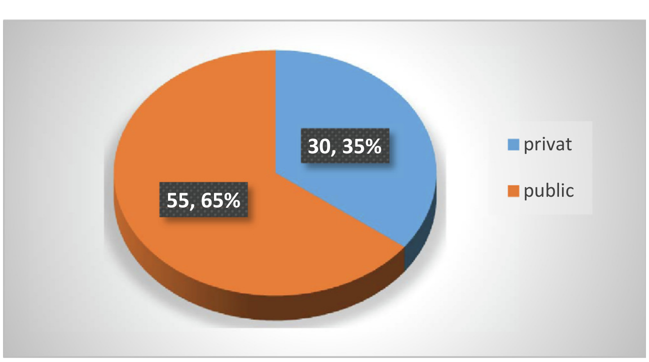

Fig. 6. Distribution of Dataset Text Summarization.

The multilingual dataset is used for documents consisting of several languages. The multilingual dataset used is multiling11 and multiling13. The news dataset that has been used is news about the ball and news with texts other than English, namely Mandarin and Thai. While the tweet dataset is trending topics, movie comments, and product-specific product comments.

Private data that is widely used is novel datasets and datasets with language domains other than English such as Malayam, Tibetan, Turkish, Bangla, Indonesian, Mandarin, Thai, and Arabic. Other private datasets are microblog, speech, assessment, and biomedical. The positive thing for private datasets, which are often used is novel datasets and datasets with language domains other than English. By using language datasets other than English, it is a challenge to use preprocessing that matches good results. One of the preprocessing stages that need special methods/algorithms to deal with this problem is stemming. Because stemming addresses the problem of word affixing, while the English affix is different from other languages. To see the distribution of datasets used from year to year for the past 10 years is presented in Fig. 7.

The graph in Fig. 7 shows the distribution of the number of datasets used each year, both public and private datasets. From this figure, it can be concluded that a significant increase in the public dataset occurred in 2015. This is comparable to the amount of research increase in text summarization that is increasing

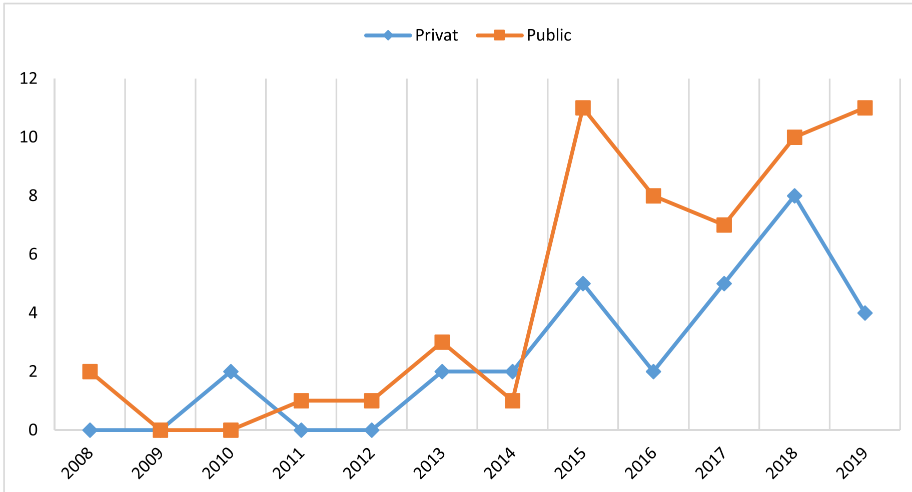

Fig. 7. Distribution Private and Public Datasets.

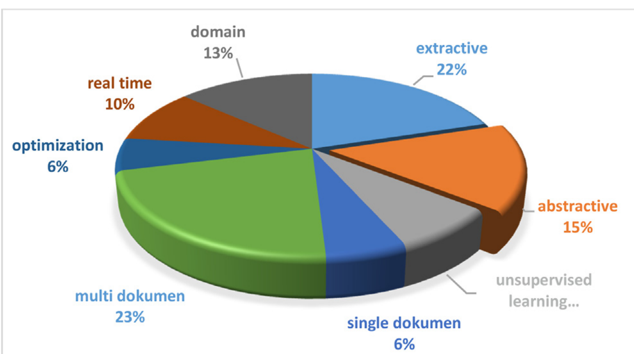

Fig. 8. Distribution of Topic or Trend Research.

significantly in 2015 and 2018 (can be seen from Fig. 4). The number of public datasets declined slightly in 2017 and again increased until 2019.

3.3. Topics or trends research

Text summarization research consists of various research topics or trends. From the last 10 years, there have been 8 research topics or trends on text summarization, namely extractive, abstractive, a single document, multi-document, optimization, domain, and real-time summarization. Distribution of trends or research topics in text summarization can be seen in Fig. 8.

The most favorite research topics or trends of the past 10 years are multi documents, which is 23%. Summarizing the topic text in multiple documents is the most popular because this topic is more challenging when compared to one document. After all, it requires a large search space and has different content in each document (Puspaningrum et al., 2019). Besides, multi-document summarizing provides information from what is on various online media (Hendy Evan and Sigit Purnomo, 2014) and it is proportional to the amount of information data available on online media or the internet at this time.

The next favorite research topic after multi-document is extractive text summarization because it is more objective without presenting viewpoints (Vázquez et al., 2018). Extractive text

Table 5
Detail Topics or Trends research in Text Summarization.

Topic/Trend	Research
Extractive	Lierde and Chow (2019), Song et al. (2011), Jaafar and Bouzoubaa (2018), Sanchez-gomez et al. (2018), Yao et al. (2018b), Wu et al, (2017), Yadav and Meena (2016), Fang et al. (2016), Ansamma et al. (2017), Krishnaprasad et al. (2016), Naik and Gaonkar (2017), Babar and Patil (2015), Shah and Jivani (2018), Khan et al. (2019), Chen et al. (2015), Chen et al. (2018a,b), Zhang et al. (2010), Liu et al. (2015a,b), Al-sabahi et al. (2018), Rastkar et al. (2014), Ren et al., n.d.)
Abstractive	Barros et al. (2019), Azmi and Altmami (2018), Fuad et al. (2019), Sahoo et al. (2018), Bhargava et al. (2016), Jaafar and Bouzoubaa (2018), Mori et al. (2018), Khan et al. (2015a), Wei et al. (2019), Khan et al. (2015b), Chi et al. (2018), Chen et al. (2018a,b), S et al. (2017), Guo et al. (2019), Dilawari and Khan (2019), Zhang et al. (2013)
Unsupervised learning	Song et al. (2011), Yousefi-azar and Hamey (2017), Tayal et al. (2016), Alami et al. (2019), Wu et al. (2015a,b), Khan et al. (2019), Sun and Zhuge (2018), Zhou et al. (2016)
Single document	Li et al. (2016), Patel et al. (2019), Sharifi et al. (2013), Goyal et al. (2013), Wang et al. (2015), Cagliero et al. (2019)
Multi-document	Malallah and Ali (2017), Patel et al. (2019), Lee et al. (2013), Padmapriya and Duraiswamy (2014), Fuad et al. (2019), Khan et al. (2015a), Khan et al. (2015b), S et al. (2017), Sanchez-gomez et al. (2018), Verma and Om (2019), Qiang et al. (2016), Ansamma et al. (2017), Widjanarko et al. (2018), Azhari et al. (2018), Sharifi et al. (2013), Alzuhair and Al-dhelaan (2019), Liu et al. (2012), Bian et al. (2013), Yulianti et al. (2017), Qiang et al. (2019), Ketui et al. (2015), Yan and Wan (2015), Baralis et al. (2015)
Optimization	Song et al. (2011), Abbasi-ghalehtaki et al. (2016), Binwahlan et al. (2009a), Khosravi et al. (2008), Sanchez-gomez et al. (2018)
Real-time	Maio et al. (2015), Rodríguez-Vidal et al. (2019), Chua and Asur (2009), Kacprzyk et al. (2008), Kacprzyk et al. (2008), Fu et al. (2015), Chellal et al. (2016), H and K, 2016, C. Liu et al., 2015, Wang et al. (2014), Wu et al. (2015a,b)
Domain	Domain Turkish Güran and Uysal (2017), domain Bangla Sarkar and Hossen (2018), domain biomedical Moradi (2018), domain assessment Goularte et al. (2019), domain Malayam Krishnaprasad et al. (2016), domain Tibetan Li et al. (2016), domain Indonesian Widjanarko et al. (2018), domain Indonesian Sabuna and Setyohadi (2017), domain novel Gupta and Kaur (2015), domain Turkish Kutlu et al. (2010), domain review film Liu et al. (2012), question answering (QA) Yulianti et al. (2017), domain multilingual Cagliero et al. (2019) and Baralis et al. (2015)

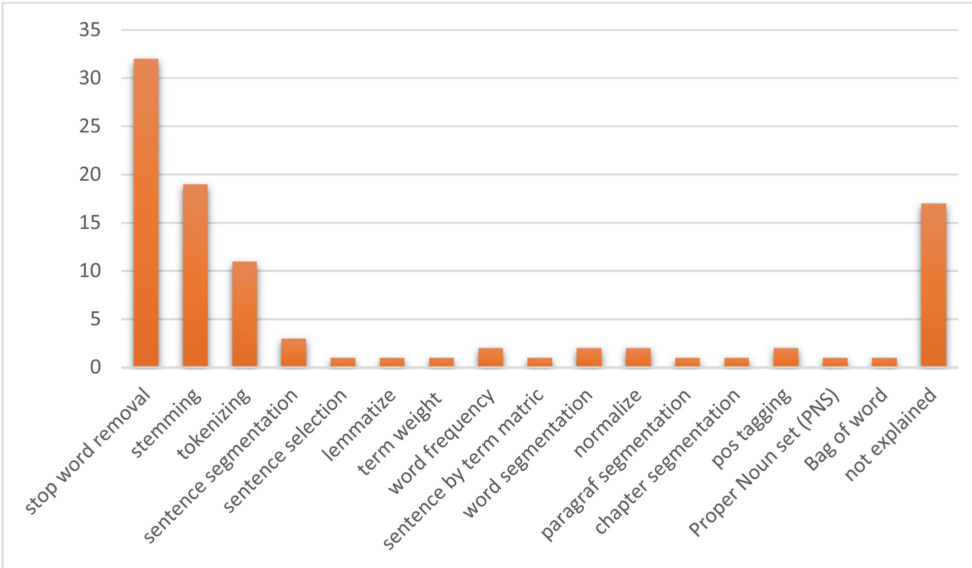

Fig. 9. Distribution of Preprocessing Used in Text Summarization.

summarization only chooses the most important words, sentences, and paragraphs to produce a summary. Extractive summarization has a weakness in terms of coherence between sentences in the summary. If compared to abstractive summarization, extractive is relatively easier than abstractive which is very complex because it requires extensive natural language processing (Gambhir and Gupta, 2017). Although extractive summaries are relatively easier than very complex abstract summaries, there are still many things that challenge researchers to do. For example, in determining the preprocessing stages that correspond to the dataset, choosing the right features, and how to maximize the features to get a better summary, determine the right approach and how to collaborate with one approach to another to improve summarizing performance better.

The most challenging topic or trend research is real-time summarization. This is because in addition to the summary must produce a relevant summary and include all information without any redundancy, the summary must also be added/updated as soon as the addition of new information has appeared (Chellal et al., 2016). The part that distinguishes real-time summarization from other text summarization topics is in the timing or updating of the information. To find out detailed information of the 8 topics or trends in text summarization that have been conducted by researchers can be seen in Table 5.

3.4. Preprocessing

Preprocessing is the initial process for preparing data. Unstructured data is changed to be structured data according to the needs for summation. Based on the study of the past ten years, preprocessing in text summarization can be seen in Fig. 9.

Based on Fig. 9, it can be concluded that preprocessing that is often done in text summarization is stop word removal. Stop word removal is a word that is ignored in processing. These neglected words are stored in the stop word list. The main characteristics for determining stop words are words that usually have a high frequency of occurrence, for example, conjunctions like "and", "or", "but", "will" and others. There are no definite rules in determining the stop word to be used, the determination of the stop word can be adjusted to the case being resolved and with the language used, for example, Hindi stopword list (Rani and Lobiyal, 2020) will be very different from English or other languages.

The second preprocessing that is often used is Stemming. Stemming is used to change words with affixes into basic forms or remove affixes that stick to the basic words. For example, "to be given" becomes "to give". The stemming process in each language is different. For example, Affixes in Indonesian are more complex when compared to affixes in English. Because of affixes in Indonesian consist of prefixes, infixes, suffixes, repeated forms, and confixes (a combination of prefixes and suffixes). Preprocessing which is often used next is tokenizing. Tokenizing is used to divide sentences, paragraphs, or documents, into certain tokens/parts. Examples of tokenizing in the following sentence: "Nina planted flowers yesterday afternoon" produces five tokens, namely: "Nina", "planted", "flowers", "yesterday", "afternoon". Usually, the spaces between tokens are spaces and punctuation.

Other preprocessing used are chapter segmentation, paragraph segmentation, sentence segmentation, word segmentation, lemmatize, term weight, word frequency, sentence by term matric, sentence selection, normalize, post tagging, proper noun set, and Bag of Word. Chapter segmentation is a preprocessing stage which separates/cuts text document into the chapter. Once separated or cut into the chapter next is paragraph segmentation, which is separating/cutting the chapter into paragraphs. Next is the sentence segmentation to word segmentation.

Lemmatize is a preprocessing stage which is almost the same goal as stemming, which is to normalize words or make words that have affection into basic words. The difference is that stemming only cuts the additions of one single word roughly without regard to context knowledge or morphological analysis. However, stemming is usually easier to apply and run faster and reduced accuracy may not be a problem for some applications. While normalization is a stage that consists of stemming or lemmatize.

Term weight is the weighting of a word or word's judgment that determines the importance of that word in a summary sentence. Word frequency is closely related to term weight that is how often the word appears so that the word value can be determined. Part of Speech (POS) Tagging is a way of categorizing word classes, such as nouns, verbs, adjectives, etc. Bag of Word is a vector space model where each sentence is described as a token and counts the appearance of words regardless of word order. Proper Noun Set is a collection of nouns or corpus nouns. Sentence selection is a preprocessing stage that selects sentences to be used as a summary.

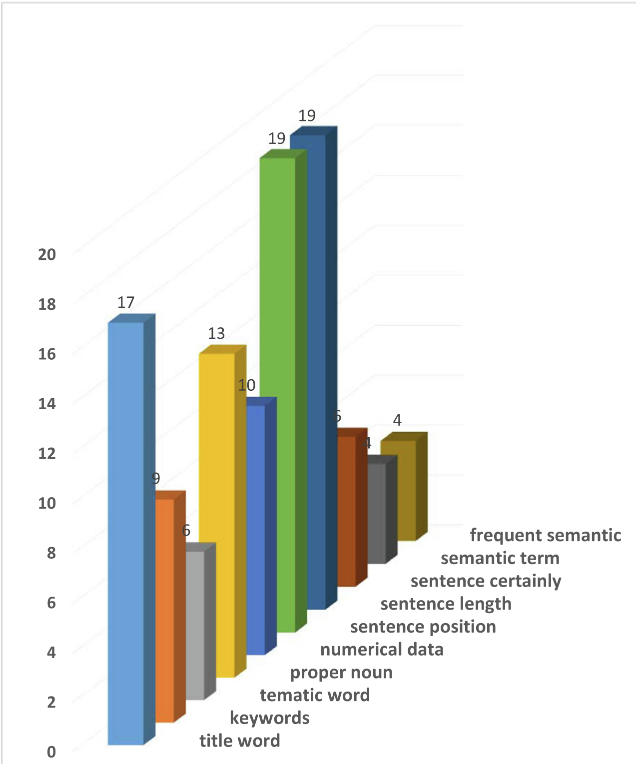

Fig. 10. Distribution of Features Used in Text Summarization.

3.5. Features

Features used in text summarization research from 2008 to 2019 are explained in Fig. 10. Features in text summarization are special characteristics or indicators to be extracted to produce a summary. Ten features are often used in the last ten years of text summarization research.

The most favorite features are sentence length and sentence position. In the sentence length feature, long sentences contain more important or relevant information. That means short sentences do not cover any relevant information, so short sentences are considered unimportant or ignored. For calculation of Sentence Length (*SL*) (Patel et al., 2019) can be seen in the following Eq. (1), where the *SL* variable is the length of the sentence, No. of a word occurring in *S* is the variable that shows the number of words in the sentence, and No. word occurring in the longest sentence is the variable that shows the number of words in the longest sentence.

$$SL_i = \frac{\text{No.of a word occurring in S}}{\text{No.Word Occurring in longest Sentence}} \quad (1)$$

Sentence position is the most studied feature in extractive text summarizing (Wu et al., 2017; Yadav and Meena, 2016; Naik and Gaonkar, 2017; Babar and Patil, 2015). Various methods have been used to feature the sentence position, one of which is weighting with the reverse sentence order. Its use for example with a text of 20 sentences, the first sentence will be 20 times more important than the last. So it's almost impossible the last sentence will appear in the summary. If a paragraph has n sentences, the score of each sentence is calculated. To calculate the sentence position score (Patel et al., 2019), it can be seen in Eq. (2), where *SP* is a variable that shows the position of the sentence, *N* is a variable that shows the total sentence in the document, and *i* is a variable that shows the sentence.

$$SP_i = 1 - \frac{i-1}{\mathrm{N}} \quad (2)$$

Other features are title words, keywords, thematic words, proper nouns, numerical data, sentence certainly, semantic terms, and frequent semantic. The title word feature is a feature to measure the similarity of a word to the title, the greater the similarity of words to the title means the more likely the word is included in the summary. The Keyword is a word that has a large judgment or main word that often appears in a sentence and words that are important words in a sentence. There have been many studies that focus on determining or finding keywords. Examples are using machine learning approaches such as SVM (Gupta and Kaur, 2015), LSA (Liu et al., 2012) and Text Rank (Wu et al., 2015a,b), using statistical approaches such as TF-IDF (Malallah and Ali, 2017; Patel et al., 2019; Güran and Uysal, 2017; Mori et al., 2018; Sabuna and Setyohadi, 2017; Wu et al., 2015a,b; Fu et al., 2015), and other approaches such as N-Gram (Liu et al., 2015a,b). A proper noun is a grouping of nouns. Semantic terms and semantic frequencies are part of the semantic features to measure the semantic relationship of sentences or words.

Recent research that uses quite complete features is (Patel et al., 2019) by using the following features: word features (title word, proper noun word, thematic word, keywords using TF-IDF, numerical data), sentence feature (sentence length and sentence position) and scoring feature using the fuzzy logic system. Combining the statistical approach with fuzzy based, namely the TF-IDF method and fuzzy logic with multi-document text input, multi-document summarization (MDS) which produces extractive summaries. The advantage of the approach taken is to use sentence assessment in a better tuning process. The disadvantage is the problem of sorting sentences in summary. Ordering sentences is a very difficult task but very important in summarizing documents. One way that can be done for the future is to improve the MDS form (Patel et al., 2019) by adding semantic and linguistic features to produce a more coherent summary.

3..6. Approach techniques

From the literature that has been obtained from the last ten years, there are six approaches or techniques used in text summarization, namely fuzzy-based, machine learning, statistics, graphics, topic modeling, and rule-based. To find out the distribution of approaches to text summarization in the past ten years, it can be seen in Fig. 11.

The most favorite approach technique used in text summarization is machine learning, with 46 studies. The machine learning approach is a favorite technique because this approach is a modern technique. The machine learning performance is automatic and learns to improve from experience without being explicitly programmed. The method used in the machine learning approach for text summarization over the past ten years such as objective artificial bee colony (ABC), semantic role labeling (SRL), Recurrent neural network (RNN), cellular learning automata (CLA), Patsum, Abstractive Summarization of Video Sequences (ASoVS), MS-Pointer Network, Sentiment Embedding (SE), title identification (TIDA), IncreSTS, Shark Smell Optimization (SSO), Discourse Supervised Tree-based summarization (DST), NN, Auto Encoder (AE), K-Means, PSO, Markov, SVM, deep learning, maximal marginal relevance (MMR), etc.

However, although machine learning is a favorite, machine learning is not the only best approach. Lots of research with the latest machine learning techniques which has many weaknesses in-text summarizing. For example (Binwahlan et al., 2009a) with weaknesses in terms of semantics, (Guo et al., 2019) which has weaknesses in the repetition of sentences in the summary which

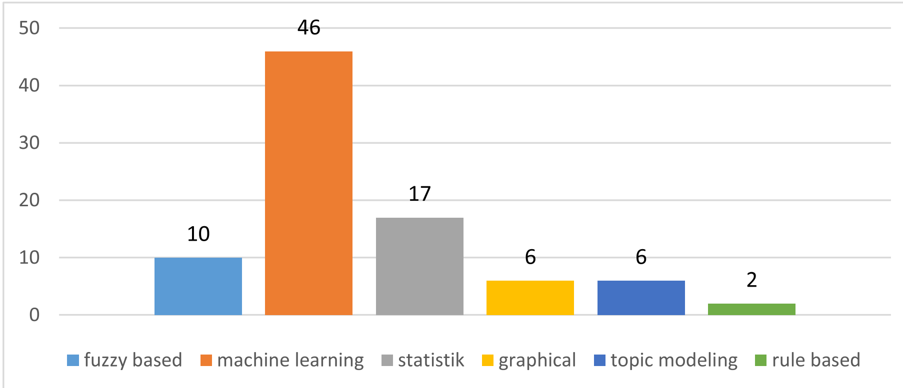

Fig. 11. Distribution of Techniques Applied in Text Summarization.

means related to the problem of sentence redundancy so that it is given the advice to add TF-IDF (statistical approach techniques) to produce a more accurate summary.

The latest research with the machine learning approach is (Binwahlan et al., 2009a), which is by hybridizing the Maximal marginal importance (MMI) method, PSO, and hybrid the other approach techniques, namely the fuzzy logic method. The input of this research is a single document and the summary results are extractive summaries. MMI is used to produce summaries that excel in terms of diversity by relying on determining the most important sentences. The most important sentences are determined by selecting the same sentence and choosing various sentences by extracting sentences from the original text (Binwahlan et al., 2009b). PSO is used to select the most important and least important features and fuzzy logic is used to help PSO to create risk and uncertainty values, and the tolerance value can be changed / flexible. The results of the method were tested on the DUC 2002 dataset and compared with Msword, sys19, and sys30 summarizers. The results outperformed the comparison system in terms of recall 0.40463 and f-measure 0.42291. For precision, this hybrid method (MMI, PSO, fuzzy) is inferior to other summaries namely Sys30 with precision 0.66374 and hybrid method (MMI, PSO, fuzzy) precision 0.45769. The weakness of this system is the semantic problem. Future work can add semantic features by labeling semantic roles and lexical databases and applying this method for multi-document summarizing.

The next research using the machine learning approach is Qian Guo with a method called MS-Pointer Network (Guo et al., 2019). This research focuses on ranking abstractive with deep learning to predict the inaccuracy of words that appear or semantic inaccuracy. The method used is to give a higher weight to words which are semantic combinations. The evaluations carried out in this study used the rouge tested on the Gigaword dataset and CNN. The results outperformed the state of the art that is compared with other machine learning approaches such as SeqtoSeq + attention baseline, abstractive model by Nallapati et al., 2016 and pointer-generator. Testing using the Gigaword dataset, this method is superior to rouge-1 40.21, rouge-2 19.37, and rouge-L 38.29. Testing with CNN dataset, this method excels with rouge-1 39.93, rouge-2 18.21, and rouge-L 37.39. However, this method loses rouge-1 measurements when compared to the baseline lead-3 system (Nallapati et al., 2017) with rouge-1 40.21 in the CNN dataset. The weakness in this method is the repetition of sentences in the summary. This means that related to the problem of sentence redundancy. Qian Guo provides suggestions for future research to add TF-IDF or RBM to produce a more accurate summary.

The less popular approach in research on text summarization in the last 10 years is rule-based. The rule-based approach has the advantage of being applied to a simple domain, so rule-based is easy to verify and validate but has weaknesses when applied to a domain with a high level of complexity, if the system cannot recognize the rules, then no results are obtained (Subali and Fatichah, 2019). Besides, if there are too many rules, the system becomes difficult in maintaining performance.

Fuzzy based is the method most often used because fuzzy logic can prevent data contradictions. After all, it involves the role of humans to determine uncertainty. The way fuzzy systems work is to use multiple inputs from various features or indexes. The score of each feature is then given to the fuzzy inference system as input for the subsequent use of the IF-THEN rule of human knowledge. The fuzzy method is widely used to produce extractive summaries, among others fuzzy combining with graphical approaches, namely Fuzzy hypergraphs (Lierde and Chow, 2019), MDS System using Fuzzy Logic and combining with TF (Patel et al., 2019), fuzzy logic combining with machine learning approach (MMI + PSO) (Binwahlan et al., 2009a), etc.

An approach technique that is easily combined with other approaches is statistics. Statistics can be combined with machine learning or statistics with fuzzy-based. Statistics are widely used to get the score or weight of a feature. For example to determine the frequency of words, determine keywords, determine similarity that appears with a statistical approach that is TF-IDF (Patel et al., 2019; Güran and Uysal, 2017; Gupta and Kaur, 2015; Sharifi et al., 2013; Khan et al., 2019; Yousefi-azar and Hamey, 2017; Malallah and Ali, 2017; Goularte et al., 2019). Then the results of the statistical approach are used as input to extract or determine the final score of the sentence chosen in the summary with a machine learning or fuzzy-based approach.

The combination of statistical approach techniques with machine learning, for example, is term frequency with hybrid Calculation scoring + SVM (Gupta and Kaur, 2015), Hybrid TF-IDF with SumBasic (Sharifi et al., 2013), TF-IDF with K-Means (Khan et al., 2019), TF-IDF with Deep learning + AE (auto Encoder) (Yousefi-azar and Hamey, 2017). The combination of statistical and fuzzy approach techniques, for example, is TF-IDF with fuzzy logic (Patel et al., 2019), TF-IDF with fuzzy logic + appriori (Malallah and Ali, 2017), TF-IDF, LSA with Fuzzy and AHP(Güran and Uysal, 2017), TF with fuzzy logic (Goularte et al., 2019).

To see what methods use machine learning, statistical, fuzzy-based, graphical, topic modeling, and rule-based approaches in this complete text summarization study can be seen in Table 6.

3.7. The problem in text summarization

Based on a text summarization research study from 2008 to 2019, several problems have become challenges that have been

Table 6
Summary of Topic, Problem, Approach Technique, and Method in Text Summarization.

Topics/Trends	Problems	Techniques	Methods
Extractive	Semantic	Fuzzy-based	Fuzzy hypergraph Lierde and Cho, (2019)
		Statistic	LSA and NMF Ansamma et al. (2017), LSA Babar and Patil, 2015)
		Machine learning	LSA + ANN Deep Learning) Shah and Jivani, 2018)
	Optimization	Machine learning	FEOM Song et al. (2011), ABC and MOABC Sanchez-gomez et al. (2018)
	Hybrid	Graphical	CGS Jaafar and Bouzoubaa, 2018)
	Clustering	Machine learning	DQN Yao et al. (2018b)
	Topic modeling	Topic model	LDA Wu et al. (2017)
	Extraction	Fuzzy-based	Fuzzy logic Yadav and Meena, 2016; Babar and Patil, 2015)
		Graphical	N-rank Krishnaprasad et al. (2016)
		Rule-based	Rule-based Naik and Gaonkar, 2017)
		Machine learning	TF-IDF and K-Means Khan et al. (2019), (RSHMMs) + SVM Zhang et al. (2010), KLM + RM + Clairty S. Liu et al. (2015), HSSAS Al-sabahi et al. (2018)
	Sentence ranking	Machine learning	Co-rank Fang et al. (2016)
	Sentence key	Machine learning	RNNLM) and ULM Chen et al. (2015), (EV) and (D-EV) Chen et al. (2018a,b)
	Feature	Machine learning	EM,EMC and BRC Rastkar et al. (2014)
	Sentence scoring	Machine learning	CNN (Ren et al. (n.d.)
Abstractive	Extraction	Machine learning	NATSUM Barros et al. (2019), ASoVS Dilawari and Khan, 2019)
	Ambiguity	Statistic	TF-IDF and NLP Azmi and Altmami, 2018)
	Clustering	Machine learning	NeuFuse Fuad et al. (2019)
	sentence scoring	Machine learning	Markov and SVM Sahoo et al. (2018)
	semantic	Graphical	AMR Bhargava et al. (2016)
		Machine learning	SRL, GA, and AS Khan et al. (2015a), dual train and single train Wei et al. (2019), SRL, GA, MMR, and AS Khan et al. (2015b), bi-RNN Chen et al. (2018a,b), MS-Pointer Network Guo et al. (2019)
	Hybrid	Graphical	CGS Jaafar and Bouzoubaa, 2018)
		Machine learning	K-Means and HAC S et al. (2017)
	Word frequency	Statistic	index IN, and or index IF, and or index H, and or index ID Mori et al. (2018)
	Feature	Statistic	SOF Chi et al. (2018)
	Sentiment	Machine learning	bi-RNN Chen et al. (2018a,b)
	Keyword	Statistic	round-robin and POS Zhang et al. (2013)
Unsupervised learning	Optimization	Machine Learning	FEOM Song et al. (2011)
	Noise	Machine learning	ENAE and Deep AE Yousefi-azar and Hamey, 2017)
	Ambiguity	Machine Learning	NLP Parser, TIDA, SVO, and N-gram Tayal et al. (2016)
	Semantic	Machine Learning	AE, NN, BOW, TF-IDF Alami et al. (2019), Semantic Link Network Sun and Zhuge, 2018)
	Extraction	Machine LearningPerformance Evaluation of Text-Mining Models with Hindi Stopwords Lists	HTI and HTI-OS Wu et al. (2015a,b), TF-IDF and K-Means Khan et al. (2019), Affinity Propagation and co-ranking (Zhou et al. (2016)
Single document	Similarity	Graphical	text-rank, lex-rank Li et al. (2016), IntraLink + bernoulli mode Goyal et al. (2013)
		Machine learning	SumBasic and Hybrid TF-IDF Sharifi et al. (2013)
	Redundancy	Statistic	similarity co-sin Patel et al. (2019), LSA = itemset-by-sentence (IS), SVD and LSA Cagliero et al. (2019)
	Extraction	Machine learning	DST Wang et al. (2015)
Multi-document	Extraction	Statistic	fuzzy logic and apriori Malallah and Ali, 2017), fuzzy logic Lee et al. (2013), TEDU + COMP Ketui et al. (2015)
		Fuzzy-based	ANFIS Azhari et al. (2018)
		Machine learning	ExpQueryOpt Yulianti et al. (2017)
		Topic model	RA-MDS Qiang et al. (2019), (DDSS) and a topic-sensitive (MTL) model Yan and Wan, 2015)
	Redundancy	Statistic	similarity co-sin Patel et al. (2019)
		Machine learning	Patsum Qiang et al. (2016)
	Hybrid	Machine learning	Fuzzy and RBM Padmapriya and Duraiswamy, 2014), K-Means and HAC S et al. (2017)
	Clustering	Machine learning	NeuFuse Fuad et al. (2019), LDA Widjanarko et al. (2018)
	Semantic	Machine Learning	SRL, GA, and AS Khan et al. (2015a), SRL, GA, MMR, and AS Khan et al. (2015b)
		Statistic	LSA and NMF Ansamma et al. (2017)
	Optimization	Machine Learning	ABC and MOABC Sanchez-gomez et al. (2018)
	Similarity	Machine learning	Shark Smell Optimization (SSO) and MMR Verma and Om, 2019), SumBasic and Hybrid TF-IDF Sharifi et al. (2013)
		Graphical	TF-IDF and Graph-Based ranking algorithm Alzuhair and Al-dhelaan, 2019)
	Sentiment	Machine learning	SVM and LSA (Liu et al. (2012)
	Keyword	Machine Learning	CMLDA Bian et al. (2013)
	Scoring	Statistic	MWI-Sum Baralis et al. (2015)
	Redundancy	Machine Learning	MMR Verma and Om, 2019)
Optimization	Optimization	Machine learning	FEOM Song et al. (2011), ABC and MOABC Sanchez-gomez et al. (2018)
	Similarity	Machine learning	CLA Abbasi-ghalehtaki et al. (2016)
	Ambiguity	Machine learning	MMI diversity, swarm diversity and Fuzzy swarm diversity Binwahlan et al. (2009a)

(continued on next page)

Table 6 (*continued*)

Topics/Trends	Problems	Techniques	Methods
	Extraction	Fuzzy-based	Fuzzy logic Khosravi et al. (2008)
Real-time	Similarity	Fuzzy-based	Fuzzy Formal Concept Analysis (Fuzzy FCA) Maio et al. (2015)
		Machine Learning	IncreSTS Liu et al. (2015a,b)
	Redundancy	Machine learning	BRP-SUM Rodríguez-Vidal et al. (2019)
	Keyword	Topic model	DTM (decay topic model), GDTM (gaussian decay topic model) Chua and Asur, 2009)
	Feature	Statistic	RSE, IS, NS dan entropy-overlap Chellal et al. (2016)
	Real-time & extraction	Machine learning	IncreSTS (H, A.S.S., K, M.M.C. (2016), LexRank dan cosf-modified-cosinus Fu et al. (2015)
		Fuzzy-based	classic Zadeh's calculus of linguistically quantified proposition Kacprzyk et al. (2008)
	Semantic	Machine Learning	LexRank, cosf-modified-cosinus Fu et al. (2015), wordnet (H, A.S.S., K, M.M.C. (2016)
	Clustering	Machine Learning	BatchSTS H, A.S.S., K, M.M.C. (2016)
	Keyword	Statistic	TF-IDF, Algoritma Apriori Fu et al. (2015)
	Real-time	Machine learning	CLR&Summ Wu et al. (2015a,b), TVC dan TVC-Rank Wang et al. (2014)
Domain	Extraction	Fuzzy-based	(FAHP (Fuzzy AHP)) for Domain Turkish Güran and Uysal, 2017)
		Graphical	(N-Rank) for domain Malayam Krishnaprasad et al. (2016)
		Rule-based	(sentence scoring and decision tree) for domain Indonesian Sabuna and Setyohadi, 2017)
		Topic model	(LDA (Latent Dirichlet Allocation)) for domain Indonesian Widjanarko et al. (2018)
		Machine learning	(Hybrid SVM + scoring) for domain novel Gupta and Kaur, 2015), (ExpQueryOpt) for question answering (QA) Yulianti et al. (2017),
	Similarity	Statistic	(WordNet + common sub-summer (LCS)) for domain Bangla Sarkar and Hossen, 2018), (TF) for domain assessment Goularte et al. (2019)
		Fuzzy-based	(Fuzzy logic) for domain assessment Goularte et al. (2019)
		Graphical	(text-rank, lex-rank) for domain Tibetan Li et al. (2016)
	Clustering	Machine Learning	CIBS (Clustering ItemSet Biomedical summarization) for domain biomedical Moradi, 2018)
	Keyword	Statistic	(Term frequency) for domain novel Gupta and Kaur, 2015), (itemset-by-sentence (IS)) for domain multilingual Cagliero et al. (2019)
	Feature	Statistic	(Sentence scoring) for domain Turkish Kutlu et al. (2010), (LSA) for domain review film Liu et al. (2012)
	Sentiment analysis	Machine learning	(SVM) for domain review film Liu et al. (2012)
	Redundancy	Statistic	(LSA) for domain multilingual Cagliero et al. (2019)
	Latent	Statistic	(SVD) domain multilingual Cagliero et al. (2019)
	Selection sentence	Statistic	MWI-Sum (Multilingual Weighted Itemset-based Summarizer) for multilingual Baralis et al. (2015)

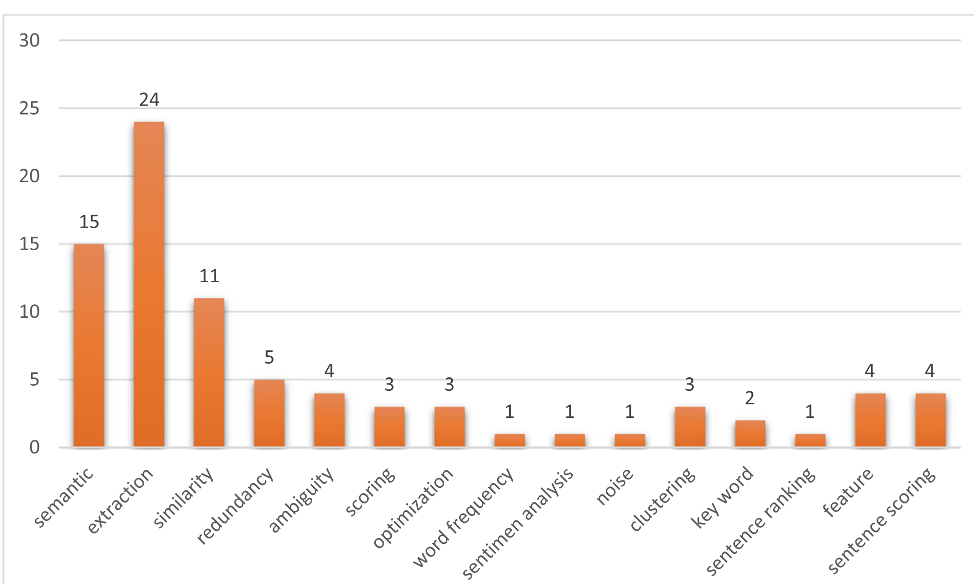

Fig. 12. Distribution of Problems in Text Summarization.

tried to be resolved. Details of the problems in the text summarization in the last ten years can be seen in Fig. 12.

The problem most often done in text summarization over the past ten years is extraction, because extraction is a fairly challenging problem. In-text summarization, extraction is the process of taking data from a data source (structured or unstructured data) to be processed to produce a summary. The technique of selection which is often used for extraction problems in the last ten years is machine learning and this is comparable to the approach technique most often used in the last ten years, namely machine learning (Fig. 11).

Problems that have rarely been done in the last 10 years are word frequency, sentiment analysis, noise, and sentence ranking. Word frequency and sentence ranking are less challenging problems because these problems can be solved by a statistical approach. While sentiment analysis is one of the problems that arise because it is part of the benefits of text summarization that is used to determine the sentiment analysis of the contents of the text.

A less desirable but quite challenging problem in text summarization is determining new features to produce a summary. Or determine the combination of features that are most suitable to be able to produce a good summary with a significant increase in evaluation.

One other problem that is still a weakness in previous studies is semantic. The output of automatic text summarization is to produce a summary with quality target content. This is very closely related to the meaning contained in the sentence summarized. In large documents, especially in multi-document cases, there can be ambiguous sentences or words (having more than 1 meaning) or synonyms. So that semantic problems need attention so that sentences or words included in the summary are by the intent of the document. Some methods for existing semantic problems are AMR (Bhargava et al., 2016), Semantic Link Network (Sun and Zhuge, 2018), SRL, MMR (Khan et al., 2015a), LSA and NMF (Ansamma et al., 2017). However, some researchers write in their research papers that are in conclusion or future work that the problem that still cannot be solved properly by them is semantic (Patel et al., 2019; Binwahlan et al., 2009a; Khan et al., 2015a; Wu et al., 2017; Kacprzyk et al., 2008; Patel and Chhinkaniwala, 2018; Guo et al., 2019; Chen et al., 2015; Liu et al., 2015a,b). This shows that the semantic problem is still challenging today.

The problem of redundancy and similarity is the same, that is, looking for sentences that are the same or similar to finally be trimmed, or discarded. So get summary results without changing the essence of the document. The methods that have been used

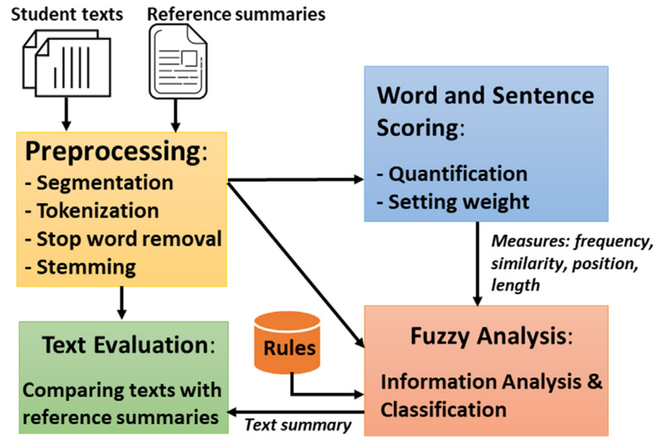

Fig. 14. Fuzzy Method in Text Summarization (Goularte et al., 2019).

in the problem of redundancy include MMR (Verma and Om, 2019), minimum redundancy and maximum relevance (mRMR) (Oufaida et al., 2014) and similarity includes text-rank, lex-rank (Li et al., 2016), IntraLink + bernoulli mode (Goyal et al., 2013), similarity co-sin (Patel et al., 2019). Shark Smell Optimization (SSO) and MMR (Verma and Om, 2019).

3.8. Methods

The method of text summarization research that is used there are various kinds of various approach techniques. The distribution of methods from 2008 to 2019 for this research is described in Fig. 13. Based on literature studies, the most widely used method in text summarization over the past ten years is fuzzy logic.

The fuzzy logic method is the most favorite because, in the last 10 text summarization research, fuzzy logic is often used to extract or determine the final value of words or sentences included in the summary. The fuzzy logic approach can prevent data contradiction because it involves the role of humans to be able to examine sentences and reach agreement on the choice of certain sentences to produce summary sentences (Abbasi-ghalehtaki et al., 2016).

The way fuzzy systems work is to use multiple inputs from various features or indices. Various features or indicators to produce a

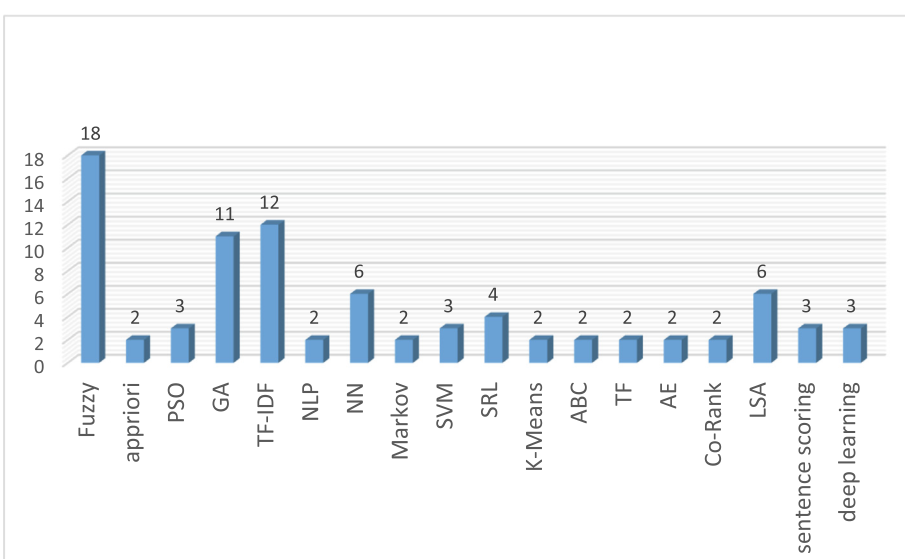

Fig. 13. Distribution of Methods Used in Text Summarization.

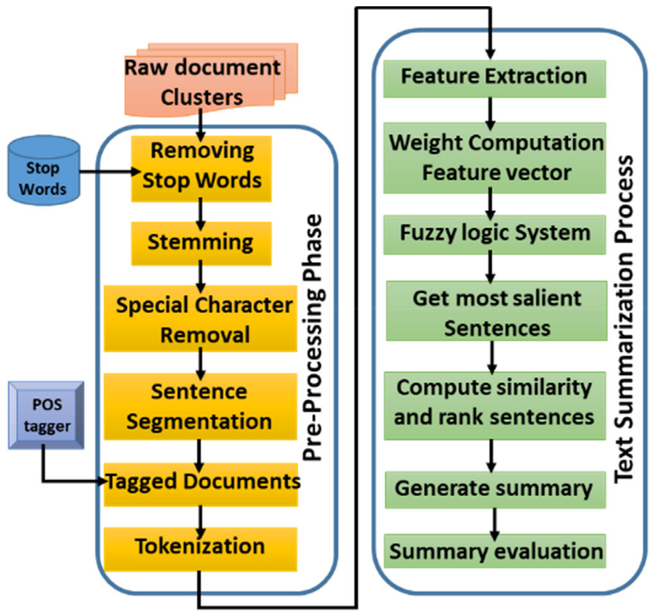

Fig. 15. MDS System using Fuzzy Logic (Patel et al., 2019).

summary, for example, the frequency of words that appear, a similarity with the title, the relevance of words or sentences, sentence length, sentence position, and so on (as explained in section e). The score of each feature is then given to the fuzzy inference system as input. Furthermore, human knowledge is used in the form of IF-THEN rules, so that we can get more precise sentences that can produce high-quality summaries (Goularte et al., 2019; Abbasi-ghalehtaki et al., 2016; Babar and Patil, 2015; Patel et al., 2019; Lee et al., 2013).

The latest research using fuzzy is research from Goularte (Goularte et al., 2019) which produces extractive summaries. The workings of this system are to find the most important information from the text using a fuzzy assessment using various features such as frequency, similarity, position, and sentence length. This system investigates features that are correlated to reduce dimensions so that the number of fuzzy rules is smaller. For more details, can be seen in Fig. 14.

Goularte's proposed experiment was tested using a private dataset of Brazilian Portuguese text provided by students. This fuzzy summary system is compared with 4 other summary systems, namely: baseline, score, model, and a sentence using precision, recall, and f1/f-measure, and CI for F1 with a summary size of 40%, 30%, and 20%. For sizes of 30% and 20%, the fuzzy method outperforms the state of the art. For a summary size of 30%, the fuzzy method produces precision 0.366, recall 0.496, F1 0.421, and CI for F1 0.389–0.450. For the size of 20%, the fuzzy method produces a precision of 0.417, recall 0.398, F-1 0.406, and CI for F1 0.369–0.436. However, for a summary size of 40%, the fuzzy method is inferior to the model system in terms of precision, the model precision is 0.316 and for the fuzzy precision is 0.315.

The most recent research using another fuzzy method is the research of (Patel et al., 2019) by adding the TF-IDF method to determine keywords (as explained earlier in chapter 3 section F. features). The combination of fuzzy and TF-IDF methods is used to summarize multiple documents so they are called MDS. To make it easier to understand this MDS system can be seen in Fig. 15.

By testing the MDS system using the DUC 2004 dataset, the results outperformed other systems such as the top-ranked DUC 2004 peers, TextLexAn, ItemSum, Baseline, YagoSummazier, MSSF, and Patsum. MDS by Patel et al. (2019) excels in measuring recall 0.1555 on Rouge-2 and superior in measuring recall 0.068 and f-measure 0.038 on Rouge-4. MDS by Patel et al. (2019) outperformed Patsum with a very thin value difference in terms of recall and Patsum excelled in terms of precision.

Lierde's research (Lierde and Chow, 2019) uses fuzzy combining with graphical approaches, namely Fuzzy hypergraphs. This model was used to produce extractive summaries and was tested on the DUC 2005, DUC 2006, and DUC 2007 datasets. The results outperformed the LDA, K-Means, Terms, AC, and DBSCAN methods with rouge evaluation. By selecting sentences using this model you can increase the scope of the summary. But it is weak in terms of clarity of summary.

The most widely used methods for summarizing texts are TF-IDF and LSA. TF-IDF is a method with a statistical approach technique. Some text summarization studies that use this method are (Khan et al., 2019; Azmi and Altmami, 2018; Alami et al., 2019; Alzuhair and Al-dhelaan, 2019), etc. This method is one algorithm that can be used to analyze the relationship between a phrase/sentence with a collection of documents. The concept is to calculate the TF value and IDF value (Robertson, 2004). For a single document, each sentence is considered as a document. TF is the frequency of occurrence of the word (t) in the sentence, which shows how important the word is in the document. While IDF is the number of sentences where a word (t) appears, which shows how common the word is. Word weight will be greater if it often appears in a document and smaller in many documents. To calculate the weighting of words in a document is to multiply the TF value by the IDF value.

LSA is a method in text summarization with statistical approach techniques to analyze the semantic structure in text. This method has the characteristic of only prioritizing keywords contained in a sentence without regard to linguistic characteristics and word order. The workings of the LSA is to place the words in the document in the form of a matrix. Where each row represents a unique word and the column represents the sentence/paragraph from which the words were taken. Some research in text summarization, among others (Ansamma et al., 2017; Babar and Patil, 2015; Shah and Jivani, 2018; Cagliero et al., 2019; Liu et al., 2012; Cagliero et al., 2019), etc.

Some methods that have not been used very often in text summarization during the past 10 years other than in the chart above are CLA, Restricted Boltzmann Machine (RBM), Analytical Hierarchy Process (AHP), AMR Abstract Meaning Representation (AMR), abstractive summarization (AS), single + dual train, MMR, SOF (WP/POS/NER/WF/HF), Recurrent neural network (RNN), Sentiment Memory (SM), (hierarchies agglomerative clustering) HAC, Multi-Objective Artificial Bee Colony (MOABC), TIDA, SVO, n-gram, NLP Parser, lowest common sub-summer (LCS), bag of word (BOW), Patsum, SSO, Non-Negative Matrix Factorization (NMF), rule-based, N-rank, Lex-rank, Text-rank, decision tree, Narrative abstractive summarization (NATSUM), rank-biased precision-summarization (RBP-Sum), decay topic model (DTM). One of these methods is a new method, namely NATSUM (Barros et al., 2019). NATSUM is an abstractive summarization method that uses a machine learning approach. The results of the NATSUM evaluation excel in rouge, grammatical, non-redundancy, and coherence evaluations.

To find out the important points of research from 85 studies of text summarization in the last 10 years, it can be seen in Table 6. The table explains the research topics, problems are taken from a research topic, approach techniques used to solve them, and then methods used for approach techniques in solving a problem in text summarization research.

3.9. Evaluations in text summarization

Evaluation is an identification process to measure/assess the performance of a method or tool. In-text summarization research,

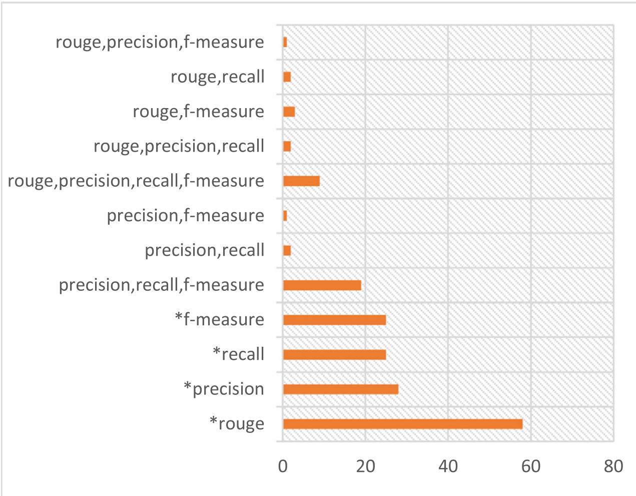

Fig. 16. Distribution of Evaluations in text summarization.

evaluation of text quality is often assessed by human annotators (Steinberger and Jezek, 2009). The annotator sets the value of the scale that has been determined for each summary. Based on studies over the past 10 years, there have been various approaches to evaluating the results of machine summaries, namely evaluation in terms of essential, extracting sentences, content-based, and task-based.

Evaluation with the essential approach is often done by comparing the results of the machine summary with an ideal summary from the expert. Essential evaluation is done by measuring in terms of grammatical, non-redundancy, and coherence. This measurement is very rarely done because it is very rare research that raises grammatical and coherent problems. Evaluate in terms of extracting sentences that are by finding how many ideal sentences are in an automatic machine summary. The evaluation was carried out using precision, recall, and f-score/f-measure measurement methods. For evaluation in terms of content, compare the actual words in a sentence, not the whole sentence. The evaluation was carried out by the measurement method of Rouge, pyramids, and cosine similarity. The advantage of the evaluation is that it can compare human extracts and automatic summarizing machines with human abstracts that contain new sentences or paraphrases. Another evaluation is a task-based approach, which measures the performance of an automatic summarizing machine by using summaries for specific tasks, for example, question answering and document categories.

From the literature studies of the last 10 years, the most evaluation approach taken is in terms of sentence extract and content-based. In terms of sentence extracts, measures that are often performed are precision, recall, and f-measure/f-score. While in terms of content-based, the measure that is often done is N-Gram matching (Rouge), which is approximately 58 studies of literature that use it, then pyramid and cosine similarity. For details of the distribution can be seen in Fig. 16.

Other evaluations used in addition to the above evaluations are BLEU, METEOR, CR, and copyrate (Fuad et al., 2019). BLEU by Papineni et al., 2002 used in the study of (Fuad et al., 2019) is an evaluation using matching N-grams that is appropriate or not and has the concept of paraphrasing. METEOR by Denkowski and Lavie (2014) is an evaluation method by matching the correct token, followed by WordNet synonyms, stemmed token, and then paraphrasing the lookup table. The compression ratio (CR) evaluates how short a compaction is. If the zero compaction ratio means the source sentence is not fully compressed. While copyrate is an evaluation by measuring how many pieces are copied to abstract sentences from source sentences without paraphrasing. Mathematically can be explained in Eq. (3). $R_{ori}$is a variable that shows the original summary, while R_{abs} is a variable that shows an abstractive summary or paraphrase summary. A lower copy rate copy score means more paraphrases involved in abstract sentences.

$$Copy\ Rate = \frac{R_{ori} \cap R_{abs}}{R_{abs}} \tag{3}$$

4. Conclusion

Text summarization is an interesting research topic among the NLP community that helps produce concise information. The idea of this paper is to present the latest research and progress made in this field with the SLR method. With the SLR method, it is proven that it can provide a more structured, broad, and diverse review, ranging from trends/topics, datasets, preprocessing, features, approach techniques, problems, methods to evaluation that are available as a guide for future work, the relationship between trends/topics, problems and challenges in each topic, technique, and method used is summarized into one to make it easier to explore and re-analyze, see Table 6.

The important thing that is considered interesting from the review that has been done is the results of the analysis which states that extractive summaries are relatively easier than abstractive summaries which are very complex, extractive summaries are still the topic of current favorite trends. This is because there are still many things that are a challenge for researchers to do. It also can be seen that the most important features to produce a good summary are keywords, frequency, similarity, sentence position, sentence length, and semantics. The machine learning approach is a favorite technique because of automatic machine learning performance and learning to enhance the experience without being explicitly programmed. Even though machine learning is a favorite, machine learning is not the only best approach. An approach that is easily combined with other approaches is statistics. Statistics can be combined with machine learning, or statistics with fuzzy based. And the problem most often solved with a statistical approach is combined with other approaches such as determining frequency, determining keywords, and similarity.

In the topic of text summarization research, future work that can be done includes i) solving feature problems, namely determining the most appropriate features to use in summarizing by the dataset by selecting features, discovering new features, optimizing commonly used features, feature engineering, using features for semantics, linguistic features, finding features to produce coherence sentences, and add grammatical features. ii) Preprocessing by the problem dataset using appropriate stemming, besides, to stop word removal and tokenizing, POS Tagging is also needed, namely to categorize word classes, such as nouns, verbs, adjectives, etc. iii) For extractive summaries, collaborating statistical techniques, fuzzy-based techniques, and machine learning are very challenging to try. Or develop MDS (Patel et al., 2019) by combining the Fuzzy Logic and TF-IDF methods with a machine learning approach to produce a better summary. iv) For abstractive summarizing, we can develop the latest method, namely NATSUM in other cases or improve the performance of NATSUM by increasing coherence. v) Use rarely used datasets such as legal documents, summarizing tourist attractions, and summarizing documents for assessment. Or you can use favorite datasets such as DUC 2002 and 2004 for testing the method of summarizing temporarily, before being tested into a private dataset to find out the performance of the method.

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