A News Summarization System using Fuzzy Graph Based Document Model

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ABSTRACT: *This paper describes a news summarization system using the Fuzzy Graph based Document Model. News articles are modelled as fuzzy graphs whose nodes are sentences and edges are weighted by the fuzzy similarity measure between the sentences. The similarity between sentences is in between 0 and 1. Centrality of the graph retrieves important sentences. The proposed system produces summaries by Eigen value convergence of the similarity matrix. The summaries are evaluated based on the human generated summaries in DUC 2007 data set. The resultd show fuzzy graph based approach for news summarization using Eigen value analysis are quite encouraging. It shows high correlation with human generated summaries.*

Keywords: News Summarization, Fuzzy Graph Based Document Model, Eigen Value Analysis

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1. Introduction

Nowadays the web contains huge and growing amount of information. The information explosion in web consumes more time to read and grasp information from different sources. The user needs a lot of analysis to understand the main idea described in the documents. The International Data Corporation's research study reveals that textual information in digital format currently amounts to 1.8 zettabytes, a number of nine times that seven years ago[1]. News articles are one of the fastest growing digital documents. The growth leads to the creation of automatic processing of documents in the field of summarization.

News summarization is a process, which creates a shorter version of multiple news articles by preserving the informaton and overall meaning. It helps humans to digest the main contents of related documents rapidly. Automatic summarization can be carried out in two ways: extractive summarization and abstractive summarization. An extractive summarizer identifies relevant and informative sentences from multiple documents. These identified sentences are included in the summary based on the score of sentences. The importance is decided based on positional and frequency related features of sentences. An extractive summary contains sentences as such in the original documents. An abstractive summarizer attempts to identify the important and informative sentences from documents and produces a summary by rephrasing the sentences to make it more readable. An abstractive summarizer needs deep Natural Language Understanding (NLU) and Natural Language Generation (NLG) capabilities.

News summarization is a kind of multi-document summarization. It is different from single document summarization in which, the summarization system wants to deal with redundant, complementary, and contradictory information. The redundancy in multiple news articles helps to identify the important concepts while, the summarizatio system has to pay more attention to avoid redundancy in the summary.

A graph based summarization system uses the similarity between sentences to produce summary of related documents. A document can be modelled as a graph in which sentences are represented by the nodes. If there is a relationship between the sentences an edge will be present. Graph based summarization method is a good way to find out a unique summary [21].

Fuzzy logic is a form of many valued logic, that deals with reasoning that is approximate. This paper aims to propose an alternative representation of text documents to model fuzziness in the similarity between sentences.

In the next section, we briefly review the main initiatives related to multi-document summarization task. Section III deals with proposed system, i.e. an extractive news summarization system using Fuzzy Graph based model. The evaluation of the proposed system with DUC-2007 data sets using ROUGE measures is discussed in Section IV. Section V deals with conclusion and future work.

2. Literatutre Survey

An approach to news summarization using sentence fusionis discussed in [17]. In [9] [10] authors discuss the ideas of gradual transition from purely extractive methods of news summarization to abstractive news summarization methods. It generates abstract summaries that contain sentences not found in any of the input documents. Even though the syntactic measures of fluency are less, it is quite promising.

Several extractive feature based summarization systems use features such as sentence length, number of title words present in sentences, position of the sentence in a paragraph etc, to compute the score of sentences and to sort the sentences in descending order to form a summary [21] [12]. An extended method for multi-document summarization incorporates fuzzy logic to compute sentence scores [14] [19] [8]. Eventhough feature based methods are simple and direct approach to multidocument summarization, it often fails to capture important and relevant information because the context is spread across the documents [22].

Cluster based multi-document summarization groups the related sentences into one cluster and extracting a sentence from each cluster to form a summary[21] [20] [5] [3]. A cluster based news summarizer which forms an extractive summary by sentence ranking and sentence ordering methods [5] [4]. Clustering methods are successful in including diverse information and to reduce redundancy in the summary. In clustering based method, relevance of a sentence is merely based on the similarity with cluster centroid which simply represents a set of frequently occuring terms.

Graph based approaches to multi-document summarization deals with the representation of documents as graph. The nodes may represent sentences, phrases or words. An edge between two nodes will be present if there exists a similarity greater than a threshold between two sentences. Important sentences will be identified from the graph if they are strongly connected to many other sentences [6]. LexRank and TexRank are two successful graph based systems based on HITS algorithm [11] and Googles Page Rank algorithm [2] [7] [15] . Cross-document Structure Theory is applied for the production of generic and informative summaries [16]. In further studies [23] [24] the ranking algorithms are modified by assigning different weights to inter-document and intra-document similarity.

Some summarizers uses a graph based method in which graph-structures are obtained from textual documents by using Part-Of-Speech (POS) tagging technique [1]. The tokens obtained from automatic decomposition of textual documents are attached to either vertex or edge to form conceptual graphs. Both document level information and sentence to document relationship are considered to explore the document impact on graph based summarization.

The binary weighted (0 or 1) graph based methods provided a positive feedback from research communities. Because, it can include prestigious sentences from different documents. This approach heavily depends on the similarity between sentences to generate graph, in which an edge will be weighted if there is a similarity. The degree of similarity between sentences is not considered. The proposed news summarization system is based on fuzzy graphs, in which, nodes represent sentences and edges connect these nodes if there exists a similarity . This weight is in between [0 – 1].

3. Fuzzy Graph Based News Summarization System

The proposed work is an extractive summarization system based on fuzzy graph based document model. It represents sentences as nodes and similarity between those sentences as edge. The edges are weighted with fuzzy similarity measure. An edge in a graph gives relation between two nodes, in which the weight will be either 0 or 1, while in a fuzzy graph the weights will be a number in the range [0 –1]. The News Summarization System summarizes similar news articles related to a topic. The proposed system is shown in Figure 1. The single document summarization module, *SDS* (d_i) summarizes each document di in a set of related articles $D = \{d_1, d_2, d_3,...d_n\}$. The generated summaries forms a document and which is fed into the single document summarization module, *SDS*. This generates the summary of multiple documents.

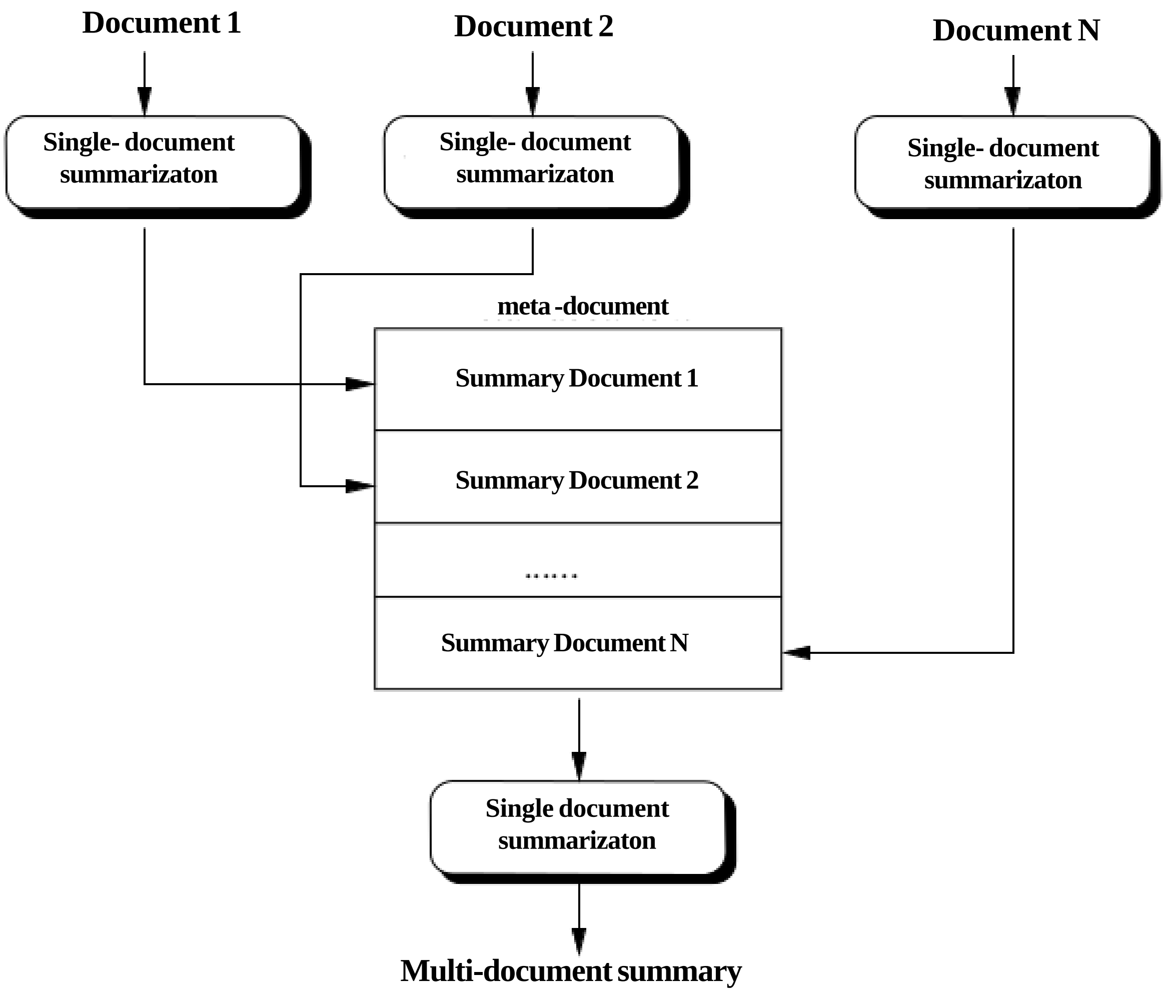

Figure 1. Multi-document summarizaton system

3.1 Single Document Summarization

The single document summarization system has four main components as shown in figure 2.

• Preprocessing

• Similarity Computing

• Sentence Ranking

• Sentence Ordering

1) **Preprocesing:** The input document is processed in order to bring it to a common format. Documents are preprocessed by sentence tokenizing and word tokenizing. Stopwords and punctuations are removed from sentences. Stemming of words is not done at this phase in order to preserve the semantics of the words.

2) **Similarity Computation:** Each document can be represented as an undirected fuzzy graph, where nodes represent sentences and edges represent the similarity between those sentences.

Algorithm 1. Algorithm for Multi-document Summarization

Require: : Set of news articles related to a news event.

Ensure: : Summary of the set of articles.

1. Read the input documents and tokenize them into sentences.
2. For each document d_i in the set, call single document summarization, *SDS* (d_i):
3. Create a set of single document summaries.
4. Create a file, *doc-summaries* containing all single document summaries.
5. Call *SDS* (*doc-summaries*):
6. Return the summary document.

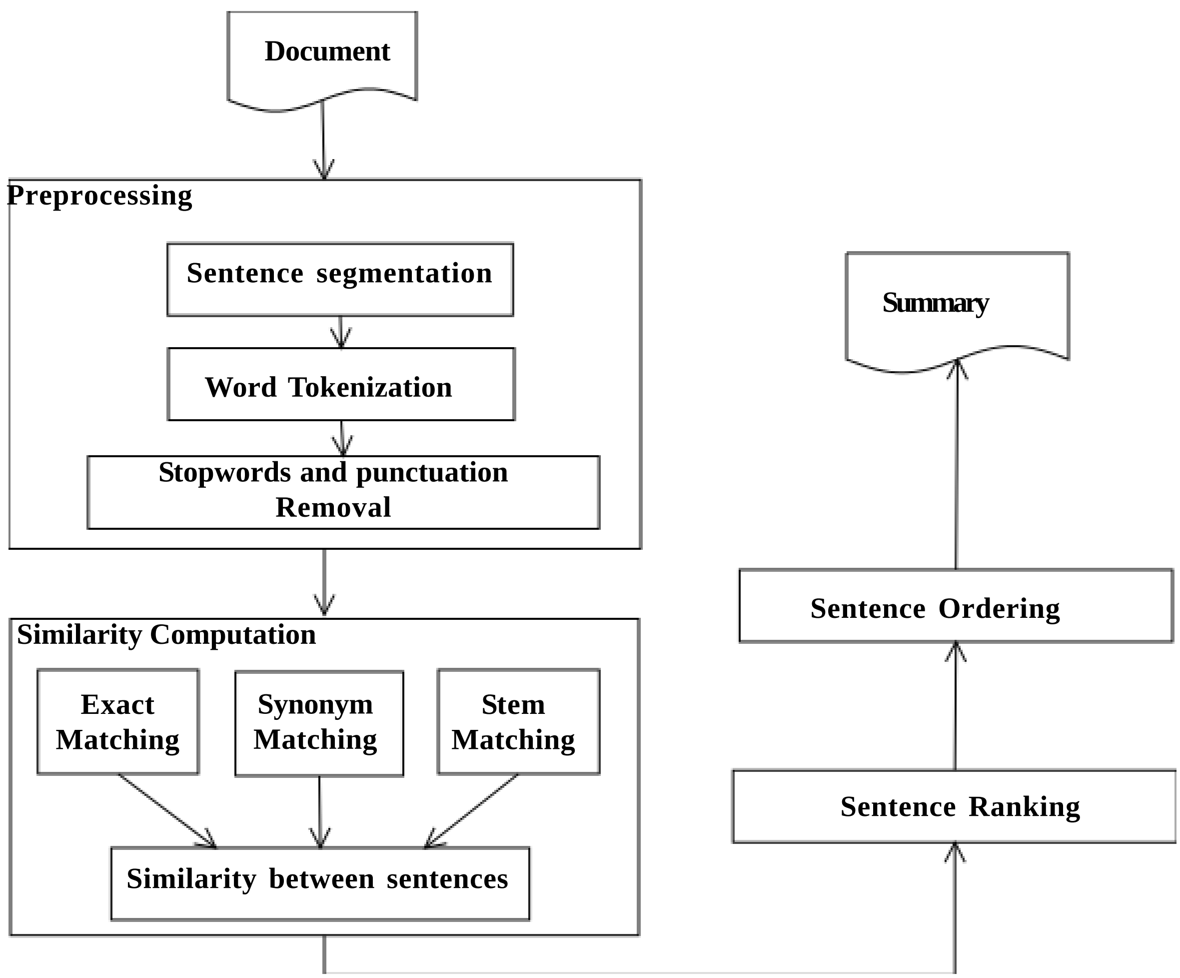

Figure 2. Single Document Summarization

Definition: Let $S = s_1, s_2,..., s_n$ be the set of sentences in the document. A fuzzy graph $G : (\sigma, \mu)$ where σ is a fuzzy subset of S and and μ is a symmetric fuzzy relation on σ. i.e. $\sigma : S \rightarrow [0, 1]$ and $\mu : S \times S \rightarrow [0, 1]$ such that $\mu (u, v) < \sigma (u) \wedge \sigma (v)$ for all u, v in S [13].

The proposed system represents sentences as nodes. If there are n sentences in the document there will be n nodes in the fuzzy graph. These sentences may share words themselves, or synonymous words, or words having common root. Similarity between two sentences are computed by considering all the three possibilities of being similar. An edge will connect two nodes in the fuzzy graph if they share common words. The edges are weighed with similarity measure which is a value between 0 and 1.

Consider two sentences i and j, the similarity between these sentences is calculated as:

$$sim\,(i,\ j) = \frac{c\,(e) \times \mu\,(e) + c\,(s) \times \mu\,(s) + c\,(r) \times \mu\,(r)}{c\,(e) + c\,(s) + c\,(r)} \tag{1}$$

where $c\,(e)$ is the number of times terms in sentence i exactly matches with terms in sentence j, $\mu\,(e)$ is the membership value of exact match of terms between sentences. Some sentences not share exact terms but they will share synonymous terms. The number of such occurences is given by $c\,(s)$ and the membership value of synonymous words is given by $\mu\,(s)$. If sentence i and sentence j not share exact or synonymous terms, but they can share terms containing same root. $c\,(r)$ is the number of such terms and $\mu\,(r)$ is the membership value of sharing root words are common terms. Thus $sim\,(i,\ j)$ of two sentences is computed by considering the all possible ways of being similar.

Algorithm 2. Algorithm for Single Document Summarization, $SDS\,(d_i)$

Require: : A document.

Ensure: : Single document summary.

1. Read the input document and tokenize them into sentences, S.
2. n = number-of-sentences in the document.
3. Create a word-list, W by tokenizing the sentences into words.
4. Remove stopwords and punctuations from the word-list, W.
5. Create an $n \times n$ matrix, sim with similarity values,

$$sim\,[i]\,[j] = \frac{c\,(e) \times \mu\,(e) + c\,(s) \times \mu\,(s) + c\,(r) \times \mu\,(r)}{c\,(e) + c\,(s) + c\,(r)}$$

6. Normalize the fuzzy matrix, sim to make it column stochastic.
7. Find the eigen vector corresponding to eigen value, 1 of fuzzy matrix sim:
8. Select the entries of the eigen vector whose absolute values are high.
9. Order the sentences as they appear in the document.

3) **Synonymous matching:** Two sentences may share synonymous terms. The proposed system uses Wordnet for finding synonymous matches. Wordnet is a large lexical database of English. Nouns, verbs, adjectives, and adverbs are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. Synsets are interlinked by means of conceptual - semantic and lexical relations. The foundational elements of wordnet are synsets (sets of synonymous words) and the hypernymy (is-a relationship) hierarchy. The quality of these two elements ensures the correctness, completeness and the usability of the resource [18]. In dictionaries, a word is usually defined in terms of its hypernyms or synonyms.

Wordnet provides synset of a word which is a collection of lemmas that are synonymous (by standards of WordNet).

For example, the synset of word news is as follows.

>>> wn:synsets (*′news′*)

[*Synset* (*′news:n*:01′);

Synset (*′news:n*:02′);

Synset (*′news program:n*:01′);

Synset (*′news:n*:04′);

Synset (*′newsworthiness:n*:01′)]

In the string *′news.n*.01′

- *news* is the canonical string name
- *n* is the Wordnet part of speech
- 01 is the sense number

Synonyms of each word in the sentence are compared with the terms of other sentences in order to find synonymous similarity. The number of synonymous terms shared by sentences *i* and *j* are counted. The degree of similarity of synonymous match is lower than that of exact match.

4) Stem matching: Let *i* and *j* be two sentences. These sentences may share common terms as such, or synonyms.

Sometimes sentences *i* and *j* do not share common terms and synonymous terms. But they may share words that have same root. For example, sentence *i* contains the word '*considering*' and sentence *j* contains the word '*reconsider*'. So when comparing these two sentences there is a similarity. This similarity arose from the fact that they share words that have same origin. Stem word similarity is thus taken into account for similarity computation. Here the degree of similarity is less than that of sharing common terms, but it may be greater than sharing synonymous terms. Sentence-sentence similarity is thus computed by considering stem word matches too. Porter stemmer is used for that purpose.

5) Sentence Ranking: Sentence Ranking is used to find out the importance of each sentence in the document. A set of most important sentences can represent the semantics of that document, that is, it represent the concept of that document. This set of sentences contain all information with minute details about the whole document. Since the proposed system produces summary of related documents, the sentences will be connected to each other. Self loops are avoided to preserve readability. A sentence similarity matrix *sim* is created from the fuzzy graph, *G*. This matrix is an $n \times n$ matrx, where n is the number of sentences in the matrix. The rows and columns of the matrix represents sentences in the document.

The similarity matrix, *sim* created from the undirected fuzzy graph is a fuzzy symmetric matrix. Each cell s_{ij} denotes the similarity of sentence *i* and sentence *j*, as computed by equation 2

$$s_{ij} = sim\,(i,\ j) \tag{2}$$

This matrix, *sim* is normalised to have its column sum equal to 1, i.e, *sim* is column stochastic by equation 3.

$$sim\,(i,\ j) = \frac{sim\,(i,\ j)}{\sum_{j=1}^{n} sim\,(i,\ j)} \tag{3}$$

A stochastic matrix *X* is the transition matrix of a Markov chain. An element *X* (*i, j*) of a stochastic matrix specifies the probability of transition from state *i* to state *j* in the corresponding Markov chain. By the probability axioms, all rows of a stochastic should add up to one. Googles PageRank is a well known system that uses the concept of centrality. Search engine ranks the pages in its search results by using this system. PageRank is a global ranking of all web pages, regardless of their content, based solely on their location in the Webs graph structure [2].

The centrality of the matrix is found out by eigen vector analysis. Eigenpairs are a lot like the roots of a polynomial. For example, all monic cubics with three real roots look more or less the same. So one of the most central facts about the roots of a polynomial is that they ground the polynomial. A root literally roots the polynomial, limiting it's shape. Eigenvectors are much the same. Very roughly, the eigenvalues of a linear mapping is a measure of the distortion induced by the transformation and the eigenvectors are about how the distortion is oriented.

Here consider the matrix $sim \in R^{n \times n}$. For the ith sentence, let the centrality score be proportional to the sum of scores of all sentences which are connected to it. Therefore:

$$s_i = \frac{1}{\lambda} \sum_{j=1}^{n} sim_{i,j} s_j \quad (4)$$

where s_i is the score of the i^{th} sentence and $sim_{i,j}$ is the similarity between i^{th} and j^{th} sentence and n is the total number of sentences and λ is a constant.

Let A be an $n \times n$ matrix, where $a_{ij} = sim_{ij}$. In vector notation, this equation can be written as

$$S = \frac{1}{\lambda} AS \quad (5)$$

Eigenvectors are the directions along which linear transformation occurs only by scaling, whereas eigenvalues $\lambda_i s$ are the scales along those directions. For symmetric matrices, Eigenvectors are orthogonal to one another. In this case of eigen vector, equation S is the required eigen vector.

$$AS = \lambda S \quad (6)$$

Consider the eigenvector corresponding to the maximum (absolute) eigenvalue. By taking a vector along this eigenvector, then the action of the matrix is maximum. No other vector when acted by this matrix will get stretched as much as this eigenvector. The important sentences are identified from the Eigen analysis, and included in the summary.

3.2 Summary Generation

Most of the news articles can be summarized into one-third, one-fourth, or one-fifth. The content of the article can be precisely described in less number of sentences. The correctness of the summary will be good when considering lesser number of sentences. More number of sentences in the summary may include irrelevant sentences. In order to avoid that situation the proposed system creates 20 % summary. Since the matrix, *sim* is a column stochastic matrix, the highest eigen value of that matrix will be a real number closer to 1. The Eigen vector corresponding to this eigen value are then computed. The Eigen vector retrieved is then arranged in the descending order. In this document model, each Eigen vector corresponds to a sentence in the document. So the sentences are retrieved and arranged in the descending order of values in the Eigen vector. These arranged sentences are candidates for producing summary. For making the summary readable, sentences are arranged in an order as they appear in original document.

3.3 Multi document summary

Multi-document summaries are built using a "*meta*" summarization procedure. A 20 % summary of related documents are generated from a set of related documents. Each document in the set is fed into the *Single Document Summarization* module and a comprehensive summary is created. This is done for all documents in the set. The generated single document summaries are then put into one file. This single document is further summarized through single document summarization module. A "*summary of summaries*" is produced using the same graph based approach [15].

4. Evaluation Metrics

ROUGE measures on DUC 2007 data set is used to evaluate the system. DUC 2007 was divided into two tasks -main task and update task. The main tasks provides 45 document sets for test evaluation. Each document set includes a fixed number - 25 documents and its query. Using these inputs, systems were expected to generate a summary of 250 words. Summaries over the size limit were truncated [28].

The documents from which summary was generated were news articles and reports chosen from ACQUIANT corpus. ROUGE is a summarization evaluation tool which evaluates the system generated summaries to model summaries based on recall, precision, and F-measures. Recall at different compression ratios has been used in summarization research to measure how well an automatic system retains the important content of original documents[26].

The proposed system is evaluated using DUC 2007 main task data set. There are 31 systems participated in DUC 2007. The average recall of ROUGE-2 and ROUGE-SU4 scores were computed. The scores of the participated systems are available with the DUC 2007 data set. The table 1 below compares the proposed system against the DUC 2007 participated systems.

SID	**ROUGE-2**	**ROUGE-SU4**
MH	0.14099	0.19158
15	0.12448 (1)	0.17711 (1)
29	0.12028 (2)	0.17074 (3)
4	0.11887 (3)	0.16999 (4)
24	0.11793 (4)	0.17593 (2)
13	0.11172 (5)	0.16446 (5)
8	0.10795 (8)	0.15991 (8)
3	0.10660 (9)	0.15990 (9)
Proposed System	**0.10732**	**0.18221**

Table 1. Duc 2007 Main Task Rouge Recall Scores

* MH indicates the mean of human summaries

The proposed system works well and it scores near to the mean of human summaries. The number denoted in brackets is the ranking of systems according to DUC 2007. The proposed system has a ROUGE-2 score lower than the 8th ranked system and higher than the 9th ranked system. The average ROUGESU4 (skip bigram) score of the proposed system is much closer to the mean of human summaries.

However, the simple sentence recall measure cannot differentiate system performance appropriately, as is pointed out by Donaway et al. in [27]. Therefore, instead of pure sentence recall score, here uses content responsiveness score, *C*. The system generated summary and human summaries of related input documents are given to five human judges. The judges given responsiveness scores to each of the system generated summaries. The content score is an integer between 1 (very poor) and 5 (very good) and is based on the amount of information in the summary. It also measures the linguistic quality of the summary. Manual evaluation checks for grammaticality, referential clarity, non-redundancy, structure and coherence.

The average linguistic quality score given by each judge for the proposed system on DUC 2007 dataset's main task is shown in Table 2.

Human ID	linguistic quality
1	3.267
2	3.4
3	3.53
4	3.12
5	3.48

Table 2. Duc 2007 Main Task Average Linguistic Quality Scores

From the table it is clear that, the summary generated by the proposed system is a well structured, brief summary. The proposed method has the ability to capture the important information spread across the documents.

5. Conclusion and Future Work

The news summarization system models the documents as undirected fuzzy graphs. The nodes represent the sentences and edges give the similarity between the sentences. Instead of considering the binary relationship between nodes, this system considers fuzzy measurements. By taking exact, synonymous, and root word matches of terms between the sentences this system computes all possible similarities between two sentences. The Eigen value analysis of the fuzzy symmetric matrix gives the centrality of the matrix. The results obtained from the proposed news summarization system using fuzzy graph based document model on DUC 2007 data set are quite encouraging. It gives ROUGE measures near to those of human summaries. The proposed system computes sentence-sentence similarity by merely considering the count of similar terms and their importance. The system has to be improved by considering the morphological aspects when computing similarity. Anaphora resolution also want to be done for providing better referential clarity.

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