Chapter 1

INTRODUCTION

1.1Introduction to Project

Document Summarization is the technique by which the huge parts of content are retrieved. The Document Summarization plays out the summarization task by unsupervised learning system. The significance of a sentence in info content is assessed by the assistance of Simplified Lesk calculation. As an online semantic lexicon WordNet is utilized. Word Sense Disambiguation (WSD) is a critical and testing system in the territory of characteristic dialect handling (NLP). A specific word may have distinctive significance in various setting. So, the principle task of word sense disambiguation is to decide the right feeling of a word utilized as a part of a specific setting. To begin with, Document Summarization assesses the weights of the considerable number of sentences of a content independently utilizing the Simplified Lesk calculation and orchestrates them in diminishing request as indicated by their weights. Next, as indicated by the given level of rundown, a specific number of sentences are chosen from that requested rundown.

Hybrid Document Summarization, is the plan to get an important data from a huge amount of information. The amount of data accessible on internet is increasing every day so it turns space and time expanding matter to deal with such huge amount of information. So, managing that large amount of data is makes a major problem in different and real data taking care of uses. The Hybrid Document Summarization undertaking makes the users simpler for various Natural Language applications, like, Data Recovery, Question Answering or content decreasing etc. Hybrid Document Summarization assumes an inescapable part by creating significant and particular data from a lot of information.

Filtering from heaps of reports can be troublesome and tedious. Without a summary or rundown, it can take minutes just to make sense of what the people will discuss in a paper or report. So, the Hybrid Document Summarization that concentrates a sentence from a content record, figures out which are the most imperative, and returns them in a readable and organized way. Hybrid Document Summarization is a piece of the field natural language processing, which is the manner by which the PCs can break down, and get importance from human dialect.

Hybrid Document Summarization that uses the classifier structure and its rundown modules to look over huge amount of reports and returns the sentences that are helpful for producing a summary. Programmed outline of content works by taking the overlapping sentences and synonymous or sense from wordnet most overlapping sentences are considered as high score words. The higher recurrence words are considering most worth. And the top most worth words and are taking from the content and sorted according to its recurrence and generate a summary.

1.2 Problem Statement

- Reading the whole document, dismembering it and isolating the critical thoughts from the crude content require some serious energy and exertion.
- Existing system increase the human effort while creating a synopsis. A few vital products compress records as well as website pages.
- The persons cannot quickly determine which points are imported for reading.

1.3 Objective and Scope of Project

In the Hybrid Document Summarization, we are using a solitary or single input content is going to outlined by the given rate of summarization utilizing unsupervised learning. In any case, the streamlined lesk's computation is associated with each of the sentences to find the guarantees of each sentence. After that, sentences with induced weights are composed in sliding solicitation concerning their weights. Presently as per a particular rate of summarization at a specific occurrence, certain quantities of sentences are chosen as an outline. The proposed computations, abridges solitary or single report content utilizing unsupervised learning approach. Here, the heaviness of every sentence in a substance is resolved using streamlined Lesk's computation and wordnet. After that, summarization procedure is performed as indicated by the given rate of synopsis. In which, we are taking solitary info content and display summarization as yield. First info content is passed, to the lesk computation and wordnet, where the weights of each sentences of the content are inferred utilizing and semantic investigation of the concentrates are performed. Next, weight doled out sentences is passed to derive the final summary according to the percentage of synopsis, where the last abridged outcome is assessed as and showed.

1.4 Importance of The Project

Reading the whole document, dismembering it and isolating the critical thoughts from the crude content require some serious energy and exertion. Perusing a document of 600 words can take no less than 10 minutes. Programmed outline programming condense writings of 500-5000 words in a brief instant. This enables the client to peruse less information yet get the most essential data and make strong conclusion. It reduces the human effort while creating a synopsis. A few vital products compress records as well as website pages. The persons quickly determine which points are imported for reading.

Chapter 2

PREAMBLE

2.1 Existing System

Currently, the number of documents retrieved by Web Search Engines is already beyond the capacity of human analysis due to the fact that hundreds of pages of search results are generated for most input queries. Thus, document retrieval is not sufficient and we need a second level of abstraction to reduce this huge amount of data - the ability of summarization. Hybrid Document Summarization condenses text contents into most important concepts and ideas under a particular context. This technology may be helpful to identify topics, categorize contents, and summarize documents. However, most previous work on Hybrid Document Summarization has emphasized on information abstraction and extraction. Some well-known approaches, like TF/IDF (Term Frequency/Inverse Document Frequency), which summarizes a text based on term frequency weight that is assigned to each term, neural network system for text summarization, statistical models, and so on, usually rank sentences and select sentences with higher ranking Score as the summary.

There are two properties of the summary that must be measured while evaluating summaries and summarization systems – the Compression Ratio, which is a measure of the length of the summary when compared to the original, and the Retention Ratio or Omission Ratio, which is a measure of how much of the document's central information is retained in the summary.

Semantic similarity is a concept frequently employed in determining the ranking of a term or sentence. A set of documents or terms within term lists are assigned a metric based on the likeness of their meaning/semantic content. Various semantic similarity techniques are available which can be used for measuring the semantic similarity between text documents. Semantic similarity methods are classified into four main categories, Edge Counting Methods that measure the similarity between two terms (concepts) as a function of the length of the path linking the terms and on the position of the terms in the taxonomy, Information Content Methods to measure the difference in information content of two terms as a function of their probability of occurrence in a corpus, Feature based Methods to measure similarity between two terms as a function of their properties (e.g., their definitions) or based on their relationships to other similar terms in the taxonomy and Hybrid methods that combine the above three mentioned methods for calculating the semantic similarity.

2.2 Problem Statement

- Reading the whole document, dismembering it and isolating the critical thoughts from the crude content require some serious energy and exertion.
- Existing system increase the human effort while creating a synopsis. A few vital products compress records as well as website pages.
- The persons cannot quickly determine which points are imported for reading.

2.3 Proposed system

In the Hybrid Document Summarization, we are using a solitary or single input content is going to outlined by the given rate of summarization utilizing unsupervised learning. In any case, the streamlined lesk's computation is associated with each of the sentences to find the guarantees of each sentence. After that, sentences with induced weights are composed in sliding solicitation concerning their weights. Presently as per a particular rate of summarization at a specific occurrence, certain quantities of sentences are chosen as an outline. The proposed computations, abridges solitary or single report content utilizing unsupervised learning approach. Here, the heaviness of every sentence in a substance is resolved using streamlined Lesk's computation and wordnet. After that, summarization procedure is performed as indicated by the given rate of synopsis. In which, we are taking solitary info content and display summarization as yield. First info content is passed, to the lesk computation and wordnet, where the weights of each sentences of the content are inferred utilizing and semantic investigation of the concentrates are performed. Next, weight doled out sentences is passed to derive the final summary according to the percentage of synopsis, where the last abridged outcome is assessed as and showed.

Where, input document will be in the form of a word document file or a pdf file. The pre-processing includes the data cleaning and data abstraction. The data will be the input to the lesk algorithm with the weights given to the words. Wordnet acts as a dictionary for comparing the importance of the word given is the input. Once the data is processed in the lesk algorithm it gives the output values which will be further converted into the summarized document format.

2.4 Advantages:

- Reading the whole document, dismembering it and isolating the critical thoughts from the crude content require some serious energy and exertion. Perusing a document of 600 words can take no less than 10 minutes. Programmed outline programming condense writings of 500-5000 words in a brief instant. This enables the client to peruse less information yet get the most essential data and make strong conclusion.
- It reduces the human effort while creating a synopsis. A few vital products compress records as well as website pages. The persons quickly determine which points are imported for reading.

2.5 Algorithms

1. Lesk Algorithm

The **Lesk algorithm** is a classical algorithm for word sense disembogues introduced by Michael. E. Lesk in 1986. The Lesk algorithm is based on the assumption that words in a given "neighbourhood" (section of text) will tend to share a common topic. A simplified version of the Lesk algorithm is to compare the dictionary definition of an ambiguous word with the terms contained in its neighbourhood. Versions have been adapted to use wordnet An implementation might look like this:

- for every sense of the word being disambiguated one should count the amount of words that are in both neighbourhood of that word and in the dictionary definition of that sense
- the sense that is to be chosen is the sense which has the biggest number of this count.

Calculation 1: This calculation compresses a single report content utilizing unsupervised learning approach. In This approach, the heaviness of each sentence in a content is determined utilizing Improved Lesk calculation and WordNet. The summarization procedure is performed as indicated by the given level of summarization

Info: Single-report input content.

Yield: Summarized content.

Step 1: The list of distinct sentences of the content is prepared.

Step 2: Repeat steps 3 to 7 for each of the sentences.

Step 3: A sentence is gotten from the list.

Step 4: Stop words are expelled from the sentence as they don't take an interest straightforwardly in sense assessment system.

Step 5: Glosses (dictionary definitions) of all the important words are extricated utilizing the WordNet.

Step 6: Intersection is performed between the sparkles and the information content itself.

Step 7: Summation of all the crossing point comes about speaks to the heaviness of the sentence.

Step 8: Weight appointed sentences are arranged in descending request concerning their weights.

Step 9: Desired number of sentences are chosen by the level of summarization.

Step 10: Selected sentences are re-orchestrated by their real sequence in the info content.

Step 11: Stop.

2. Single Document Summarization

Input:

1.Text Data for which Summary is required.

2.Value of N – for generating top N frequent Terms.

Output:

1.Summary for the Original Text Data.

2.Compression Ratio.

3.Retention Ratio.

Steps:

1. Data Preprocessing Phase Retrieve data
   Eliminate Stop Word

2.For the entire text content

   Get the N frequent Terms

   Generate Term-Frequency List

3.For all N-Frequent Terms

   Generate Sentences from the Original Data

      If the sentence consists of a term that is present in frequent-terms-list then

      add sentence to summary-sentence-list.

4.Calculate Compression Ratio and Retention Ratio

2.6 System Architectures of Proposed System

The proposed system depicts the three stages for Automatic Text Summarization and they are listed below.

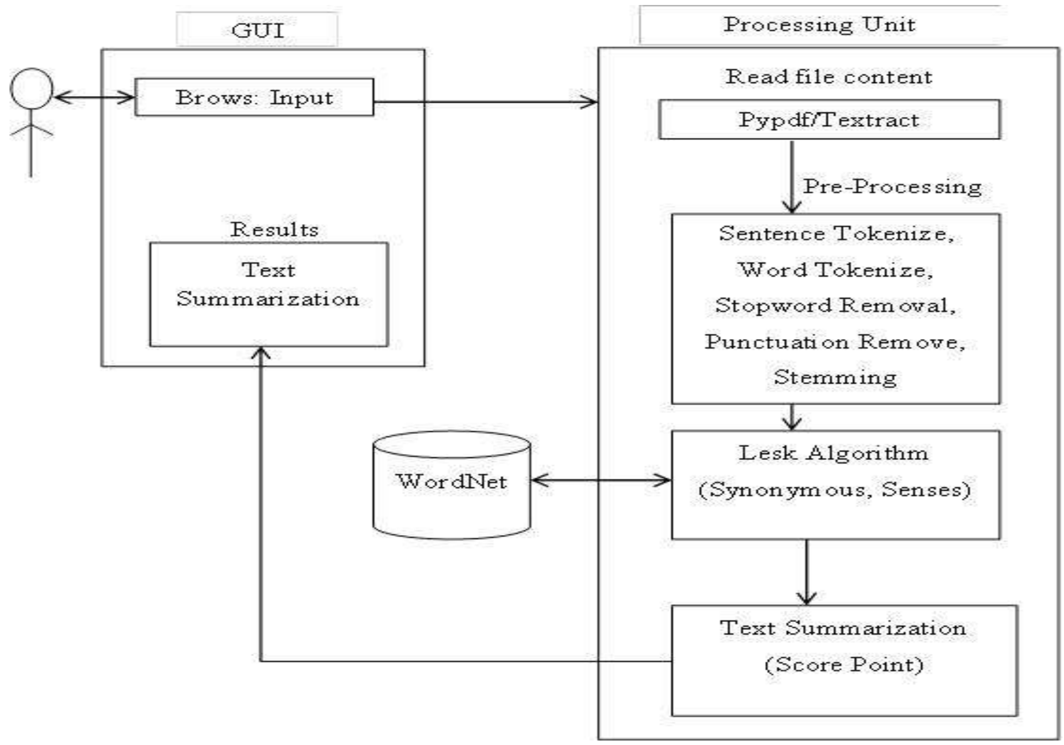

Fig -2.1: System Architecture for Automatic Text Summarization Using Common Handling Dialect.

Stage 1: Data Pre-Processing

Stage 2: Evaluation of weights

Stage 3: Summarization

Stage 1: Data Pre-Processing

Programmed record outline generator is for clearing the undesirable things which exist in the substance. Henceforth it will additionally process it will be performing sentence part, tokenisation, empty stop word, clear accentuation and perform stemming.

Stage 2: Evaluation of weights

This stage processes the repeat of the sentences of a substance utilizing lesk count and wordnet. In the first place finding the total number of spreads between a particular and the radiance this philosophy is performed for the all n number of sentences. By then once-over a particular sentence of the substance is set up for each of the sentences. A sentence is snatched from the once-over. Stop words are removing from the sentence as they don't take an intrigue particularly in sense task method. Sparkles of each vital word removed using wordnet. Union is performed between the sparkles and the data content itself. Once-over of all the intersection guide comes to fruition talks toward the largeness of the sentence.

Stage 3: Summarization

This stage evaluates the last outline of a substance and the introductions the yield, which is surveyed at the period of arranging the sentences. In the first place it selects the once-over of weight named sentences are planned in jumping demand concerning their weights. Pined for number of sentences is picked by the rate of summary. Picked sentences are re-composed by their genuine gathering in the information content. The modified substance summary will gather a substance without depending upon the association of the substance, rather than the semantic information lying in the sentence. Modified substance once-over is without vernacular. To remove the semantic information from a sentence, only a semantic word reference in the last vernacular is required.

Chapter 3

LITERATURE SURVEY

3.1 Phases of Document Summarization

There are basic three phases of document summarization as follows:

1. **Pre-processing,**
2. **Processing,**
3. **Summary Generation.**

Pre-processing

Pre-processing is defined here as cleaning the data. For cleaning unwanted characters, symbols, extra spaces, hyperlinks etc are removed. The stop words like ‘a’, ‘the’, ’and’. Stemming is done where the words are reduced to their word root for example ‘playing’ would be reduced to ‘play’. Moreover the parsing of the above data is done where the words are bifurcated into nouns, adjectives, verbs etc. The pre-processing is done as per the requirement using one or combination of the above defined techniques.

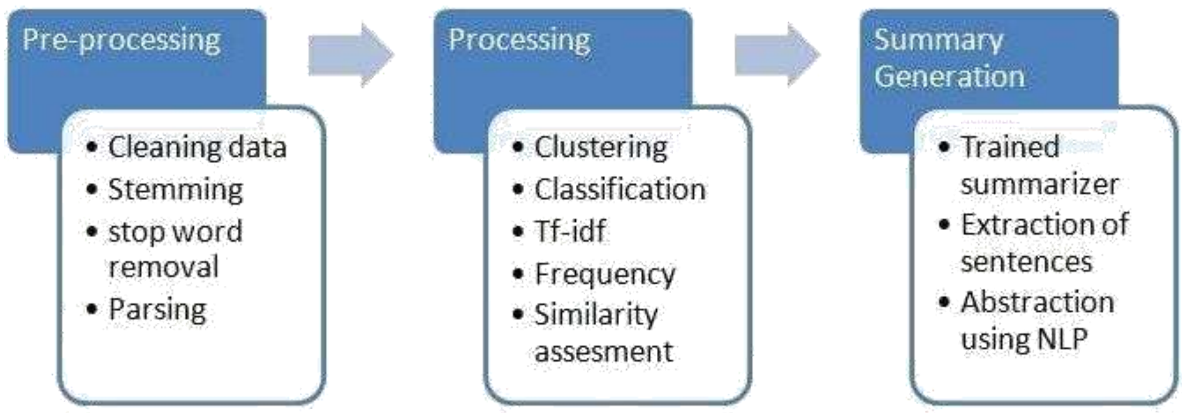

Fig 3.1 Phases of Summerization

This is the next phase of document summarization. After the Text data is cleaned and pre-processed, the processing techniques are applied in which the tf-idf scores, frequency of words are calculated. The data is grouped on the basis of similarity, dissimilarity so that the summary generation can be made efficiently. For this different clustering techniques are used.

Summary Generation

After the data is processed, the summary is to be generated based on the requirement. Extraction of sentences is done from the processed data and the summary is processed. The words to added to sentences, reducing the sentences based on score etc is done in this step to produce summary. The representation of the summary can be in the form of words, sentences, paragraphs, graphs etc. for the summary to be generated different summarizers are used.

3.2 Automatic Keyword Extraction

On the premise of past work done towards automatic keyword extraction from the text for its summarization, extraction systems can be classified into four classes, namely, simple statistical approach, linguistics approach, machine learning approach, and hybrid approaches.

3.2.1 Simple Statistical Approach

These strategies are rough, simplistic and have a tendency to have no training sets. They concentrate on statistics got from non-linguistic features of the document, for example, the position of a word inside the document, the term frequency, and inverse document frequency. These insights are later used to build up a list of keywords. Cohen, utilized n-gram statistical data to discover the keyword inside the document automatically. Other techniques in- side this class incorporate

word frequency, term frequency (TF) or term frequency inverse document frequency (TF-IDF), word cooccurrences, and PAT-tree. The most essential of them is term frequency. In these strategies, the frequency of occurrence is the main criteria that choose whether a word is a keyword or not. It is extremely unrefined and tends to give very unseemly results. An improvement of this strategy is the TF-IDF, which also takes the frequency of occurrence of a word as the model to choose a keyword or not. Similarly, word co-occurrence methods manage statistical information about the number of times a word has happened and the number of times it has happened with another word. This statistical information is then used to compute support and confidence of the words. Apriori technique is then used to infer the keywords.

3.2.2 Linguistics Approach

This approach utilizes the linguistic features of the words for keyword detection and extraction in text documents. It incorporates the lexical analysis, syntactic analysis, discourse analysis, etc. The resources used for lexical analysis are an electronic dictionary, tree tagger, WordNet, engrams, POS pattern, etc. Similarly, noun phrase (NP), chunks (Parsing) are used as resources for syntactic analysis.

3.2.3 Machine Learning Approach

Keyword extraction can also be seen as a learning problem. This approach requires manually annotated training data and training models. Hidden Markov model, support vector machine (SVM) , naive Bayes (NB) , bagging , etc. are commonly used training models in these approaches. In the second phase, the document whose keywords are to be extracted is given as inputs to the model, which then extracts the keywords that best fit the model's training. One of the most famous algorithms in this approach is the keyword extraction algorithm (KEA). In this approach, the article is first converted into a graph where each word is treated as a node, and whenever two words appear in the same sentence, the nodes are connected with an edge for each time they appear together. Then the number of edges connecting the vertices are converted into scores and are clustered accordingly. The cluster heads are treated as keywords. Bayesian algorithms use the Bayes classifier to classify the word into two categories: keyword or not a keyword depending on how it is trained. GenEx is another tool in this approach.

3.2.4 Hybrid Approach

These approaches combine the above two methods or use heuristics, such as position, length, layout feature of the words, HTML tags around the words, etc. These algorithms are designed to take the best features from above mentionedapproaches. Based on the classification we bring a consolidated summary of previous studies on automatic keyword extraction. It discusses the approaches that are used for keyword extraction and various domains of dataset in which experiments are performed.

3.3 Document Summarization Process

Based on the literature, text summarization process can be characterized into five types, namely, based on the number of the document, based on summary usage, based on techniques, based on characteristics of summary as text and based on levels of linguistics process.

3.3.1 Single Document Text Summarization

In single document text summarization, it takes a single document as an input to perform summarization and produce a single output document. Thomas designed a system for automatic keyword extraction for text summarization in single document e-Newspaper article. Marcu developed a discourse-based summarizer that determines adequacy for summarizing texts for discourse- based methods in the domain of single news articles.

3.3.2 Multiple Document Text Summarization

In multiple documents text summarization, it takes numerous documents as an input to perform summarization and deliver a single output document. Mirroshandel presents two different algorithms towards temporal relation-based keyword extraction and text summarization in multi-document. The first algorithm was a weakly supervised machine learning approach for classification of temporal relations between events and the second algorithm was expectation maximization (EM) based unsupervised learning approach for temporal relation extraction. Min used the information which is common to document sets belonging to a common category to improve the quality of automatically extracted content in multi-document summaries.

3.3.3 Query-based Text Summarization

In this summarization technique, a particular portion is utilized to extract the essential keyword from input document to make the summary of corresponding document. Fisher developed a query- based summarization system that uses a log-linear model to classify each word in a sentence. It exploits the property of sentence ranking methods in which they consider neural query ranking and query-focused ranking. Dong developed a query-based summarization that uses document ranking, time-sensitive queries and ranks recency sensitive queries as the features for text summarization.

3.3.4 Extractive Text Summarization

In this procedure, summarizer discovers more critical information (either words or sentences) from input document to make the summary of the corresponding document. In this process, it uses statistical and linguistic features of the sentences to decide the most relevant sentences in the given input document. Thomas designed a model based extractive summarizer using machine learning and simple statistical method for keyword extraction

from e-Newspaper summarize the text in multi-document. They used information which is common to document sets belonging to a common category as a feature and encapsulated the concept of category-specific importance (CSI). They showed that CSI is a valuable metric to aid sentence selection in extractive summarization tasks. Marcu developed a discourse- based extractive summarizer that uses the rhetorical parsing algorithm to determine discourse structure of the text of given input, determine partial ordering on the elementary and parenthetical units of the text. Erkan developed an extractive summarization environment. It consists of three steps: feature extractor, the feature vector, and reranked.

Features are Centroid, Position, Length Cut-off, SimWithFirst, Lex PageRank, and QueryPhraseMatch. Alguliev developed an unsupervised learning based extractive summarizer that optimizes three properties: relevance, redundancy, and length. It split documents into sentences and select salient sentences from the document. Aramaki destined a supervised learning based extractive text summarizer that identifies the negative event and it also investigates what kind of information is helpful for negative event identification. An SVM classifier is used to distinguish negative events from other events.

3.3.5 Abstractive Text Summarization

In this procedure, a machine needs to comprehend the idea of all the input documents and then deliver summary with its particular sentences. It uses linguistic methods to examine and interpret the text and then to find the new concepts and expressions to best describe it by generating a new shorter text that conveys the most important information from the original text document. Brandow developed an abstractive summarization system that analyses the statistical corpus and extracts the signature words from the corpus. Then it assigns the weight for all the signature words. Based on the extracted signature words, they assign the weight to the sentences and select few top weighted sentences as the summary. Daume developed an abstractive summarization system that maps all the documents into database-like representation. Further, it classifies into four categories: a single person, single event, multiple event, and natural disaster. It generates a short headline using a set of predefined templates. It generates summaries by extracting sentences from the database.

3.3.6 Supervised Learning Based Text Summarization

This type of learning techniques used labelled dataset for training. Thomas designed a system for automatic keyword extraction for text summarization using hidden Markov model. The learning process was supervised, it used human annotated keyword set to train the model. used a set of labelled datasets to train the system for the classification of temporal relations between events. Destined a supervised learning based extractive text summarizer that identifies the negative event. Article used freely available, open-source extractive summarization system, called SWING to and also investigates what kind of information is helpful for negative event identification. An SVM classifier is used to distinguish negative events from other events.

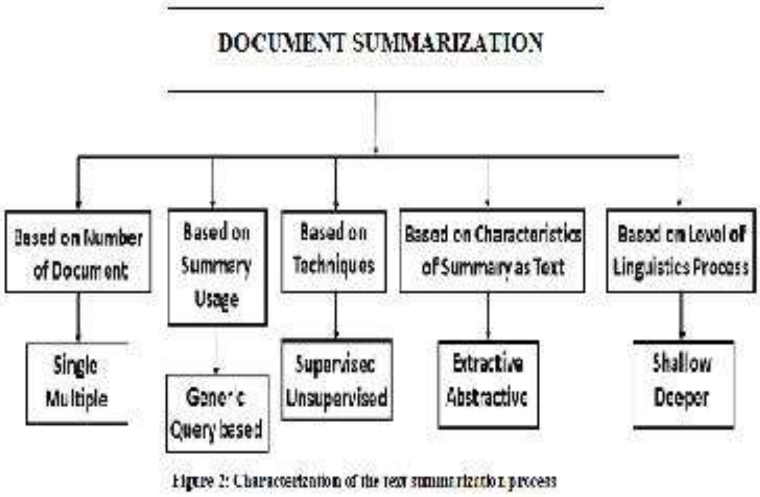

Fig 3.2 Text summarization process

In this technique, there are no predefined guidelines available at the time of training. Mirroshandel. proposed a method for temporal relation extraction based on the Expectation-Maximization (EM) algorithm. Within EM, they used different techniques such as a greedy best-first search and integer linear programming for temporal inconsistency removal. The EM-based approach was a fully unsupervised temporal relation-based extraction for text summarization. Alguliev developed an unsupervised learning based extractive summarizer that optimizes three properties: relevance, redundancy, and length. It split documents into sentences select salient sentences from the document.

3.4 Issues and Challenges Occurs in Text Summarization

In the area of text summarization, there are following research issues and challenges occurs during implementation.

3.4.1 Research Issues

• In the case of multi-document text summarization, several issues occur frequently while evaluation of summary such as redundancy, temporal dimension, co-reference or sentence ordering, etc. which makes very difficult to achieve quality summary. Some other issues occurs such as grammaticality, cohesion, coherence which is harmful for summary.

- The quality of summaries are varying from system to system or person to person. Some person feels some set of sentences are important for summary, at the same time other person feel the other set of sentences are important for required summary.

3.4.2 Implementation Challenges

- To get the quality summary, quality keywords are required for text summarization.
- There is no standard to identify quality keywords within or multiple documents. The extracted keywords are varying for applying different approaches of keyword extraction.
- Multi-lingual text summarization is another challenging task.

3.5 Table of Reference

REF NO	TITLE	METHODLOGY	ALGORITHM	ACCURACY
1	A Neural Attention Model for Abstractive Sentence Summarization	local attention-based model	Beam Search	43.81%
2	Abstractive Text Summarization using Sequence-to-sequence RNN and Beyond	RNN	-	74.57%
3	Automatic Keyword Extraction for Text Summarization : survey	-	-	-
4	Summarization with Pointer-Generator Networks	Pointer generator network and CNN	-	-
5	Text Summarization Techniques: A Brief Survey	Frequency Driven Approaches	-	-
6	Ranking Sentences for Extractive Summarization with Reinforcement Learning	CNN/RNN	REINFORCE algorithm	37.98%
7	Neural Document Summarization by Jointly Learning to Score and Select Sentences	RNN	-	66.34%
8	Machine Learning Techniques for Document Summarization: A Survey	Talks about all the methods	-	-
9	Ranking with Recursive Neural Networks and Its Application to Multi-Document Summarization	R2N2/RNN	-	-

10	A Neural Attention Model for Sentence Summarization	local attention-based model	Beam Search	23.97%
11	A Review Paper on Text Summarization	Natural Language Processing	-	-
12	Automatic Text Summarization Using Natural Language Processing	Natural Language Processing	LESK Algorithm	-
13	A Novel Technique for Efficient Text Document Summarization as a Service	Natural Language Processing	LESK Algorithm	33%
14	Automatic Text Summarization and its methods : A Review	Term frequency-based method/ Graph based method/ Time based method/Clustering based method	-	-
15	A Review on Automatic Text Summarization Approaches	Frequency Based Approach/Term Frequency–Inverse Document Frequency/Machine Learning Approach/Discourse Based Method	-	-

Fig 3.3 Table of References

Chapter 4

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