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AUTOMATIC ABSTRACTIVE SUMMARIZATION A SYSTEMATIC LITERATURE REVIEW

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ABSTRACT

Automatic summarization systems condense documents by extracting the most relevant facts. Extractive summary extract the important sections of the text and reproduce them verbatim. In contrast the abstractive summary aims to produce the important ideas in the text using new phrases. In this paper, a Systematic Literature Review (SLR) on abstractive summarization is presented and various abstractive techniques are discussed along with their evaluations.
Keywords: *Summarization, Abstractive Summary, Summarization Techniques, Summarization Evaluation*

1. INTRODUCTION

With the wide spread use of internet and the emergence of information exploration era, quality text summarization is essential to effectively condense the information. Text summarization is the process of producing shorter presentation of original content which covers non-redundant and salient information extracted from a single or multiple documents. attempts to generate automatic summaries started 50 years ago [16] [29] recently, the field of automatic Text Summarization (TS) has experienced an exponential growth due to new technologies.

Summarization Methods are classified into two categories. The first one is the Extractive approach and the second is the Abstractive one. Extractive approach is selection of an important terms from the original Text and combining them into a summary, which normally includes the first sentence of each paragraph, special names, italic or bold phrases into the final summary[20]. Here, the text is reduced using the same words mentioned in the original text. The most important content is treated as the most frequent or the most favorably positioned content.

In abstarctive summary, there are three main steps for summarizing documents which presented in [16] . These steps are topic identification, interpretation and summary generation.

Abstractive summarization techniques can be classified into two categories.

- Structured based approaches encode most important information from the document(s) through cognitive schemas such as frames, scripts, and templates[30] [31]. Script for example is a structured template with slots used to identify common important events over the domain. Each domain has its own script.

- Semantic based method which uses Semantic representation of document(s) to feed into natural language generation (NLG) system. This method concentrates on identifying noun phrases and verb phrases by processing linguistic data. Phrases consequently are obtained and then linked to concepts, attributes and relations of a domain-specific ontology[7] [8].The important document regions (sentences, paragraphs) are identified by using ontology-based annotations and clustering techniques. Resultant information are used to convert regions into semantic representation. This representation are then fed to an NLG system which produces abstracts.
This paper will present a systematic literature review on abstractive summarization methods. The rest of the paper is organized as follows. Section II describes the review method and the research questions , section III presents the results and the answers for the research questions

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, section IV provide some discussions and we conclude the papers in section V.

2. THE REVIEW METHOD

A Introduction

Systematic literature reviews retrieve, appraise and summaries all the available evidence on a specific health question. They are designed to reduce the effect of the reviewer's own bias, and a full protocol should be written to define and guide the process. The appropriate resources should be in place before undertaking a review[32].

TABLE 1. Summary of PICOC

Population	Text documents
Intervention & Comparison	Different Techniques used for As, choosing the most effective one according to specific measurement
Outcomes	Measurement of Recall & precision
Context	Within the domain of scientific text articles

B Research Questions

Table I shows the Population, Intervention, Comparison, Outcomes and Context(PICOC) structure of our research questions. The SLR Included all the previous and state of the art of the work that have been done for generation of abstractive summarization.

The main important focus of our SLR was to have knowledge about the techniques that have been used for the abstractive summarization. As we discussed earlier, abstractive summarization can be categorized into two categories:

- Approaches using prior Knowledge [30] , which needs manual effort to define template to be filled with the use of information extraction techniques. This approach is used to summarize news article.
- Approaches using Natural Language Generation (NLG) Systems [31] which uses deep NLP analysis with specified techniques for text generation.

Therefore, our SLR aims to answer the following Main research question (RQ):

Main Question. What techniques have been used for
abstractive Summarization (AS)?

Our SLR also aims to answer the following subquestions:

Subquestion1. What features have been used for AS?

Subquestion2 .What are the techniques (selection techniques) and component that have been used for AS?

Subquestion3. How are the component modified to produce the final AS?

Subquestion4. How are the techniques used for AS evaluated?

C Identification of Relevant Literature

The strategy we used to construct the search strings was as
Follows:

- Major terms can be derived from the review questions based on the population, intervention and outcome
- List down all keywords mentioned in the articles.
- Other search terms can also be identified by looking at the synonyms or alternative words. The words can be searched from the Words Thesaurus function. Content expert, subject librarian or information specialist should also be consulted for further advice in the proper use of the terms.
- Use the Boolean OR to incorporate alternative spellings and synonyms
- Use the Boolean AND to link the major terms from population, intervention and outcome.

The complete search string initially used for the searching
of the literature is as follows:
(Abstractive summarization OR summarization fusion OR paraphrasing summarization) AND (Technique OR Method OR Approach) AND (Feature OR Attribute OR Element).

D Selection of Studies

For inclusion criteria, we looked at studies that investigated abstractive summarization for text and it’s important needs for researchers. In addition to that, our concern was more on papers describing techniques for abstractive summarization beside feature selection. Related papers involving corpus on their subjects were also considered if the studies conducted were relevant to abstractive summarization approaches and Methods. In terms of exclusion criteria, we excluded studies which focused on any of the following aspects:

a) Papers or experiences of author(s) without backing up with proper experiments or

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evidence to support the claim made (i.e. Advocacy research).

b) Papers describing issues of other summaries in general.
c) Papers describing or focusing on extractive summary only.
d) Papers describing summary for speech , graphic or multimedia.
e) Papers not written in English.

E Data Extraction and Study Quality Assessment.

To make the data extraction process the researcher has designed a form to be used for collecting information relevant to the research questions that is used to evaluate the quality of the primary studies. The questions were proposed as the literature found in [32] .Our checklist was composed of ten general questions as shown in the table below to evaluate the previous studies so far according to the following degree scale: for answer by Yes = 2 points, for answer by Partially = 1 point , and answer by No = 0 points . The optimal total scores for each study ranged between 0 and 20. If the total score is 0 this evaluated as (out of scope) , if the total scores between (1-9) it was evaluated as weak , if the total scores between (10-14) it was evaluated as good and if the scores was between(15-17) it was evaluated as very good ,if the scores between(18-20) it was evaluated as excellent. The researcher made an evaluation to each paper by answering the questions found on the table II below after reading the paper carefully . The questions were taken mostly from several previous studies [5][6][33][34][35].

3. RESULTS

A Introduction

In this section, we present the synthesis of evidence of our
SLR, beginning with the analysis from the literature search
results. During the selection process titles and abstracts were screened relevance check of the sources. Full papers were obtained whenever they met the minimum requirement of the inclusion criteria. Then we went through the reference list to decide on including or excluding a study. If the paper not meet the minimum requirement of inclusion then the study excluded, and the reference was removed from the Mendeley Desktop library.

TABLEII . Study Quality Check List

Item	Answer (Yes OR Partially OR No)
Was the article referred to before? At least 5 times	Yes/No
Were the objectives of the study stated clearly?	Yes/No/Partially
Were the steps used for AS described enough?	Yes/No/Partially
Were the Feature selection for AS cleared?	Yes/No/Partially
Was the analysis of the techniques stated well?	Yes/No/Partially
Were the Tools helped in performing the AS process conveyed?	Yes/No/Partially
Was the conclusion of the study trusted? How much?	Yes/No/Partially
Was any dataset used in this paper?	Yes/No/Partially
Was there any performance measure used?	Yes/No/Partially
Was the benchmark techniques used?	Yes/No/Partially

In the following section, we present the results for the SLR's main research question and four subquestions. Each study is identified as [N] where N is a reference number.
The evaluation for papers is done for the methods and analysis papers but survey papers are not included. After examining each paper against the questions shown in tableI the assessment marks formulate the evaluation as follows :

- Six of papers their marks are (18,18,18,18,19,20)out of 20 their evaluation as excellent.
- Six of papers their marks are(15,15,15,15,16,16) out of 20 their evaluation is very good.
- four of papers their marks are (13,13,14,14) out of 20 their evaluation is good.
- None of the papers are weak.

Figure 1 shows the evaluation for the papers.

B Research Question

Main Question. What are techniques have been used for Abstractive Summarization (AS)?
Abstractive summarization has various techniques as we mention this earlier in section I , tableIII shows these techniques in which the first columns is the technique itself followed by a description of that technique followed by studies using that technique.

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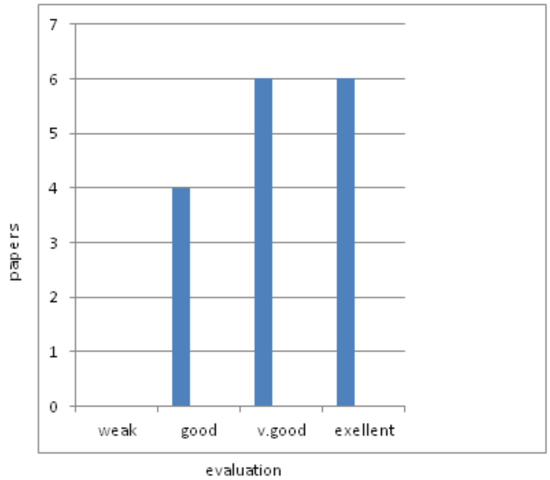

Fig1. Evaluation For AS Method Papers

TABLE III .Abstractive Summarization Techniques

Methods/Techniques	**Description**	**Study(s)**
Word-graph,RSG (Rich Semantic Graph)	The graph consists of nodes for each word and the edges conform the adjacency relation between words , words map to the same node if they have same POS	[7], [11], [23]
Extraction of INIT	Information Item is the sentence to be extracted from the document that conform to SVO.	[21], [4]
Lexical Chains	The use of lexical chains as a model of the source text for the purpose of producing a summary	[3]
Speech act-guided summarization	word-based and symbol-based features are used to capture both the linguistic features of speech acts and the particularities of Twitter text. The recognized speech acts in tweets are then used to direct the extraction of key words and phrases to fill in templates designed for speech acts	[8]
Information Extraction (IE) Techniques	uses IE-style templates, either from a prior	[10]
CVSM (Conceptual Vector Space Model)	EstablishCVSM, calculate it's importance and generate the final summary by calculating the importance of sentences and reducing the redundancy of summary.	[9]
Sentence Fusion	A group of similar sentences (a theme)the problem is to create a concise and fluent fusion of information, reflecting facts common to all sentences.	[26]
Sentence compression	Acompression ratio must be specified or computed example 10%	[2]

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The Abstractive Techniques can be divided into structured-based (Template_based) such as Speech act-guided summarization and information Extraction techniques, and NLG based techniques such as RSG (Rich Semantic Graph) and lexical

chains . Both of techniques have its advantages and disadvantages,NLG techniques can not generate text unless they have a representation of information that the text is supposed to communicate and in the great majority of today's application systems, such representations do not exist,but NLG System are maintainable that is easy to change unlike template-based when making a slight change in the output this may require large amount of recoding also few people can build NLG systems where millions of programmers who can build template systems. These two techniques can be merged to give a hybrid one in which we can use the NLG. The basic goal of such systems is to use NLG where it really adds value, and to use simpler approaches where NLG is not needed or would be too expensive. The decision on where NLG should be used can be based on cost-benefit analysis .

Subquestion1: What are the features that have been used for AS.

Abstractive summarization for document texts to take place there are some features must be found .At least one or two of those features must be found.these features are shown in table IV along with the description of the specified feature and the studies using that feature .
Abstractive features are features that are used for selection of sentences to be a candidate for abstractive summary . Four features are identified in a total of eight studies which investigated how these features helps in selection of candidate sentences as shown in tableIV .
TableIV shows that the Highest TF-IDF feature is a dominant feature.
Subquestion2 .What are the components that have been used for AS?
Abstractive summarization has many component that can be used to choose phrases from document texts as a candidate for the abstractive summary. tableV shows these components in which the first column is the picked component itself followed by it's description followed by effectiveness and the study/Ref columns.

Table Iv.Abstractive Summarization Features

Features	**Description**	**Study**
Highest tf-IDF .	Term frequency-inverse document frequency (tf-IDF) accounts for frequent terms in the document, but not very frequent in the whole collection of documents. With this strategy, we keep the most important terms and the information related to them.	[7],[11],[18]
Any sentence conforms to (SVO)	Sentences that are selected to be as a candidate INIT should consist basically from Subject- Verb- Object	[21],[4]
Word cues,keyword extraction	Words which assist in providing Information about the data being analyzed	[10]
Concept-based	Use of concept extraction rather than word extraction	[8]

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Table V.Abstractive Summarization Components

Component Picked	**Description**	**Effectiveness**	**Study/Ref**
Shortest path	By applying Dijkstra's algorithm we obtain all shortest paths from one node and remaining one's	highly number of resulting sentences.	[7]
Top generated sentences	We rank the generated sentences by the rank of the original sentences in which their InIt appeared.	linguistic quality summaries was very low .	[21],[4]
RSG	Rich Semantic Graph	A proposed approach succeeded to fifty percent of the original text.	[11]
Extractive summary	Word cues +keyword extraction +sentence selection = extractive summary	The result is extractive	[10]
Top important concepts	the importance of all sentences has been carried by digree of similarity calculation	The result is a rough summary with redundant sentences	[8]
Common phrases	selects the phrases that can adequately convey the common information of the theme and arrange them	The result is common phrases needs to be paraphrased.	[25],[26]
Semantically related nodes	nodes semantically related to the topic are determined	all those nodes that are semantically linked to the given activated nodes are determined	[23]
Choosing the strong chains among the candidate chains	Ranking chains according to their score, strong chains are those which satisfy the strength specified criterion: Score(Chain)	85% of the paraphrasing is achieved by syntactic and lexical transformations.	[2][26]

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SubQuestion3 How are the component modify to produce the Final AS?

Table Vi . Modification For Abstractive Summarization Components

Modification	**Description**	**Effectiveness**	**Study/Ref**
Discard new sentences which not satisfy to the constraints And combine AS to the ES	Sentences must be:3 word in length(SVO),contain a verb,not end in anarticle, preposition, nor a conjuction.	The result is High	[7]
Add date and location to the selected sentences	Each InIt with a knownlocationhas its generated sentenceappended with a post-modifier "in location", except if that location has already been mentioned in a previous InIt of the summary	The size of the summary is always above the word limit of 100	[21],[4]
(Rich Semantic Graph) RSG is reduced	Heuristic rules are spplied to the generated RSG to reduce it by deleting or merging or consolidating nodes of graph	The result of the Reduced RSG will be concise	[11]
Paraphrasing +commpression	The extractive summary is pharaphrased and commpressed	The result is a coherent abstractive summary	[10]
Calculation of (DOS)Degree Of Similarity for sentences	Calculation of degree of similarity for the sentences if result > than 0.7 discard the less important one	High accuracy summary with no redundancy	[8]
Paraphrasing	produce fluent sen- tences that combine these phrases, arrang- ing them in novel contexts.	generation to merge similar information is a new approach that significantly improves the quality of the resulting summaries, reducing repetition and increasing fluency.	[25],[26]
comparing graphs which have been activated by a common topic	these Graph nodes and their relationships can be compared to establish similarities	candidate common topics can be selected from the intersection of the activated concepts in each graph (i.e., which will be denoted by words, phrases, or names).	[23]

TableVI shows Modifications that have been done to the components in order to give the final abstractive summary, the first column conveyed the modification made to the picked component followed by brief description followed by effectiveness and the studies used the same modification.The

Journal of Theoretical and Applied Information Technology
31st August 2013. Vol. 54 No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table Vii . Evaluation Measure Techniques

Evaluation measure	Description(formula)	Study
ROUGE,ROUGE1, ROUGE2, ROUGE-SU4, F-measure(Recall,Precision	Equation(1)	[7],[9],[2]
Scores of pyramid, linguistic quality and overall responsiveness	Equation(5),(6),(7)	[37][21],[4]
Precision, Recall	Equation(3) Equation(4)	[2],[10],[26] [23]
Text Coherence,most frequent word synonyms	Equation(2)	[11]

Most dominent modification is paraphrasing as shown in tableVI
Paraphrasing is considered as the dominant

SubQuestion4 How can Abstractive summarization be evaluated?

After we make the summary ready we must test and evaluate it using any of the measurement units, tableVII shows these measurements in which the first columns are the evaluation measurement followed by a description of that measure followed by studies using that measurement.
Formula's usd by above measurements are described below:

$$\text{ROUGE-N}(S) = \frac{\sum_{r\in R}\langle \Phi_n(r), \Phi_n(s)\rangle}{\sum_{r\in R}\langle \Phi_n(r), \Phi_n(r)\rangle}, \qquad (1)$$

Where R is set of reference summaries $R=\{r_1,\ldots,r_m\}$ and s is a summary generated automatically by some system. Let $\phi_n(d)$ is a binary vector representing the n-grams contained in a document d; the i-th component $\phi^i_n(d)$ is 1 if the i-th n-gram is contained in d and 0 otherwise.

Suppose a word occur f times with certain rank r then

$$f = a/r_b \qquad (2)$$

Where a and b are constants and b is close to 1

$$p \quad = \# x/\# y \qquad (3)$$

$$r \quad = \# x/\# z \qquad (4)$$

Where p is the Precision and x is the(#) number of sentences extracted by the system which are in the target summaries , y is the number of sentences extracted by the system. r is Recall
and z is the total number of sentences in the target summaries.

The Score of pyramid(considered as multiple tiers) is calculated according to following formula's :

$$D = \sum_{n=1}^{n} i \times Di \qquad (5)$$

Where *i* is the weight of SCUs(Summarization Content Units)
In teir T_i , D_i is the number of SCUs in the summary , SCUs not appear in the summary are assigned weight zero, the Total SCUs weight is calculated using the formula number (5)
The optimal content score for a summary with *X* SCUs
Is calculated using the formula number (6)

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$$Max = \sum_{i=j+1}^{n} i \times |T_i| + j \times \left(X - \sum_{i=j+1}^{n} |T_i| \right) \qquad (6)$$

$$where\ j = \max_{i} \left(\sum_{t=i}^{n} |T_t| \geq x \right) \qquad (7)$$

j is equal to the index of the lowest tier which an optimally informative summary will draw from. This tier is the first one top down such that the sum of its cardinality and the cardinalities of tiers above it is greater than or equal to *X* (summary size in SCUs).

For example, if *X* is less than the cardinality of the most highly weighted tier, then $j = n$ and Max is simply$X \times n$

(the product of *X* and the highest weighting factor). Then the pyramid score *P* is the ratio of *D* to Max.

4. DISCUSSION

As we know generating extractive summarization is easier than generating abstractive summarization because the former only needs selection of salient phrases or sentences using any of the selection techniques but it does not guarantee the coherency for the output summary unlike the latter which need deep Natural Language Generation(NLG) in order to produce the final summary but the coherency ratio is higher if compared.

Different techniques have been used in abstractive summarization as shown in tableIII but we realized that the dominant one is the graph technique which ensures high ratio of coherency for the produced summary. AS mostly uses the term frequency (tf-idf) feature which is considered as a predominant feature as shown tableIV.Moreover various components have been used and the salient one is the most ranked text : that is the text which have a higher score as shown in tableV.

Selection for phrases and sentences are done for the final summary, these selected phrases are the components of the final summary , the common phrases and t-he top generated sentences are the two dominant one's these components are modified by paraphrasing or compressing or discarding .

The most used modification is the paraphrasing as shown in table VI..

Various evaluation techniques are used for measuring the relevance of the summary to the original text, with the recall and precision used more than the other evaluation techniques, as shown in tableVII.

5. CONCLUSION

This paper described an SLR targeted at studies of Abstractive techniques to generate abstractive summarization. Various studies were shown in table III to tableVII demonstrating the techniques used for abstractive summarization and features, and components of AS as well as the evaluation techniques.

However still more effort should be made towards this effective approach in the way of selecting the candidate phrases and the use of effective parsers.

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