Summarization of Stock Market Investment News Articles For Stock Traders

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Declaration

I, J.Logeesan(15020398) hereby certify that this dissertation entitled Summarization of stock market investment news articles for Stock Traders is entirely my own work and it has never been submitted nor is currently been submitted for any other degree.

Signature :

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I, Y.Rishoban (15020606) hereby certify that this dissertation entitled Summarization of stock market investment news articles for Stock Traders is entirely my own work and it has never been submitted nor is currently been submitted for any other degree.

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I, Dr H.A.Caldera, certify that I supervised this dissertation entitled Summarization of stock market investment news articles for Stock Traders conducted by J.Logeesan and Y.Rishoban in partial fulfillment of the requirements for the degree of Bachelor of Science Honours in Information Systems.

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Abstract

Stock market word itself is something powerful in the Finance world. Field which is used to generate more profit for the organization and individuals. Movement of the stock market can be predicted using different factors such as past stock numeric data, stocktwits, company's portfolio, financial news articles etc. There are researches that were carried using stock numeric data to predict the movement of stock, but only numeric data itself is not possible to predict the movement without the real time information about the organization. If we want to gain real time information about the organization, we must gather information from the financial news articles.

Stock traders aren't able to read many news articles within a small time to gain more information unless it is in the summarized form. If traders can read a lot they will get a lot of information and profit gaining may increase. To make the traders read many articles, we need to provide the summarization tool that gives the summary of the significant contents needed for the stock traders. So we carried out this research to identify how far the summarization of stock market news articles will be helpful for the stock traders to carry out their trading activities.

We carried this research by collecting news articles from the popular websites and collecting keywords which are used by the stock traders to read the news articles, then pre processing was done on the news articles , then sentences were weighted based on the keywords and the graph analysis is performed to retrieve the salient sentences for the stock traders from the news articles. Generated summary was compared with the summary of the domain experts summary for the corresponding article. Accuracy of the model was more than 55% for every article. So can conclude that summarization of stock market news articles is helpful for the stock traders to carry out their trading activities

We believe that, this is the first time, the summarization techniques have been applied specifically in the stock market investment news articles in such a way it is helpful for the stock traders to carry out their trading activities.

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1 Introduction

Finance can be categorized into four parts such as public finance, private finance, personal finance and corporate finance. Corporate finance is a field of finance that involves sources of funding, the corporations capital structure, the actions that are taken by the managers to increase the value of the firm to the shareholders, and the tools and analysis used to allocate financial resources. As our research will be focused on the stock market, it will fall under the corporate finance category. Stocks are a way of company incurring investment for its company from the public. Stock market is a place where investors can buy and sell these stocks to get the fraction of ownership of the company. These stock prices can vary per day according to the companies financial movement.There are two types of traders such as institutional traders and retail traders. Institutional traders are people who do trading for banks, insurance companies or even hedge funds. Individual traders are referred to as traders, buy or sell securities for personal accounts. These individual traders and institutional traders make use the help of financial news articles, past stock data, stocktwits, company's portfolios etc to predict the movement of stocks on the next day. There are different types of stock trading such as short term trading, market order, intra day trading, swing trading, positional trading, long term trading, quantitative trading, arbitrage trading and high frequency trading [51].

Extractive summarization is summarizing the document by extracting the important sentences as in the original document to create a summary.It has two subtypes such as indicator representation approach and topic representation approach. In topic representation approach it consists of topic words approach, Bayesian model approach, latent semantic analysis approach and frequency driven approach.Indicator representation approach comprise of Graph based and machine learning based summarization [52].Graph based summarization does not depend on the language for which we are going to do summarization and also it analyses relationship of every sentence with other sentences in the text. Those are the the reasons it is used in many of the summarization and also it can be applied to single and multi document summarization [52].

1.1 Background of the problem

There is a lot of research in the stock market news articles and stock data. Stock news articles have been used to identify the sentiments of the people and also have been used to identify the company specific financial information using query based approach while stock data are still being used in the algorithmic trading and still many lot of research works are done to create an efficient model to predict the stock prices of organizations. Stock traders consider stock market investment news articles as valuable insightful resources to gain information about different organizations. Stock traders aren't able to get a lot of information from few news articles, if they want to get a lot of information, they should read a lot of news articles. Only way to make this achievable by providing a summarization tool for the stock traders.

On the other hand, many researches are being done on the text summarization side. Text summarization can be categorized as Abstractive summarization and Extractive summarization. Extractive summarization is still being explored to effectively retrieve sentences efficiently while research in the abstractive summarization still hasn't achieved as extractive summarization. In extractive summarization, graph based approach and machine learning approach are the most popular fields where researches are being performed. Still the main problem behind these summarization is generating effective summarization which is much useful for the stock traders.

1.2 Problem Statement

Stock traders can't stick with only one news article to gain more insights, instead they need to read many news articles to know about different organizations and their performance before their trading activities. Stock traders use news articles as it gives the real time information about the different organization and it gives information about many unknown companies which and If they want to gain a lot of information quickly, they need to read many articles. So this problem motivates us to summarize the stock market investment news articles for stock traders. If we can summarize these stock market investment news articles, stock traders can read a lot of news articles about different organizations and their performance to gain more information.

1.3 Research questions

1. How to enrich the stock market investment domain in the text summarization?
   a. Though there are many text summarization techniques available, research in the particular domain of summarization is very less. Medical news articles have been summarized using medical domain knowledge [49]. If we want to summarize news articles in a particular domain, we need to integrate some of the essential knowledge which can capture the sentences that are relevant to the particular domain. These findings in the stock market investment domain will be much useful for the news article summarization to generate effective and efficient results. This finding will be helpful for improving the future research on the stock market investment related news articles too.

2. How to carry out the summary evaluation complying with stock market investment domain?
   a. Though there are some existing evaluation techniques to evaluate the output of the text summarization result[reference] such as Pyramid model and ROUGE, they are general evaluations techniques for summarization. When it comes to a particular domain, we should find some alternative methods which will be helpful to evaluate the output of those summaries. So we need to find some methods which can help to evaluate the summaries generated by our summary generation model. This finding can help to improve the evaluation of our end model to identify the efficiency of our model.

3. How far summarized stock market investment news articles will be helpful for stock traders?
    a. If we take any particular text summarization, it should be able to give us some insights about the whole document. If it didn't give any insight information on that document, that summarization is not worth.If we consider our research, final output summary of the stock market investment news article should be helpful for stock traders to carry out their stock trading activities. So our findings can be helpful to derive us a conclusion whether summarization of stock market investment news articles with our research methodology is useful in providing information to stock traders and and other financial workers who are involved in equity based work.

1.4 Goals and Objectives

1.4.1 Goal

- Provide an effective stock market investment news article summarization tool for stock traders.

1.4.2 Objective

- Capture the insights present in the stock market investment news articles such that it is helpful for stock traders to trade efficiently and effectively.

1.5 Significance of the research

These summarization of stock market investment news articles are helpful for stock traders to capture the significant content inside the stock market investment news article efficiently. This can reduce the time of the stock traderers for reading the news articles and at the same time it can improve the number of reading articles by stock traders to carry out their trading activities.

If they read a lot of stock market investment news articles about different organizations, they can trade on different companies to gain more profit.

This research can also be used by the stock market news websites to deliver a summary of whole news articles at the top of the news to readers. This can give the readers a quick insight about the news articles and it can enrich the understanding of the content of news articles efficiently and effectively to the readers.

1.6 Research Approach

To carry out the above research, first we went through some literature reviews related to the application of information technology techniques in stock market and text summarization. In text summarization, literature review was done in the pre processing, graph based techniques(as it had more efficient results compared to other approaches) and evaluation techniques of summarized results. In the stock market domain, literature review was done in how information technology is applied in stock market data and in text data from different social media(such as twitter data related to stock market, data from stocktwits, financial stock market investment news article etc. Then we collected all digital news articles related to stock market investment from the website related to investment and carried out the pre processing techniques and then created graph based model and summary was generated from it. Then evaluation was done by comparing The output of the results with the summaries from the domain experts.

1.7 Limitations, Delimitations and Assumptions

1.7.1 Limitation

- Our summarization tool can be used for the news articles which are enriched in the stock market investment
- Carried evaluation results are based on how far the summarization is useful for stock traders to carry out their trading activities.
- Summarization could be only understood by people who have some prior knowledge on the domain.

1.7.2 Delimitations

- Our evaluation is not biased as we have considered different domain experts for different news articles
- Semantic similarities between the sentences are also taken into consideration.

1.7.3 Assumption

- There is no hate speech available in the news article as we have collected the news articles from the popular website pages.

1.8 Contributions

We fill an existing issue by providing the following

- Providing the stock market investment news article summarization tool for stock traders

We will contribute to the research community with a publications as of the writing of this thesis as

- Stock market investment news article summarization for stock traders

We have contributed to the stock trading community by providing this summarization tool.

2 Background Study

2.1 Financial Study

Information plays a vital role in investment in the Stock market. Investors are seeking information to identify the best company for investment. More specifically, information from corporate news, financial news articles, market announcements are reflected in volatile stock market reactions. In the online world each information is published online on a real time basis. Twitter, online news articles and forums are better examples of information resources. Financial news is a major information resourcer and is increasing in both its volume and broadcasting speed[1][2].

Li, Xiaodong, Haoran Xie, Yangqiu Song, Shanfeng Zhu, Qing Li, and Fu Lee Wang investigated the problem whether news articles impact the stock market prediction. They conducted controlled research using five year Hong Kong stock exchange data. They build two kinds of framework. First one is a generic stock price prediction framework that takes textual documents as inputs and generates predicted price movements as outputs. Other one is news article summaries and feed the framework with either the summarized or the full-length articles. They evaluated the results with statistical analysis using Hong Kong Stock exchange data and news data reported by Finet[1]. Based on their results they concluded that giving summary increase the prediction level of stock market price. Instead of analyzing the stock market, we can go beyond and think about factors which affect investors' decisions.

Joanna Strycharz, Nadine Strauss, and Damian Trilling made exploratory research on selected three companies to identify the reciprocal relationships between the fluctuation of the closing prices. They collected the corporate topics about the selected companies using automated content analysis. The results of this research show a positive relationship between the amount of coverage and emotionality with the fluctuation of stock prices[5]. Moreover they pointed out this study advances past research in showing that the prediction of stock price fluctuation based on media coverage can be improved by including sentiment, emotionality, and corporate topics.

Above research are based on the particular company but the following research considers query based multi-document summarization to particular companies. Purpose of the research is that such summaries is to provide information useful for the short-term trading of the corresponding company for example, to facilitate the inference from news to stock price movement in the next day[8]. In this research they used symbols that are the abbreviation of the name of the company as query. Then the query expanded and searched the relevant sentences through the multi-documents. They used graph algorithms to find related sentences. In the graph, node is the set of all sentences from all input documents, and edge is the set of edges representing normalized sentence similarities. Then rank all the sentence as nodes based on the inter-sentence relations as well as the relevance to the query q. Sentence ranks are found iteratively over the set of graph nodes. Finally, from the relevant sentence graph summary is generated.

Finance can be categorized into four parts such as public finance, private finance, personal finance and corporate finance. Corporate finance is an area of finance that deals with sources of funding, the capital structure of corporations, the actions that managers take to increase the value of the firm to the shareholders, and the tools and analysis used to allocate financial resources[2]. As this research will be focused on the stock market, this will fall under the corporate finance category. Stocks are a way of company incurring investment for its company from the public. Stock market is a place where investors can buy and sell these stocks to get the fractional ownership of the company. These stock prices can vary per day according to the companies financial movement.There are two types of traders such as institutional traders and retail traders. Institutional traders are making trades for banks, insurance companies or even hedge funds. Individual traders are referred to as individual traders, buy or sell securities for personal accounts. These individual traders and institutional traders make use the help of financial news articles, past stock data, stock tweets etc to predict the movement of stocks on the next day. There are different types of stock trading such as short term trading, market order, intra day trading, swing trading, positional trading, long term trading, quantitative trading, arbitrage trading and high frequency trading. There are many research which has been done in this domain, most of the research focused on predicting stock market using stock data and stock based news articles[10] while research on tweets related to stock market to identify the sentiments and moods of the public with the change in the stock prices of a company and also to identify the stock movement using Twitter sentiment analysis[2][9]. Many investment companies invest in corporate finance research for their company development.

Human's decision are based on sentiments. This statement is also suitable for investments on the particular company by investors. Fortunately, the new concepts called machine learning is opened up the human sentiment analysis[3][4][5][7]. Attigeri and Girija V investigated stock market price using statistical analysis and sentiment analysis. They hypothesized that from fundamental and technical analysis we can predict the stock prices[3]. Technical analysis considers statistical analysis of stock market and fundamental analysis considers every detail available and behavior of economic agents that may affect price such as Twitter data and News articles. They concluded that volatility of the markets and the future performance of the system is affected by the economic and political news and influence of social media.

So far researchers are interested in single category summarization. But naturally these kinds of news articles are very rare because financial news articles are not only concerned about the stock market. Then Shynkevich and Yauheniya expanded this research to multiple domain. They used the Global Industry Classification Standard to classify the news articles[6]. The categories are stock-specific (SS), sub-industry-specific (SIS), industry-specific (IS), group-industry-specific (GIS) and sector-specific (SeS). For the integration purpose Multiple Kernel Learning (MKL) technique is used to integrate different types of data The experiments showed that an attempt to divide articles into different categories, analyze them separately and then combine the resulting predictions into a single decision demonstrates a promisingly improved performance when compared with approaches based on a single subset of news.

2.2 Text summarization

Text summarization methods are mainly categorized as extractive text summarization and abstractive text summarization. Extractive text summarization selects important sentences from a document and then produces the selected sentences as summary. Abstractive text summarization is a human-like summary. Machine can read and understand the text document then generate sentences from the understanding of the text.

Text summarization is retrieving important information from large sets of information to get the main content in a short period of time by users. It mostly falls under data mining and machine learning. Text summarization can be done in two ways such as extractive and abstractive. In extractive, important sentences are extracted in the same way as in the document and summarization is done. In abstractive summarization, new sentences are generated using natural language generation techniques , which is mostly similar to human summarization. Though abstractive looks similar to human summarization, handling process is much more difficult as it deals with inference, semantic representation where as extractive summarization . Therefore most of the research is done using extractive summarization techniques. In the below sub chapters we'll look broadly, how it has evolved from the beginning.

2.2.1 Extractive summarization

Extractive summarization mainly follows three steps in creating a summarization of the text, 1) Constructing intermediate representation of the text considering the main aspects of the text 2) score the sentence based on the representation 3) Creating summaries considering the importance of sentences [11] . Intermediate representation can be done using Topic representation approaches and indicator representation approaches .Topic representation approach can be divided into topic words approach, Bayesian topic model approach, Frequency driven approach and Latent Semantic Analysis. Indicator representation approach comprises of machine learning and graph based approaches.

2.2.1.1 Topic representation approach

2.2.1.1.1 Topic words

In this approach, first Luhn suggests by defining the frequency threshold for the different words in the document and identifying the importance of sentences which can be fit for summarization [12]. Then Luhn's idea was further developed to identify the important words of the document which can give an effective summarization by using the “log likelihood ratio” and this method was called as topic signature [13]. This method increased the accuracy of the multi document summarization of news articles. Then scoring of the sentences were computed based on the number of topic signatures in each sentence or proportion of the topic signature in the sentences to conclude the sentences needed for the summarization.

2.2.1.1.2 Frequency driven approach

In the frequency driven approach, most commonly used methods are Word probability and TFIDF based methods. If we look at the word probability method, it considers the probability of a particular given word out of all the words in a document or multiple documents. This method was used in the SumBasic system of Vanderwende [14] where he assigned the weight of each sentence considering the probability of words and sentences were collected which has more weight.

Yih et al carried out research considering that in summarization, rather than considering the most commonly occurring words, need to consider the words which are less occurring. So he updates the probability of words, when it appears again [15] .

TFIDF approach came into research after word probability didn't consider the stop word list and what are the words which needs to be included in the stop word list to provide an effective summary. This method was used in the centroid based summarization research to rank the most important sentences [16].

2.2.1.2 Latent Semantic Analysis

After Latent Semantic Analysis was introduced in 1990, it was used by Yihon Gong and Xin Liu in their research [17] . Here topic sentence matrix are used to identify how each topic represents the sentence. For each topic sentence is selected for summarization and finally summary is created from that. Later this method became an issue as each topic can represent many relevant sentences for summarization. Then weight for each topic is calculated using some formula and number of sentences for each topic weight is pre assumed and summarization is created. Another advancement that they were researched into was calculating topic weights and from that identifying the weight of sentence using a certain formula and grabbing the sentence with more weight for summarization [18] .

2.2.1.3 Bayesian Topic model

Many of the multi document summarization had two limitations [19] such as 1) They consider the sentences are independent of each other and topics embedded in the document are disregarded 2) Sentence scores were calculated without using any probabilistic based approach and some heuristics methods. Bayesian topic models are probabilistic models that uncover and represent the topics of documents. Their advantage in describing and representing topics in detail enables the development of summarizer systems which can determine the similarities and differences between documents to be used in summarization. Then KL divergence method was introduced to calculate the divergence between the probability of words. It is used to identify how the importance of words differ in summary with the input.

2.2.1.4 Indicator Representation Approaches

2.2.1.4.1 Graph based summarization

Then the evolution of Graph based summarization arose. Here the sentences are considered as nodes and relationships between them were represented as edges with weight scores. Similarities between the sentences are calculated using cosine similarity or TFIDF weights. This is the most commonly used method. Current research makes use of Wordnet to construct relationships between sentences. Pagerank algorithm is applied on graph to identify ranking of nodes in the graph to select the sentences for summarization [20] .

Graph based summarization does not depend on the language for which we are going to do summarization. That's the reason it is used in many of the summarization. And also it can be applied to single and multi document summarization. Though TFIDF and cosine similarity techniques are used to score the relationship between the sentences, it only takes account of the statistical relationship, so it is not going to produce effective summarization as humans does. So researchers started to find similarity using semantic and syntactic information of sentences [21] .

2.2.1.4.2 Machine Learning for Summarization

Text summarization can be done using a classification method[21] has used some summarization techniques using machine learning in early days. Mostly used algorithm for classification is naive bayes classifier: It is classified as summary sentences and non summary sentences. This classification is done by passing the training documents which has summaries and let the model train itself. Then the document which needs summary will be input to the model to get the output [22].

2.2.2 Abstractive Summarization

Abstractive summarization is a human-like summary. In this approach machine try to understand the meaning of the sentences and generate summary from the document. It is much harder task because it involves generating sentences that requires Natural Language Processing techniques and reducing its redundancy as well as keeping good compression rate.[23] Abstractive summarization broadly classified into two categories Structure based approach and Semantic based approach.[24]

Structure based approach is captured information from cognitive schemas such as templates and extraction rules. In this approach, based on different methods there are five approaches available such as tree based method, template based method, ontology based method, lead and bode based method, rule based method.

2.2.2.1 Tree based method

The text document is represented as a partial dependency tree format then each tree is merged in a single tree dependency tree is converted to a sentence which is called a fusion sentence. In the past years multiple algorithms were used to select content of summary such as theme intersection algorithm or algorithm that uses local alignment across pair of parsed sentences.

Yimai Fang et al. [24] proposed a first prototype of the feasibility of basing a summarization algorithm on Kintsch et al. (1978) model.It creates flexible-length summaries. The limitations of this technology is semantics is not fully determined by syntax.

In another similar approach, at first similar sentences are preprocessed with shallow parser.Shallow parser identifies constituent parts of sentences such as noun and verb and then links them to higher order units that have discrete grammatical meanings such as noun groups and verb groups. Then using algorithms like theme intersection to determine common phrases. Finally Functional Unification Formalism Interpreter/ Syntactic Realization Grammar for Text Generation language to generate sentences and make summary.

2.2.2.2 Template Based Method

In this approach, text documents are matched with patterns and rules which are defined by template to make a summary. Text which fits into the template makes a summary. This approach proposed in generating single and multi document summary by Harabagiu and Finle. This research used topic representation as content of template and extract information from multiple documents. Topic is represented as a set of related concepts and implemented as a frame or template containing slots and fillers. This type summary generated is highly coherent. Templates has relevant content and it requires detailed semantic analysis hence it is the main problem faced by template based method[26]

2.2.2.3 Ontology Based Method

Many researchers are using ontology concepts to improve their semantic understanding of the text documents. Ontology is simply domain knowledge. Same words are interpreted with different meanings in different context. To solve this ambiguity researchers used ontology concepts.

Chang-Shing, Zhi-Wei and Lin-Kai used a fuzzy ontology concept in Chinese news summarization. This summarization is done by a news agent based on fuzzy ontology. A set of membership degrees of each fuzzy concept is associated with various events of the domain ontology. The fuzzy inference mechanism calculates membership degree for each sentence according to term classifier based on domain ontology. Major drawbacks of this approach are ontology defined by domain experts, which is time consuming work and this used ontology can't be used to any other languages.

2.2.2.4 Lead and Body Phrase Method

In this approach, sentences which are informative in context and have good length are rephrase by inserting and substituting phrases. Mark Wasson [27] Leading text extracts created to support some online Boolean retrieval goals are evaluated for their acceptability as news document summaries. The results of this investigation show that leading text can provide acceptable summaries for most general news documents. These results are consistent with Brandow et al. (1995). The weakness of this approach is parsing degrade the performance and no generalized model for summarization.

2.2.2.5 Rule Based Method

In this approach the user is defined terms of categories and list of aspects. Content of the summary is generated by information abstraction rules which answer aspects and categories. Major advantage of this method is it creates summaries with greater information density.The higher density of information in our short summaries is one key to address the performance ceiling of extractive summarization methods.

Major drawback of this method is that rules are manually specified. Pierre-Etienne Genest. [28]showed that full abstraction can be accomplished in the context of guided summarization and describes a work in progress that relies on Information Extraction, statistical content selection and Natural Language Generation.

2.2.2.6 Semantic based approach

These approaches are used Natural Language Processing to realize the meaning of the sentences then generate summary. In this approach based on the method there are three methods available such as multimodal semantic model, information item based model and semantic graph based model.

2.2.2.7 Multimodal Semantic Model

This method not only covered text but also covered images. This semantic model captures concepts and relationships among concepts. Greenbacker [26] proposed approach which works in three stages first it uses an ontology to build a semantic model which represents the multimodal document. Second with information density matrix which rates a concept based on a factor such as completeness of attribute, the number of connections. Information density matrix is used to score concept and finally, summary is generated with high score concept.

Important point about this method is coverage of information content.The limitation of this framework is that it is manually evaluated by humans. An automatic evaluation of the framework is favourable.

2.2.2.8 Information Item Based Method

Information items are a basic element of coherent information in text. In this approach summary is generated from abstract representation of source document. Abstract representation is constructed with information items. At first, Pierre-Etienne Genest [29] proposed a new, ambitious framework for abstractive summarization, which aims at selecting the content of a summary not from sentences, but from an abstract representation of the source documents. They proposed framework having information item retrieval, sentence generation, sentence selection and summary generation.

Strength of this method is that it produces short, coherent, information rich and less redundant summary. This method has its own limitations such as many candidate information items are rejected due to the difficulty of creating meaningful and grammatical sentences from them and linguistic quality of summaries is very low due to incorrect parses.

2.2.2.9 Semantic Graph Based Method

Aim of this method is giving concise, grammatically correct and meaningful summary. In this method semantic relationship between sentences are represented in graph model called Semantic graph. It consists of three phases. The first one is to make Rich Semantic graph second is reduction of Rich Semantic Graph third is generating summary. In the first phase there are plenty of methods to make graph such as subject-object-predicate triplet and Semantic Role labelling. For the graph reduction researchers used many approaches for example machine learning methods and minimum spanning tree. Limitation for this method is that it is only applicable for single document summarization.

Khan, Atif, and Naomie Salim pointed out the different methods that are used in abstractive text summarization. Abstractive text summarization techniques are classified into two categories such as Structure based approach and Semantic based approach. Structured based approach encodes most important information from the document(s) through cognitive schemas[48] such as templates, extraction rules. Tree based method, ontology based method, lead and body phrase method and rule based method are used in structure based approach Multi model semantic model, information item based model and semantic graph based model are semantic based approach.True abstractive text summarization is a dream of researchers[24]. Semantic graph based models are used with different techniques to improve redundancy and conciseness of summary and most recent advancement technique in the text summarization world.

Han and Xu suggested that text redundancy is a major issue in the text summarization and naive similarity measure isn't enough to solve this solution. They used Framenet, a traditional semantic representation method, to parse the document and annotate the sentences with Lexical Unit(LU) and Frame Elements(FE) then generate sentence node. They used word embedding method to find similarities between the sentences. Similarity value is represented in edges of the graph. Importance of the sentence based on the similarity is calculated by graph ranking algorithm. Finally, high ranked sentences are extracted as a summary of the document[31].

The above approach is somewhere between Abstractive and Extractive summarization. Because they used semantic graph method to consider the meaning of the text as well as extract the important sentences from the document. The main problem that they needed to address is eliminating text redundancy and covering the informative contents. Maybe that is the main reason they used semantic approach.

At present researchers use machine learning concepts to identify relevant structures for summary extracts.Leskovec, Jure, Marko Grobelnik, and Natasa Milic-Frayling used Support Vector Machine method to summaria the documents.As an input for model Linguistic attributes, Semantic graph tags, location of the sentence in the document, frequency and location of the word inside the sentence which were derived from linguistic analysis[34]. They mentioned less advanced linguistic analysis for corresponding semantic graph doesn't affect the summarization. Interestingly DUC dataset which was used in research has multiple domain specific news article. They used a topic based model and the result is a performance that is higher from the performance of the topic independent summaries, when the same sample of training data is used.

Another popular machine learning model which is used in text summarization is K-means clustering[35][38]. Researchers used tokenization to separate the sentences and remove unnecessary characters, for example punctuation marks. Then they calculate the importance of TF-IDF scores which is measured how frequently the words occurred. These sentence scores are used to represent the sentences as unique coordinates in the single dimensional Cartesian plane[40]. This coordinates used in K-means clustering to group the sentence cluster. Eventually, pick the cluster with the maximum number of sentences and generate the summary by producing the sentences in the same order in which they appear in the original document.

Yasunaga, Michihiro made a Neutral Network model to summarize the multi document[37]. This method is an Extractive summarization method. At first the model creates a sentence relational model where interacting sentence nodes are connected by edges from given documents cloud. For each sentence, we apply a Recurrent Neural Network with Gated Recurrent Units and extract the last hidden state as the sentence embedding[36]. Then they applied Graph Convolutional Networks on the sentence relation graph with the sentence embeddings as the input node features, to produce final sentence embeddings that reflect the graph representation. They used cosine similarity methods to find similarities between sentences.

In graph based summarization modified TextRank algorithm is frequently used method to identify the important sentences. Mallick, Chirantana pointed out usage of this method. Each sentence is taken as nodes and their relationship between them is represented with the edges using the weights obtained by cosine similarity. Then the textrank of each node is set considering the incidence weight of edges and PageRank concept. Then obtained the top “n” sentences from the ranking for summarizing[30]

Semantic graph based model was only suggested to single document summarization until Khan, Atif, proposed adjustment for multi document summarization. In the multi document context previously bag of words methods used in graph based model. But the problem with this method is that it ignores the semantic relationship[33]. Their approach automatically merges similar information across the documents, and employs language generation to generate abstract summary[25]. Clustered semantic based graph to find semantic relation then use modified graph based ranking algorithm to find high score Predicate Argument Structure.

Using lexical chain to identify the semantic relationship is another extractive text summarization method. In this method first segments the text,then for each noun in the segment, for each sense of the noun, it attempts to merge these senses into all of the existing chains in every possible way, hence building every possible interpretation of the segment[37][39][44]. Next, the algorithm merges chains between segments that contain a word in the same sense in common. The algorithm then selects the chains denoted as “strong” (more than two standard deviations above the mean) and uses these to generate a summary.

Graph based Text summarization models are very frequent research for example Pagerank algorithm and minimum spanning tree[35]. Joshi, Monika, Hui Wang, and Sally McClean took sentence formation called subject-object-predicate to identify the sentence skelton from that made semantic graph[40]. They used Pagerank score algorithm to give weight to edges then use shortest path algorithm to simplify the graph[13]. From the simplified graph they generate a summary. Similarly, Raj, M. R., & Haroon, R. P seeked a summarization method in Malayalam language and used a minimum spanning tree to extract the summary[41].

Based on literature study if we order the research in chronological order, we can find that abstractive text summarization is most influential method in summarization field but still haven’t achieved its expected level. But purely extractive summaries often give better results compared to automatic abstractive summaries. This is due to the fact that the problems in abstractive summarization, such as semantic representation, inference and natural language generation, are relatively harder compared to a data-driven approach such as sentence extraction.

Finding similarity between sentences determine which sentences are going to be included in summary. Identifying the structure of the sentences make this easy to analyze the similarity. In English subject-object-predicate triplet is the most fundamental structure of the sentences. Sentences are broken according to the structure then nodes are represented each component of structure[34]. Entity recognition, coreference resolution and pronominal anaphora resolution are some key operations to identify the structure of the sentences. Person, organization, monetary value and quantity are entity recognition, pronominal anaphora resolution means finding exact entity for pronouns and coreference resolution point out different form of entities. Those key things make a comprehensive graph. Pagerank score algorithm is used to calculate similarity based on the above factors.

Similar work is done on Text representation approach for Arabic language. Text is analyzed morphologically and syntactically[32]. Then coreference resolution and pronominal resolution is performed on the text. This analysis differs from English. Each language has their own sentence structure and text analysis. Single word has several different meanings. For example, the word ‘card’ is interpreted in the computer science field as ‘Punch Card’ and in the banking sector as ‘Credit Card’. This scenario is called ontology. With the help of Arabian ontology they found exact meaning of sentences.

Apart from using sentence structure, words are labelled using a concept called Semantic Role Labelling(SRL). Semantic Role Labelling extract predicate argument structure in order to capture the meaning of the text[33]. SRL method parse the sentence then label semantic word phrases. Those phrases are semantic arguments. Semantic arguments are categorized as core arguments and adjunctive arguments. Between them they used core arguments which are subject, object and indirect object

After getting predicate argument structure, researchers split it into meaningful words or tokens. Then they removed stop words and normalized the words. Then they compared the noun-noun, verb-verb, location-location, time-time arguments. The comparison process was used Lin semantic similarity measure as scale.Lin’s measure based on WordNet which is a lexical database for English language and consists of synonyms and antonyms of words. Then they made sparse matrix which represents the similarity between the sentences. The above steps not only apply for English but also apply to other languages such as Malayalam[41]. Sentences are extracted from raw text then removed the special characters and stop words and performed stemming to convert word to base model.

Most of the graph based methods which are semantic graphs are shared common procedures which are data preprocessing, graph generation, graph reduction and make summary. Different researchers used different methods for each process to make a summary. For example in the graph reduction phase some researchers used machine learning methods and others used Pagerank algorithm. In graph generation phase is used not only in abstractive summarization but also used in extractive summarization[31].

Semantic graph is ontology based representation developed to be used as an intermediate representation for Natural Language Processing application[47]. But some researchers didn't use ontology in research because of unavailability[41]. Then they make assumptions like search similar words in the sentences to find similarity. So far WordNet is the popularly used ontology but it is available only for English. But other than English, Hindi language has its own ontology called Hindi WordNet[47]. Similarity measure is a difficult task without ontology. There aren't any ontology exits for business domain.

2.2.2 Evaluation Method in Text Summarization

After generating the summary it must be evaluated on the basis of the purpose of summary. For example, in our research, we should focus on whether summary gives benefit for the stock traders to carry out their trading activities. But human evaluation is an expensive and dependable method. Researchers seek common, inexpensive and reusable methods to overcome evaluation problems but this led to some more difficult questions on the evaluation field. Some researchers pointed out those kinds of difficulties[42].

1. Summary is machine generated output for a particular question. The problem is what is the meaning of the correct answer. There is a possibility to get a good summary which is a computer generated summary and it differs from any other human summary used as approximation of correct input.

2. Summarization depends on compression rate which is the amount of summary. Evaluation methods give consideration on different compression rates summary.

There are lots of evaluation methods available in the summarization field[46]. But those are easily categorized into two groups which are extrinsic evaluation and intrinsic evaluation[43]. Extrinsic evaluation methods are to determine the effect of summarization on some other tasks such as information retrieval, document summarization and question answering. Intrinsic evaluation methods evaluate summary based on quality and informativeness. Based on our study ROGUE and Pyramid methods are used by many researchers.

Recall Oriented Understudy of Gisting Evaluation(ROGUE) measures the quality of machine generated summary by counting overlapping units with human generated summaries. This method uses n-grams, word sequence and word pairs to count the overlapping. This method has some drawbacks. For example, ROGUE doesn't capture synonymous concepts, it assumes two summaries are identical which means this method is suitable for extractive summarization. Another well used method is Pyramid. Aim of this method is to show that an automatic method is a reasonable approximation of human judgments. This method concerns finding contents between two summaries instead of human judgements. Summary Content Unit(SCU) is a basic unit to evaluate the computer generated summary[45]. SCU involves semantic matching of content units to which differential weights are assigned based on their frequency in a corpus of summaries. This makes meaningful and informative evaluation.

3 Methodology and Design

3.1 Introduction

This chapter is focused on research methodology. Our research is focused on whether summarization of stock news articles is helpful for stock trading. This chapter will get us through research questions, research design and significance of each step on generating the final summary and its evaluation to identify the usefulness for the stock traders.

3.2 Research Questions

1. How to enrich the stock market investment domain in the text summarization?
2. How to carry out the summary evaluation complying with stock market investment domain?
3. How far summarized stock market investment news articles are helpful for stock traders?

3.3 Research Design

Our research design is exploratory research as we are going to study about the usefulness of summarization in stock market investment domain. We have collected news articles which are related to stock market investment from popular websites related to investment.. Then summaries of those articles are generated and evaluated to see how far it is helpful for stock traders to carry out their trading. Evaluation is based on qualitative approach as we are comparing our summary with the summary received from the domain experts who are involved in stock market investment domain or stock traders.

3.4 Research purpose

We focused on this research because most of the stock traders go through many news articles per day prior to trade. For example when a company has some unexpected change or has faced some unexpected situation, this will make an impact in the partner company stocks and its own stocks. This can be brought out immediately to the public only through digital news articles. So these news articles play a major role in the stock trading activities of the stock traders. Though much of the research is focused on stock data and algorithmic trading which is mostly based on Time series based prediction, on other side text based data are used to predict the sentiments of the traders but nothing has focused on the summarization of financial stock market investment news articles in a way for stock traders. Then with the discussion of the stock market domain experts, we came up with some of the issues they face on reading the stock market investment news article. Then this lead us to explore on how the stock news article summary will be helpful for stock traders to carry out their trading efficiently and effectively. So we planned to develop a tool for generating stock market investment news articles. This would not only helpful for the stock traders but will be helpful for the future financial researchers to initiate their research on financial stock market investment news articles.

3.5 Research Approach

To carry out the above research, first we went through some literature reviews related to information technology techniques in stock market and text summarization. In text summarization, literature review was done in the pre processing, graph based techniques as it has produced more efficient results compared to other approaches and evaluation of summarized results. In the stock market domain, literature review was done in how information technology is used in stock market data and in text data from different social media(such as twitter data related to stock market, data from stocktwits etc. Then we collected all digital news articles related to stock market investment from the website related to investment and carried out the pre processing techniques and then created graph based model and summary was generated from it. Then evaluation was done with the help of the domain experts to evaluate the output of our research.

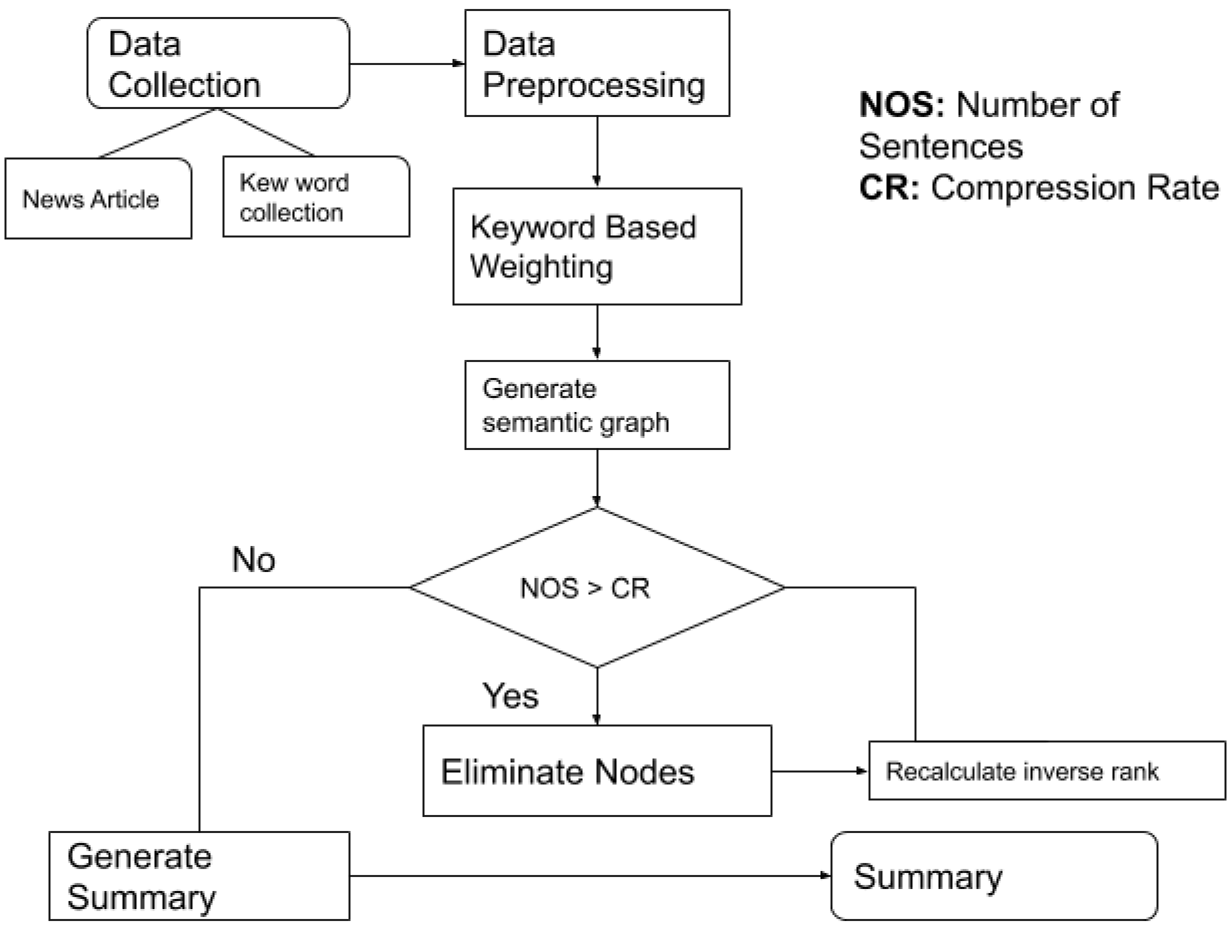

Figure 3.1 Research Approach

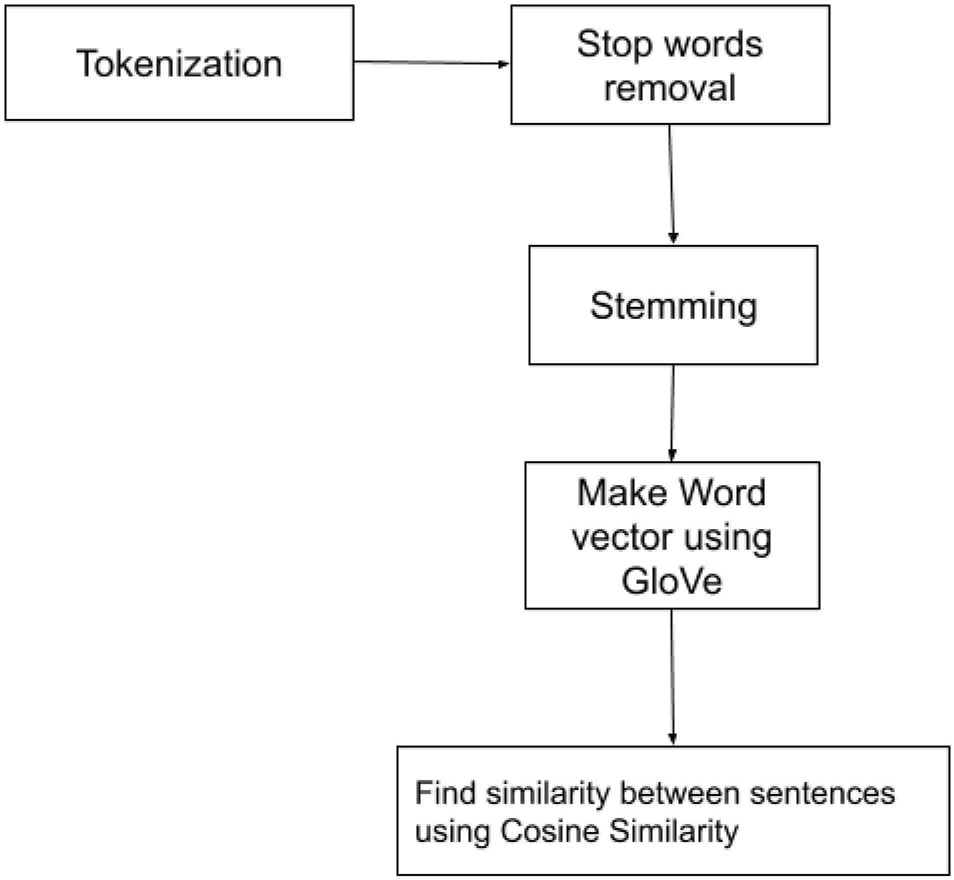

Figure 3.2 Data Preprocessing stages

3.6 Data collection

3.6.1 News article collection

We collected digital news articles related to stock market investment form the most popular investment websites which are used by stock traders frequently. Our data collection wasn't restricted to a particular country but only news articles which are enriched in stock market investment content were selected. Some of the popular sites where our data were collected are Yahoo Finance, Wall Street, Morning Star, NASDAQ, MarketWattch, Investopedia, MotleyFool, Forbes etc. These news articles were collected with the help of the domain experts in stock market investment domain.

3.6.2 Keywords collection

As our research is centered on stock market investment, according to the discussion with the stock market domain experts, News articles are read mostly through key words by stock traders. We collected keywords from the financial websites and from the domain experts. Our keywords are categorized as technical and general key words. General keywords are which are used in the financial domain and technical keywords involve which is used mostly in the stock market investment domain to determine the stock trading movement. List of keywords which are being used in our research are

These are the general keywords which are used in the stock market investment domain that is being used in the research area .

['annual', 'report', 'arbitrage', 'average', 'down', 'bear', 'market', 'beta', 'shareholder', 'strategy','sales', 'financial', 'solvency', 'buy', 'sell', 'stock', 'invest', 'share', 'trade', 'price', 'stable', 'dividend', 'fiscal', 'exchange', 'bourse', 'bull', 'broker', 'bid', 'close', 'execution', 'high', 'index', 'ipo', 'public', 'offer', 'leverage', 'low', 'margin', 'purchase', 'minimum', 'balance', 'marginal', 'account', 'open', 'order', 'portfolio', 'rally', 'quote', 'sector', 'spread', 'volatility', 'volume', 'yield', 'bottom', 'line','perform','revenue','loss', 'profit', 'grow', 'increase', 'decrease']

Technical keywords which are used in the stock market investment domain that is being used in the research are

['nikkei 225', 'forward P/BV', 'Dividend Yield', 'Penny stocks', 'Value stocks', 'Growth stocks', 'risk adjusted return', 'mean reverting', 'S&P 500', 'FTSE 100', 'MSCI Emerging markets', 'technical charts', 'moving averages', 'book value', 'EBITDA growth', 'EBITDA margin', 'all time high', 'all time low', 'price gains', 'Earnings exceeding forecasts', 'Last Twelve Months', 'intrinsic value', 'upside potential', 'stock futures']

Discussion with many stock traders would help us to get many more keywords, but due to some time constraints and project schedule, we have got only these keywords. Though we have categorized keywords as general and technical key words, for our research we have taken generally as key words.

3.7 Pre processing

3.7.1 Stopword removal

This is the pre processing technique used in many text analysis to remove the unwanted characters in the text. Python stopword removal gives us a text without any unwanted characters which makes it easy to do analysis. This helps in analysing text in the more significant content.

3.7.2 Stemming

This pre-processing technique is used to get the base word of any word to get the actual meaning of the text. For example, if we take a word such as ***increasing,*** stemming of this word will produce ***increase*** as the base word. This is much needed for our research to find the sentence which has stock keywords that we mentioned earlier. Many sentences may have different words in different tenses, to get it to the base word, we use this pre processing technique. In python, we use **PorterStemmer.**

3.7.3 Tokenizing

This is used in the pre processing as to separate the sentences in the news article. As we are going to deal with the relationship between sentences in the graph analysis and also keyword weighting for every sentence, this is much needed in our methodology to obtain efficient results.

3.7.4 Glove word vector representation

Word embedding is a common representation of words as vectors. In the early days words were represented as a Bag of Words(BoW). If the word presents in the text then BoW assigned the 1 bit to that particular word otherwise it is 0. Problem of this model is that it doesn't take into account the meaning of the word. It only shows whether a particular word exists in text or not.

Word embedding are n-dimensional vectors of real values that are built with a large corpus of plain text. One of the main characteristics of word embedding that make it special is the capability of keeping a relative meaning of the words. Word embedding can be learned by two most popular methods which are Word2Vec and GloVe. Word2Vec is one of the most popular techniques to learn word embeddings using shallow neural network. Hindocha, E., Yazhiny, V., Arunkumar, A., & Boobalan presented evidence that GloVe has overpreformed Word2Vec on the basis of semantic information[50].

GloVe is a more sensitive tool to identify relationships between words. For example, man and woman are similar words in the context of human domain and those are opposite words in the gender context. This relationship graphically explained in Figure 3.1. GloVe is designed in order that such vector differences capture as much as possible the meaning specified by the juxtaposition of two words. The GloVe model is trained on the non-zero entries of a global word-word co-occurrence matrix, which tabulates how frequently words co-occur with one another in a given corpus.

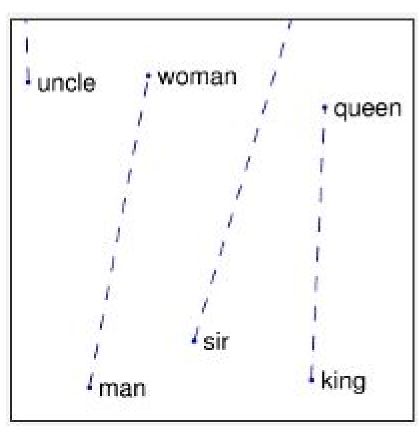

Figure 3.3:"man-woman" words and their neighbours

3.7.5 Cosine similarity

It is used to identify the syntactic similarity between sentences. We used cosine similarity as it has generated better results in finding the semantic similarity between the sentences too. It can be considered as the dot product of their vector representation. Sentences can be represented in vector in different ways. In our research we are using the Glove word vector representation. After finding similarity of each sentence with other sentences, adjacency matrix will be constructed to get a numerical score of the similarity between sentences. In the following adjacency matrix, we can see the similarity between the score as 0. When we weight the sentences with the keywords, value will be changed. Figure 3.4 shows a similarity matrix.

	0	1	2	3	4	5
0	0	0.851607	0.792462	0.823224	0.859356	0.848539
1	0.851607	0	0.937557	0.952669	0.858333	0.908173
2	0.792462	0.937557	0	0.924858	0.790962	0.873995
3	0.823224	0.952669	0.924858	0	0.853766	0.908186
4	0.859356	0.858333	0.790962	0.853766	0	0.880939
5	0.848539	0.908173	0.873995	0.908186	0.880939	0

Figure 3.4 Similarity matrix between sentences before adding keyword based weighting.

If we take a small example of how it computes the value.

John had dinner last night with me.

Jane had lunch with john yesterday.

John	1	0
Jane	0	1
Had	1	1
Last	1	0
Night	1	0
Lunch	0	1
Yesterday	0	1
Me	1	1

s1=[1,0,1,1,1,0,0,1]   s2=[0,1,1,0,0,1,1,1]

Then both sentence vectors will be created in the following way and cosine angle between these two vectors are calculated. In our research we used cosine similarity and was able to identify the adjacency similarity between those sentences.

3.7.6 Sentence weighting with keywords

This is the part which we used to enhance the stock market investment domain in our research. As we described in the data collection, all the keywords which we collected were used in this part to give additional weight to every sentence with stock key words to increase the priority of those sentences. Though there will be semantic similarity between the sentence, addition of this weight also will be integrated into the graph to obtain sentences with more domain relevancy.

For example, if a sentence consists of 3 key words and the total number of keywords in the whole document is **n.** If we weigh the sentence, we can weigh the sentence as **3/n.** This weight is integrated with nodes in a graph. Now we can see in the below figure, after adding weight for the sentences with keywords, we can see the value changing from 0 to other values. There will be a value change only in the sentences which have the keywords. Figure 3.5 shows a similarity matrix after keyword based weighting.

Index of Sentences

	0	1	2	3	4	5
0	0.4	0.851607	0.792462	0.823224	0.859356	0.848539
1	0.851607	0.8	0.937557	0.952669	0.858333	0.908173
2	0.792462	0.937557	0.4	0.924858	0.790962	0.873995
3	0.823224	0.952669	0.924858	0.8	0.853766	0.908186
4	0.859356	0.858333	0.790962	0.853766	0.4	0.880939
5	0.848539	0.908173	0.873995	0.908186	0.880939	0.4

Index of Sentences

Figure 3.5 Similarity Matrix after keyword based weighting

3.8 Graph Analysis

After constructing an adjacency matrix from the cosine similarity, this adjacency matrix will be converted into a fully connected graph. Fully connected graph is where each and every node will be connected to other nodes in a graph. In graph each sentence is represented as a node while edge is represented as a relationship between nodes. Similarity scores will be represented as weight of edges. In addition to weight edges, some node(sentence) with stock keywords will have additional weights to it. Below figure 3.6 shows the generated graph of a stock market investment news article.

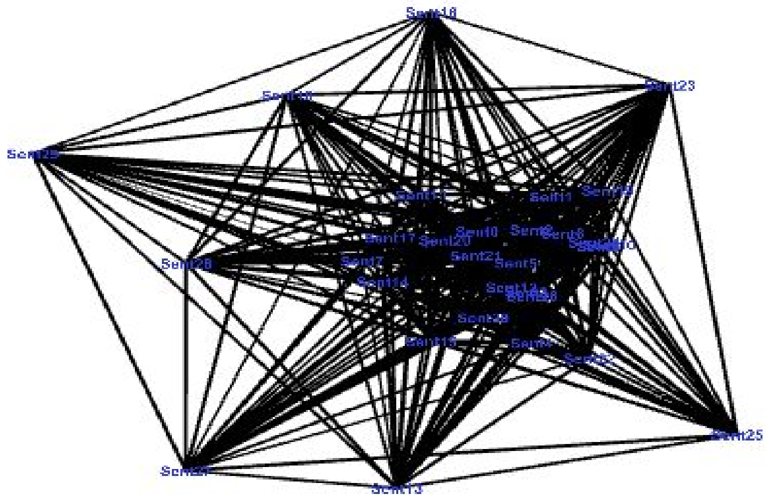

Figure 3.6 Semantic Graph

3.9 Summary Generation

After the graph creation, the total weight of the incoming edges to the node is added and it is represented as 1/n where n represents the total weight of the node. Then least weight node is removed iteratively until the fraction of the total sentences that is needed for our summary. Initially we tried 0.25 as a fraction and then we tried with 0.5 as a fraction. With 0.25, we wouldn't be able to get effective results comparing our summaries with the summaries of our domain experts. So we moved onto 0.5, this helped us in retrieving the effective summaries.

If we take a sample document with 8 sentences, where each sentence will be linked with every other sentence with their similarity scores. With similarity scores, each node will also have an additional score if it possesses keywords which we have mentioned earlier. Figure 3.7 shows the graph.

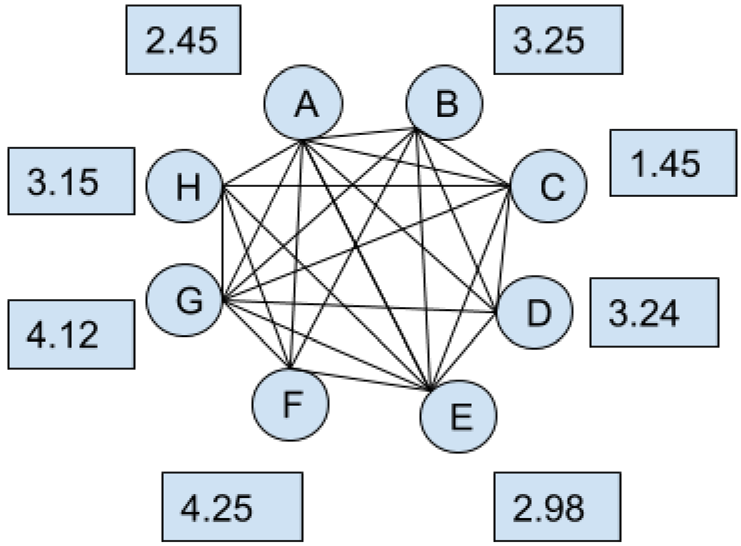

Figure 3.7 Before eliminating the node.

In phase 1, Node C is with the least score was removed in the second phase. When we removed that node, subsequent inverse scores of each node too were also changed. Figure 3.8 shows the graph after eliminating the node.

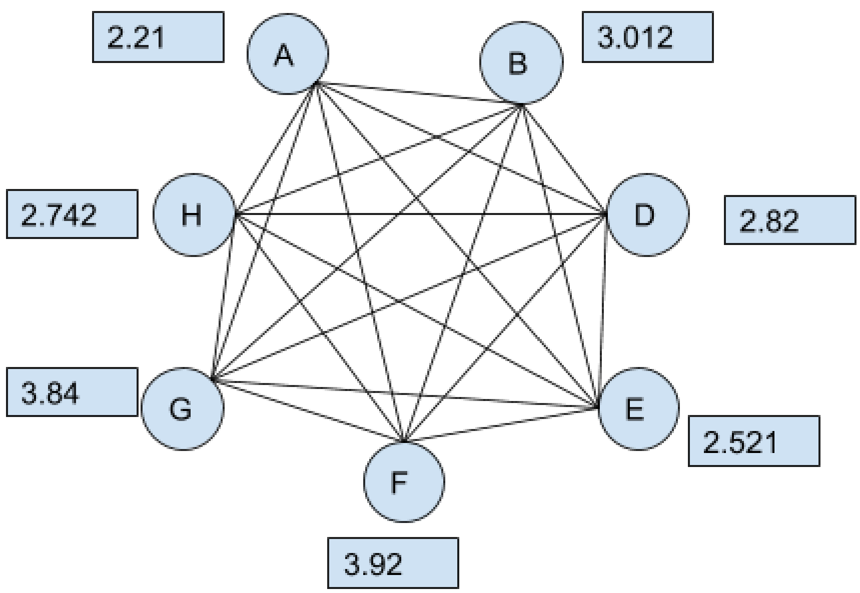

Figure 3.8: After eliminate the node from the graph

Similarly, we keep on iterating until we get our needed fraction of our summary. This is how our graph analysis is performed to retrieve the salient sentences which will be useful for the stock traders.

3.10 Evaluation

We have done evaluation for 14 documents. As our research is to check whether the summarized stock market investment related news article is useful for stock trader, we carried out evaluation manually. We chose 6 people as domain experts.They are working in the financial domain in the stock market and some people are involved in stock trading activity.

<u>Approach 1</u>

Step 1: We gave the news articles to domain experts and let them to highlight the important sentences which are most important for stock traders.

Step 2: Generated the summary of those news articles in our model

Step 3: Identified the number of sentences which are matching in both summaries out of the summary given by domain experts.

Step 4: Calculate the percentage of accuracy

$$\text{Percentage of Accuracy} = \frac{\text{No. of matching sentences in both summaries(Domain Expert and Model)}}{\text{No. of sentences in domain expert summary}} \times 100$$

We have attached the news articles, summary generated by our model, summary generated by domain experts and percentage of accuracy of the generated summary in the results chapter below. List of people from whom the summaries of stock market investment news articles were obtained are

Name of the people who has given summaries	**Current Job**
Raguram Raamakrishnan	Manager Equity Research at NDB
Atchuthan Srirangan	Research for Investments at First Capital Holding
Chamil Senaratne	Stock trader for more than 4 years (Reading PhD)
Thenuwaran Indrasenan	Senior Investment Analyst, Assurance, Economics at New South Wales government
Vijinthini Prabakaran	Senior Assistant Director at the Central Bank of Sri lanka.

Table 3.1 Domain Experts and their qualifications

Approach 2

Another approach we carried in evaluation is providing the summary generated by the model to some domain experts and let them rate(in percentage) “how far the summary generated by our model is useful for them to carry out their trading activities”.

4 Results

Our focus of the research is to identify how far the summarization of stock market investment news articles will be helpful for stock traders. We identified whether our generated model is successful or failure by using the above evaluation method with the help of the domain experts. We were able to get more than 50% of accuracy for the summary generated by our model from the 15 documents from different domain experts in the stock market investment domain.

News Articles	Percentage of accuracy(**fraction of summary=0.5**)
European stocks climb as ‘phase one’ trade deal boosts sentiment; Stoxx 600 hits record high	55%
Stocks rise as investors cheer preliminary U.S.-China trade deal	60%
Sri Lanka announces tax reliefs; cuts VAT to 8-pct, removes PAYE, WHT & Capital Gains Tax	80%
Sri Lankan bonds slammed by new govt's aggressive tax cuts	60%

13 stocks gain, 51 stocks decline amid high retail investor activity	90%
Buy Amazon (AMZN) Stock on the Dip Before a 2020 Rally?	66%
Microsoft (MSFT) Outpaces Stock Market Gains: What You Should Know	55%
A Downgrade for This Vanguard Bond Fund	60%
Apple stock dips after Credit Suisse says iPhone shipments drop 35% in China	70%
This new trend in house selling could cast a cloud over America's property market	80%
What Impeachment Could Mean for the Stock Market	60%
Alibaba Stock Still Has Lots of Room to Rise. Analyst Sees a 44% Gain.	60%

Walmart Beats Earnings, Stock Fails at a Risky Level	60%
US STOCKS-Wall St at record levels after U.S. extends Huawei reprieve	40%

Table 4.1 News articles and their accuracy

European stocks climb as 'phase one' trade deal boosts sentiment; Stoxx 600 hits record high

The pan-European Stoxx 600 added 1.1% by mid-morning to surpass 416.6 and hit an all-time high. Basic resources led the way with 2.3% gains as all sectors and major bourses entered positive territory. Banks and financial services stocks climbed 1.4% and 1.5% respectively. Washington and Beijing announced on Friday that an agreement had been reached pending legal procedures, a significant step forward after a bruising 18-month trade war. However, questions have been raised by market participants over some details of the deal which remain hazy, notably the scale of agricultural purchases and the prospect of China balancing bilateral trade flows. U.S. Treasury Secretary Steven Mnuchin told CNBC on Saturday that the deal would be signed in early January and that phase two may then be negotiated in stages. Asian stocks were mixed Monday with mainland Chinese stocks jumping on the back of better-than-expected industrial output data, while indexes in Japan and Hong Kong edged downwards. Back in Europe, British Prime Minister Boris Johnson will welcome 109 new Conservative lawmakers to parliament on Monday, promising to move forward swiftly with Brexit and to increase funding to the National Health Service (NHS). In corporate news, Reuters reported Sunday that China's BAIC plans to double its stake in German automaker Daimler in a bid to win a board seat and challenge rival Geely. On the data front, IHS Markit euro zone flash composite PMI estimates for December was recorded in line with expectations at 50.6, with service sector outperformance offsetting more disappointing manufacturing numbers. Manufacturing PMIs came in at 45.9 against a forecast of 47.3, down from 46.9 in November. U.K. flash readings showed that both the services and manufacturing sectors had declined more sharply than expected in December. Composite PMI came in at 48.5, its lowest level since mid-2016, suggesting the world's fifth-largest economy is on course to contract in the fourth quarter

Stocks on the move

British American Tobacco (BAT) shares were up 4.4% by mid-morning along along with price comparison site Moneysupermarket. Electrolux shares plummeted 11.7% after the Swedish home appliance company issued a profit warning owing to the costs of its U.S. manufacturing transition. Tullow Oil tumbled 14.2% as the British energy giant continues to be blighted by problems with its Ghanaian operation. Shares of Italian banks edged higher across the board after the government approved a bailout of unlisted co-operative lender Popolare Di Bari.

Summary provided by Raguram

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- Shares of Italian banks edged higher across the board after the government approved a bailout of unlisted co-operative lender Popolare Di Bari.

Summary provided by our model

- The pan-European Stoxx 600 added 1.1% by mid-morning to surpass 416.6 and hit an all-time high.
- Banks and financial services stocks climbed 1.4% and 1.5% respectively.
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- Shares of Italian banks edged higher across the board after the government approved a bailout of unlisted co-operative lender Popolare Di Bari.

Results= 50% for 50% extraction

Stocks rise as investors cheer preliminary U.S.-China trade deal

LONDON (Reuters) - World stock markets rose on Monday, trading a notch below a record high hit last week on the back of a preliminary trade deal agreed between the United States and China. European shares built on the previous week's gains at the open. In early deals, the pan-European STOXX 600 index was up by 1% and hit a record high. Germany's DAX rose 0.5%. Britain's

FTSE 100 index was up 1.14%, moving in tandem with the pound which rose 0.4%. U.S. stock futures also pointed to stronger gains to start the week, with the S&P 500 e-minis up 0.3%. U.S. Trade Representative Robert Lighthizer said on Sunday a deal was "totally done", notwithstanding some needed revisions, and would nearly double U.S. exports to China over the next two years. The "phase one" agreement suspended a threatened round of U.S. tariffs on a $160 billion list of Chinese imports that was scheduled to take effect on Sunday. The United States also agreed to halve the tariff rate, to 7.5%, on $120 billion worth of Chinese goods. The 17-month-old trade dispute between the world's two largest economies has roiled financial markets and taken a toll on world economic growth. German private sector activity shrank for the fourth month running in December as a downturn in manufacturing offset services sector growth in Europe's largest economy, a survey showed, although it was taken before news of the trade deal. French business grew at a steady pace in December despite a nationwide strike against pension reform, although activity in the manufacturing sector came unexpectedly close to stagnating. Positive sentiment helped push MSCI's All Country World Index up 0.15%. The index, which tracks stocks across 47 countries, hit an all-time high on Friday when the trade deal was agreed. "We may have reached the point of 'peak tariffs' and this deal could be the start of a series of phased rollbacks, which could unlock further upside for equity markets, driven by an improvement in business confidence and a recovery in investment," said Mark Haefele, chief investment officer, UBS Global Wealth Management in a note to clients. Earlier in Asia, MSCI's broadest index of Asia-Pacific shares outside Japan to its highest level since April 18. It was last up 0.13%. Australia's S&P/ASX 200 led the way as it jumped 1.63%, while shares in Taiwan added 0.22%. Japan's Nikkei 225 succumbed to some profit-taking, falling 0.29% after surging 2.55% to a 14-month closing high on Friday. Ryan Felsman, senior economist at CommSec in Sydney, said the trade deal and the receding risk of a disorderly Brexit after the British election produced a strong Conservative majority provided support for sentiment in Australia. A lower-than-expected Australian budget surplus due to a sluggish economy has also "built expectations by markets for further easing from the Reserve Bank (of Australia)," he said. Chinese investors initially had a more tepid reaction to the trade news, with the blue-chip CSI300 index struggling to rise further after trade hopes fanned a near 2% rise on Friday. But after a lackluster morning session, the CSI300 index turned higher in the afternoon and was last up 0.3%, helped by data showing the country's industrial output growth and retail sales jumped more than expected in November. Felsman at CommSec said investors wanted more details and the reduction in U.S. tariffs may have disappointed some looking for more aggressive action. "Certainly there were expectations perhaps that the rollback would be more significant than just 50%," he said.

U.S. shares had struck a cautious note on Friday, paring initial gains to end barely higher as weary investors awaited signs of a concrete deal. However, the news of a deal was still enough to send the S&P 500 to a record closing high of 3,168.8, up 0.01%. The Nasdaq Composite added 0.2% to end at 8,734.88, also a record, and the Dow Jones Industrial Average rose 0.01% to 28,135.38. U.S. Treasury yields moved higher on Monday, reflecting a more positive mood. Benchmark 10-year Treasury notes rose to 1.8452% compared with their U.S. close of 1.821% on Friday, and the two-year yield touched 1.6304% compared with a U.S. close of 1.604%. The dollar was slightly higher against the yen at 109.45 and the euro was up 0.13% at $1.1135. The dollar index, which tracks the greenback against a basket of six major rivals, was down 0.17% at 97.006. Oil prices, which had risen on Friday following the deal, climbed further on Monday. Brent crude rose 0.1% to $65.28 per barrel, and U.S. West Texas Intermediate crude was down 0.05% at $60.11 per barrel. Spot gold prices were down 0.06% at $1,474.64 per ounce.

Summary provided by Raguram

- World stock markets rose on Monday, trading a notch below a record high hit last week on the back of a preliminary trade deal agreed between the United States and China.
- Britain's FTSE 100 index was up 1.14%, moving in tandem with the pound which rose 0.4%.
- U.S. stock futures also pointed to stronger gains to start the week, with the S&P 500 e-minis up 0.3%.

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Summary provided by our model

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- "Certainly there were expectations perhaps that the rollback would be more significant than just 50%," he said.
- The dollar was slightly higher against the yen at 109.45 and the euro was up 0.13% at $1.1135.

Results=60% for 50% summary extraction.

Sri Lanka announces tax reliefs; cuts VAT to 8-pct, removes PAYE, WHT & Capital Gains Tax

Nov 27, 2019 (LBO) – Sri Lanka's new Cabinet of Ministers has given its approval to reduce Value Added Tax (VAT) and various other taxes, Co-Cabinet Spokesperson Minister Bandula Gunawardana said. "Required amendments and gazette notifications are currently being prepared," Gunawardana told reporters. "This will be a stimulus to all areas of the economy and it will allow us to widen the current tax base as well. We need to increase the non-tax revenue in the future." Accordingly, the current VAT rate of 15 percent and 2 percent of NBT will be collectively reduced to 8 percent. The new VAT rate will be applicable from next month. The Tax-free threshold for VAT has also been raised to 25 million rupees turnover per month from the existing one million rupees. The VAT on banking, financial services and insurance to be maintained at 15 percent and the income from agriculture, fishing & livestock to be made income tax free. Capital Gains Tax, VAT on condominiums, Nation Building Tax on domestic production, Economic Service Charge, Bank Debit Tax, Pay as You Earn Tax and Withholding Tax on interest has been removed. The Cabinet has also decided to reduce the telecommunications levy by 25 percent and the income tax on the construction industry from 28 percent to 14 percent.

The Cabinet announced that all religious places are exempted from taxes. Workers' remittances have also been exempted from income tax. IT and enabling services to be made tax free. Tourism business will be treated as export for zero rates provided that 60 percent of the turnover is sourced from local suppliers. These decisions were taken during the first Cabinet meeting of the newly formed government held this morning at the Presidential Secretariat.

Summary provided by Chamila

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Results=80% for 50% extraction

Sri Lankan bonds slammed by new govt's aggressive tax cuts

Sri Lanka's benchmark government bonds slumped to their worst- ever week on Friday, after the new government's move to immediately slash value-added tax (VAT) and other major taxes stoked worries about the cost of plans. Dollar-denominated bond due to be paid back in 2027 and 2028 fell for the eighth straight session between 3.4 cents and 4.1 cents, taking them from roughly 96 cents on the dollar to around 90 cents and pushing yields up to 8% from 6.8%. LK180520376=, LK161142611= In its first week of office, the new Sri Lanka Podujana Peramuna (SLPP) government led by former civil wartime defence chief Gotabaya Rajapaksa, has cut VAT from 15% to 8%, reduced some corporate taxes, scrapped a 'nation-building' tax and a PAYE tax on wages, and introduced a zero tax rate for tourism sectors which source 60% of inputs locally. Analysts at Citi calculated the VAT cut alone could cost 200 billion Sri Lankan rupees ($1.11 billion), or 1.3% of the country's GDP, while the overall package of cuts would significantly widen the gap between revenues and expenditure. "We are forecasting the budget deficit at about 5.8% of GDP in 2019, but the annual deficit run-rate could approach closer to 7% of GDP in the 1H20 barring corrective fiscal measures," they said in a note to clients. The changes are also likely to add pressure to the country's lowly 'B' sovereign credit rating, with both S&P Global and . Fitch both already warning about fiscal loosing in recent weeks.

Sri Lanka's debt-to-GDP ratio is currently around 75% but was expected to gradually subside in coming years. "While we highlighted fiscal risks given the tax-cut filled campaign policies in Gota's manifesto, we weren’t sure how much would be carried out given fiscal constraints. We underestimated their political resolve," the Citi note said

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Results=60% for 50% extraction

13 stocks gain, 51 stocks decline amid high retail investor activity

The improvement of the external sector performance, local exports, lower interest rates and decrease of imports have created some positive investment sentiment. Due to that the retail market participation in stock trading improved significantly during the last few days, stock market analysts said yesterday.The Sri Lanka rupee has appreciated by 4.1 percent against the US dollar during the year up to 17 July 2019, latest External Sector Performance report of the Central Bank of Sri Lanka outlines also helped the stock market in a conducive manner, market sources said. Foreign investments in the government securities market recorded a net outflow of US dollars 64 million in May 2019.

Amid those developments Colombo's All Share Price index (ASPI) closed 38.83 points up at 5,684.48.The S&P SL20 index of more liquid stocks closed 1.40 percent or 37.73 points up at 2,732.26.

The market turnover stood at Rs 391.7 million with two crossings with 113 stocks gaining and 51 stocks declining amid high retail investor activity. Those crossings were Melstacope, which crosses one million shares to the tune of Rs 45 million per share value Rs 45 and TJ Lanka 1.2 million shares crossed for Rs 45 million per share value Rs 37.50.

In the retail market companies that mainly contributed to day's turnover were Dialog Rs 99.9 million (9.1 million shares traded), Softlogic Rs 41.1 million (2.8 million shares traded), BIL Rs 33.16 million (15.2 million shares traded), Sampath Bank Rs 32.8 million (215,000 shares traded) and HNB Rs 24.4 million (171,000 shares traded), During the day 1.9 million share volumes changed hands in 8694. Further stocks closed 0.69 percent higher yesterday on buying interest in John Keells Holdings, Dialog Axiata and Ceylon Cold Stores, provisional data showed.

John Keells Holdings closed Rs 2.90 up at Rs 151.00 a share, Dialog Axiata gained 40 cents to Rs 11.10 a share and Colombo Cold Stores was Rs 30.00 up at Rs 600.00 a share, pushing the ASPI up.

On a cumulative basis, net outflows in the government securities market amounted to US dollars 90 million during the first five months of the year.

Foreign investments in the CSE, including primary and secondary market transactions, recorded a net **inflow of US dollars 3.7 million during the month of May 2019.**

On a cumulative basis, the CSE recorded a net outflow of US dollars 20 million in the first five months of 2019.

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Results=90% for 50% extraction

Buy Amazon (AMZN) Stock on the Dip Before a 2020 Rally?

Before a 2020 Rally?

Amazon AMZN stock has fallen 6% in the past six months, while the S&P 500 has climbed 9% and fellow FAANG stocks Apple AAPL, Alphabet GOOGL, and Facebook FB have all surged over 15%. Wall Street has pulled back from the e-commerce powerhouse over profits concerns.

The downturn came as Amazon invested heavily in its one-day shipping program for Prime members as it fights back against Walmart WMT and other traditional brick and mortar retailers who have found success in the e-commerce age. This brings us to the question: Is now the time to buy Amazon stock on the dip heading into 2020?

What's Going On?

Amazon made headlines to start the week after it said that President Trump put "improper pressure" on the Pentagon to assure that the Joint Enterprise Defense Infrastructure contract, worth $10 billion over the next decade, would not go to the Seattle firm. The JEDI contract instead went to Jeff Bezos' cloud rival Microsoft MSFT.

The contract itself doesn't mean that much for a company that is projected to pull in $280 billion in sales this year. Therefore, we won't linger over the seemingly political dispute.

More importantly, Amazon has slipped recently because investors are worried about its profits and slowing top-line growth. Last quarter, Amazon posted its first year over year quarterly earnings decline since 2017, with its adjusted EPS figure down 26% from Q3 2018—which also fell short of our Zacks estimates. This came after AMZN missed bottom-line estimates in the second quarter, where it also ended its streak of record quarterly profits.

As we mentioned at the top, Amazon's profits dipped during Q3 because it spent significantly to introduce one-day shipping. AMZN's world-wide shipping costs soared 46% to $9.6 billion from a year earlier. These efforts are expected to help the firm long-term and fight back against the likes of Walmart, Target TGT, Costco COST, and others who have all bolstered their e-commerce and delivery options.

Amazon's CEO also noted that the transition means that products will ship from "fulfillment centers very close to the customer," which could help lower costs down the road. "Customers love the transition of Prime from two days to one day—they've already ordered billions of items with free one-day delivery this year. It's a big investment, and it's the right long-term decision for customers," Bezos said in prepared Q3 remarks.

Meanwhile, Amazon's high-margin cloud computing business, known as Amazon Web Services, saw its revenue surge 35%. This did mark a slowdown compared to recent periods of growth. The firm's advertising-heavy "other" division helped make up for the slowdown, with sales up 45%. Plus, AMZN is projected to grab the third-largest share of U.S. digital ad dollars in 2019, behind only Google and Facebook.

Other Fundamentals

AWS' continued success has helped the company expand further into everything from logistics to pharmaceuticals. Amazon is also prepared to compete for years against the likes of Netflix NFLX and Disney DIS in the streaming TV age and it boasts its own Spotify SPOT competitor.

Investors can see in the chart above that AMZN stock has outpaced its Electronic Commerce Market over the past three years, up 130% against its industry's 76% average climb. This gap, however, has narrowed over the last year, where Amazon stock has now fallen behind the S&P 500 in 2019—16% vs. 24%.

Amazon shares, which are trading at $1,738, currently rest below both their 50 and 200-day moving averages. This is not a place that AMZN stock likes to hang out for too long. Therefore, with AMZN trading roughly 15% below its 52-week highs the stock could be due for a climb.

As one might expect, AMZN's recent downturn has created a more favorable valuation picture. Amazon is currently trading at 2.6X forward 12-month sales estimates. This marks a discount against its industry's 3.5X average and its own two-year median of 2.9X and 3.7X high.

Summary provided by Thenuwaran

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- Wall Street has pulled back from the e-commerce powerhouse over profits concerns.
- The JEDI contract instead went to Jeff Bezos' cloud rival Microsoft MSFT.
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- More importantly, Amazon has slipped recently because investors are worried about its profits and slowing top-line growth.
- This came after AMZN missed bottom-line estimates in the second quarter, where it also ended its streak of record quarterly profits.
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Results 66% for 50% extraction

Microsoft (MSFT) Outpaces Stock Market Gains: What You Should Know

Microsoft (MSFT) closed at $151.70 in the latest trading session, marking a +0.38% move from the prior day. This change outpaced the S&P 500's 0.29% gain on the day. At the same time, the Dow added 0.11%, and the tech-heavy Nasdaq gained 0.44%. Heading into today, shares of the software maker had gained 2.76% over the past month, outpacing the Computer and Technology sector's gain of 1.17% and the S&P 500's gain of 1.51% in that time. Wall Street will be looking for positivity from MSFT as it approaches its next earnings report date. The company is expected to report EPS of $1.32, up 20% from the prior-year quarter. Meanwhile, our latest consensus estimate is calling for revenue of $35.70 billion, up 9.96% from the prior-year quarter. For the full year, our Zacks Consensus Estimates are projecting earnings of $5.35 per share and revenue of $140.11 billion, which would represent changes of +12.63% and +11.34%, respectively, from the prior year. Any recent changes to analyst estimates for MSFT should also be noted by investors. These revisions typically reflect the latest short-term business trends, which can change frequently. With this in mind, we can consider positive estimate revisions a sign of optimism about the company's business outlook. Our research shows that these estimate changes are directly correlated with near-term stock prices. We developed the Zacks Rank to capitalize on this phenomenon. Our system takes these estimate changes into account and delivers a clear, actionable rating model.

The Zacks Rank system, which ranges from #1 (Strong Buy) to #5 (Strong Sell), has an impressive outside-audited track record of outperformance, with #1 stocks generating an average annual return of +25% since 1988. The Zacks Consensus EPS estimate has moved 0.11% higher within the past month. MSFT currently has a Zacks Rank of #2 (Buy). Digging into valuation, MSFT currently has a Forward P/E ratio of 28.24. For comparison, its industry has an average Forward P/E of 31.07, which means MSFT is trading at a discount to the group. We can also see that MSFT currently has a PEG ratio of 2.37. This popular metric is similar to the widely-known P/E ratio, with the difference being that the PEG ratio also takes into account the company's expected earnings growth rate. MSFT's industry had an average PEG ratio of 2.19 as of yesterday's close.

The Computer - Software industry is part of the Computer and Technology sector. This industry currently has a Zacks Industry Rank of 60, which puts it in the top 24% of all 250+ industries. The Zacks Industry Rank includes is listed in order from best to worst in terms of the average Zacks Rank of the individual companies within each of these sectors. Our research shows that the top 50% rated industries outperform the bottom half by a factor of 2 to 1.

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Results 50% for 50% extraction

A Downgrade for This Vanguard Bond Fund

Vanguard GNMA is losing an experienced contributor, but it's thoughtful and risk-aware approach to the agency mortgage markets remains compelling. This is enough to award the strategy’s cheapest share class a Morningstar Analyst Rating of Silver, while its more expensive share class earns a Bronze rating. After two decades contributing to this Wellington-subadvised strategy, long-tenured lead manager Michael Garrett will retire in June 2020. In 2012, Garrett selected Brian Conroy, a former bond trader, as an agency mortgage analyst here; in mid-2019, Conroy was formally appointed to the portfolio management roster along with Joe Marvan, a senior fixed-income markets generalist at the firm. Though a structured finance analyst, two traders, and two quants are identified as further contributors here, relative to peers, this team is both thinly staffed and, without Garrett, a rather fresh configuration. The team employs a value-leaning approach and selects bonds that look cheap relative to their likely cash flows, primarily focusing on GNMA mortgage pass-throughs. Fannie Mae- and Freddie Mac-backed fare (around 16% of assets as of September 2019) function as modest out-of-benchmark allocations along the portfolio’s periphery. As of September 2019, roughly 75% of holdings were GNMA securities--around 10 percentage points lower than the year prior--as the team found more-attractive valuations in Fannie Mae- and Freddie Mac-backed fare. The strategy’s steadfastness has paid off over time. For instance, it performed comparatively well in2008's risky credit markets, when some of its more adventurous peers fell behind. Over the 15-year period ended October 2019, the strategy’s investor share class delivered an annualized 4.0% and topped 85% of a subgroup of distinct mortgage-focused peers in its intermediate government Morningstar Category; it also kept pace with its Bloomberg

Barclays U.S. GNMA Bond Index. Of note here, rock-bottom fees translate to a persistent edge relative to peers that must clear a higher performance hurdle.

Process|Above Average|by Emory Zink Nov 26, 2019

A disciplined and risk-conscious approach to this agency mortgage-centric mandate justifies an Above Average Process rating. Comanagers Michael Garrett and Brian Conroy primarily stick to buying GNMA mortgage pass-throughs, which come with an explicit U.S. government guarantee. The strategy will also hold small allocations to mortgages backed by Fannie Mae and Freddie Mac or U.S. Treasuries when GNMA pass-throughs start to look relatively expensive. Such exposures usually make up 10%-15% of assets combined. The team avoids more-esoteric

fare, such as interest-only mortgage derivatives, which are more sensitive to prepayment risk. The strategy's duration is kept within a half year ofthe Bloomberg Barclays U.S. GNMA Bond Index, but on occasion the team has shortened or lengthened it by more than a year than that benchmark when it believes the environment merits the positioning. The team also actively calibrates the portfolio's prepayment risk profile, which is where its careful evaluation of macroeconomic factors and government policies and bottom-up assessment of underlying loan characteristics come into play.At times, Treasury futures or mortgage TBAs (a type of forward agreement used to gain generic exposure to various coupons and collateral) are employed when the team thinks these are priced attractively relative to
cash bonds.

The comanagers stick to the strategy's mandate, resulting in a portfolio overwhelmingly dedicated to GNMA mortgage pass-throughs with modest allocations to Fannie Mae- or Freddie Mac-backed mortgage bonds when they present a good value. As of September 2019, roughly 75% of holdings were GNMA securities--10 percentage points lower than the year prior--as the team found more-attractive valuations in Fannie Mae- and Freddie
Mac-backed fare. Though the team reduced its exposure to Fannie Mae delegated underwriting and servicing bonds to 3% from 6% over that period, as spreads tightened on those holdings, Michael Garrett and Brian Conroy took the opportunity to rotate into agency collateralized mortgage obligations that it viewed as having a better convexity profile. Around a percentage point of Freddie Mac seasoned credit-risk transfer securities also debuted in the portfolio. The team extensively models prepayment risk and selects securities that are priced attractively relative to their projected cash flows. Over time, the strategy has used a mix of TBAs and mortgage pass-through securities, adjusting allocations depending on relative valuations. The portfolio's average duration of 2.6 years in late 2019 ran modestly longer than the bogy's 2.5 years. The Vanguard Group entered a new era in early 2019 with the passing of its founder and conscience, John C. Bogle. Unlike its mid-1970s origins, when outflows were the norm and its survival was in question, Vanguard now wears the crown as the world's biggest retail asset manager. More than 90% of its USD 5.6 trillion in global assets under management, as of June

2019, are in the United States; but the firm has designs to grow its non-U.S. business, especially in the United Kingdom, Australia, Canada, Japan, China, and Mexico. Vanguard gained its stature by following Bogle's playbook: pairing relatively predictable strategies, both passive and active, with minimal costs. That's enriched Vanguard's investors, and those outside its flock who have benefited from industrywide fee compression. While Vanguard's passive business now faces stiff price competition from its biggest rivals, inflows into its U.S. strategies still dominate. Not content, Vanguard aims to transform investment advice, too. In May 2015, it launched Personal Advisor Services, a burgeoning discretionary asset-management business that pairs automation and human advice; and in September 2019 it disclosed plans to launch a digital-only counterpart. Vanguard's industry leadership readily merits a High Parent rating, but the firm must stay on its guard to prioritize investor interests over merely expanding its kingdom.

Performance

A record of deft mortgage-pool selection contributes to a compelling long-term performance profile on this strategy. Over the trailing 15 years ended October 2019, the strategy's Investor share class returned an annualized 4.0% and topped 85% of a subgroup of distinct mortgage-focused peers in its intermediate government category; it also kept pace with its Bloomberg Barclays U.S. GNMA Bond Index. In a category where differences in performance may come down to a handful of basis points, the strategy's low price tag provides a reliable advantage versus peers with higher price hurdles, enabling the team to deliver competitive returns with less risk. Over the aforementioned period, the strategy's risk-adjusted returns (as represented by its Sharpe ratio) have landed in the best quartile of that distinct peer group. The strategy's conservative approach helps it avoid potholes that trip up rivals trafficking in more-esoteric fare. It gained more than 7% in both 2007 and 2008, landing in the best third of its distinct mortgage-focused subgroup, as the financial crisis laid low credit-sensitive, nonagency residential and commercial mortgage-backed bonds held by more-adventurous peers. Through recent interest-rate shocks (the second half of 2016 and first 10 months of 2018), the portfolio held up better than its typical rival.

Price

It’s critical to evaluate expenses, as they come directly out of returns. The share class on this report levies a fee that ranks in its Morningstar category’s cheapest quintile. Based on our assessment of the fund’s People, Process and Parent pillars in the context of these fees, we think this share class will be able to deliver positive alpha relative to the
category benchmark index, explaining its Morningstar Analyst Rating of Silver.

Summary provided by Atchuthan

- As of September 2019, roughly 75% of holdings were GNMA securities--around 10 percentage points lower than the year prior--as the team found more-attractive valuations in Fannie Mae- and Freddie Mac-backed fare.
- Over the 15-year period ended October 2019, the strategy’s investor share class delivered an annualized 4.0% and topped 85% of a subgroup of distinct mortgage-focused peers in its intermediate government Morningstar Category; it also kept pace with its Bloomberg Barclays U.S. GNMA Bond Index.
- The strategy will also hold small allocations to mortgages backed by Fannie Mae and Freddie Mac or U.S. Treasuries when GNMA pass-throughs start to look relatively expensive.
- Such exposures usually make up 10%-15% of assets combined.
- The team also actively calibrates the portfolio’s prepayment risk profile, which is where its careful evaluation of macroeconomic factors and government policies and bottom-up assessment of underlying loan characteristics come into play.

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Summary provided by our model

- This is enough to award the strategy's cheapest share class a Morningstar Analyst Rating of Silver, while its more expensive share class earns a Bronze rating.
- After two decades contributing to this Wellington-subadvised strategy, long-tenured lead manager Michael Garrett will retire in June 2020.
- In 2012, Garrett selected Brian Conroy, a former bond trader, as an agency mortgage analyst here; in mid-2019, Conroy was formally appointed to the portfolio management roster along with Joe Marvan, a senior fixed-income markets generalist at the firm.
- As of September 2019, roughly 75% of holdings were GNMA securities--around 10 percentage points lower than the year prior--as the team found more-attractive valuations in Fannie Mae- and Freddie Mac-backed fare.
- The strategy's steadfastness has paid off over time.
- A disciplined and risk-conscious approach to this agency mortgage-centric mandate justifies an Above Average Process rating.
- Such exposures usually make up 10%-15% of assets combined.
- The team avoids more-esoteric fare, such as interest-only mortgage derivatives, which are more sensitive to prepayment risk.
- The team also actively calibrates the portfolio's prepayment risk profile, which is where its careful evaluation of macroeconomic factors and government policies and bottom-up assessment of underlying loan characteristics come into play.

- Over time, the strategy has used a mix of TBAs and mortgage pass-through securities, adjusting allocations depending on relative valuations.
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- The Vanguard Group entered a new era in early 2019 with the passing of its founder and conscience, John C. Bogle.
- Unlike its mid-1970s origins, when outflows were the norm and its survival was in question, Vanguard now wears the crown as the world's biggest retail asset manager.
- More than 90% of its USD 5.6 trillion in global assets under management, as of June 2019, are in the United States; but the firm has designs to grow its non-U.S. business, especially in the United Kingdom, Australia, Canada, Japan, China, and Mexico.
- Vanguard gained its stature by following Bogle's playbook: pairing relatively predictable strategies, both passive and active, with minimal costs.
- That's enriched Vanguard's investors, and those outside its flock who have benefited from industry wide fee compression.
- Not content, Vanguard aims to transform investment advice, too.
- In May 2015, it launched Personal Advisor Services, a burgeoning discretionary asset-management business that pairs automation and human advice; and in September 2019 it disclosed plans to launch a digital-only counterpart.
- A record of deft mortgage-pool selection contributes to a compelling long-term performance profile on this strategy.
- Over the aforementioned period, the strategy's risk-adjusted returns (as represented by its Sharpe ratio) have landed in the best quartile of that distinct peer group.
- The strategy's conservative approach helps it avoid potholes that trip up rivals trafficking in more-esoteric fare.
- It's critical to evaluate expenses, as they come directly out of returns.
- The share class on this report levies a fee that ranks in its Morningstar category's cheapest quintile.

Results=60% for 50% extraction

Apple stock dips after Credit Suisse says iPhone shipments drop 35% in China

Chinese consumers are cooling on the iPhone, according to a new report by Credit Suisse analysts. iPhone shipments in China dropped 35.4% in November compared to the same time last year, the analysts wrote in a note Thursday, despite a slight increase in the Chinese smartphone market at the same time. The analysts said Chinese iPhone sales declined 10.3% year-over-year in October, making this the second straight month of double-digit percentage drops. Since the launch of the iPhone 11 family, total shipments in China are down 7.4% compared to last year, the analysts said, adding that "we estimate China iPhone revenue fell by >17.5% y/y over the past three months (Sept-Nov)." Apple's stock was down slightly Thursday morning. The analysts cited the looming December 15 deadline that could see more tariffs imposed on Apple products as part of the ongoing U.S.-China trade war as more cause for concern. The analysts wrote that a 15% tariff could increase U.S. iPhone costs by almost $70 per unit. "Our (and we believe investors') base case continues to factor in a favorable resolution (i.e., no tariffs); however, we think Apple would have a difficult time pushing through tariff-related price increases to U.S. consumers (~35% of CY18 iPhone units, per Gartner) without a commensurate impact on demand." The analysts also pointed to aggressive local competition from Chinese manufacturers as a reason for the drop in sales. The analysts' rating of Apple remains neutral, and they announced a price target of $221 per share in October. Apple has had a hard time in China recently. In the second-quarter of 2019, its shipments declined 14% year-over-year while its market share dropped to 5.8% from 6.4% in the same period last year, according to market research firm Canalys. Apple analysts were nonetheless optimistic about the performance of the latest iPhone line in China when it launched. Some of the new iPhone models had wait times in China of two to three weeks in September. Delivery times for devices can give an indication of consumer demand. Leading Apple analyst Ming-Chi Kuo said in September that he expected

Chinese demand for the new iPhones to beat expectations. “The demand for iPhone 11 in the Chinese market is stronger than that in the U.S. market,” Kuo said at the time. When the new line launched in September, Chinese consumers had to pay a marked up price between 10.5% to 12.5% more for the iPhone 11, and 18.6% to 23% more for the iPhone 11 Pro and Pro Max compared to U.S. prices. Apple does not make an iPhone that can connect to 5G networks, the next-generation mobile networks that promise super-fast data speeds with the ability to support technologies like self-driving cars. 5G networks are slowly being rolled out around the world and in China they are slated to come online as early as this year.

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- Apple does not make an iPhone that can connect to 5G networks, the next-generation mobile networks that promise super-fast data speeds with the ability to support technologies like self-driving cars.

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- Apple does not make an iPhone that can connect to 5G networks, the next-generation mobile networks that promise super-fast data speeds with the ability to support technologies like self-driving cars.
- 5G networks are slowly being rolled out around the world and in China they are slated to come online as early as this year.

Results=70% for 50% extraction

This new trend in house selling could cast a cloud over America's property market

America's property market Planning to sell a home in Raleigh, N.C.? There's a decent chance that an "iBuyer" will purchase it. Raleigh had the largest share of homes bought by companies that use technology to make instant offers on homes. Nearly 7% of homes sold in Raleigh in the third quarter of 2019 were bought by iBuyers, according to a new report from real-estate firm Redfin RDFN, +0.14%, a reflection of the city's affordable housing market and tech-savvy population. Redfin operates an instant-offer program called RedfinNow. Other iBuyers include Zillow ZG, +0.52%, Offerpad and Opendoor.

The Redfin report examined public real-estate records across all markets that Redfin serves, whether through its traditional brokerage program or RedfinNow. To calculate the market share of iBuyers, Redfin compared all known iBuyers purchases in a metropolitan area with all single-family, condo, and townhouse sales, excluding new construction and bank-owned homes.

There are potential drawbacks to the rise of iBuying. Some research has shown that homeowners may lose money by selling to an iBuyer. A MarketWatch investigation found that people who sold their homes to iBuying companies Opendoor and Offerpad earned 11% less than people who sold their homes on the open market. (A report from Zillow, however, showed that sellers who declined a Zillow Offer and sold traditionally
only made 0.22% more on average.)

And some economists have argued that as iBuying gains steam, it could make certain real-estate economic indicators less reliable, clouding the picture of the housing market's health.

"With these types of transactions gaining market share, it reduces the accuracy and usefulness of data that is based on traditional multiple listing service sources," Joshua Shapiro, chief U.S. economist at consulting firm Maria Fiorini Ramirez, wrote last month. "The National Association of Realtors periodically benchmarks its pending and actual sales data to attempt to account for this (and other) factors that can affect the accuracy of its data, but it is unlikely that even this benchmark process can fully deal with the effects of such market changes." Through its analysis, Redfin identified 18 metropolitan areas where iBuyers have achieved at least 1% market share, two-thirds of which were in the so-called Sunbelt. Beyond Raleigh, there were three other cities where iBuyers now account for more than 4% of sales: Phoenix (5.1%), Atlanta (4.4%) and Charlotte, N.C. (4.3%). "iBuyers are concentrating their efforts in southern markets where both home sales and prices are poised for strong growth," Redfin chief economist Daryl Fairweather said in the report. "We think that iBuyers are likely to accelerate home sales in these markets. Homeowners who may have been reluctant to sell because they didn't want to deal with the hassle may be persuaded by the convenience of an iBuyer sale." The median home sales prices in roughly all of these cities was at or below the national median of $270,900, according to the National Association of Realtors. The Redfin report also indicated how iBuyers tend to focus on homes at the lower end of the market. In all but two of these cities, the median price of homes iBuyers sold after purchasing them was lower than the local median sales price. Homes owned by iBuyers also sold faster than average in all but five markets: Portland, Ore., Sacramento, Calif., Minneapolis, Denver and Austin, Texas. The Redfin report sheds further light on this growing trend across the country's housing market. Zillow Z, +0.56%, for instance, has expanded its iBuying program to 22 markets since it launched 19 months ago, announcing Monday that it would begin making instant offers in Los Angeles.

Summary provided by Atchuthan

- Raleigh had the largest share of homes bought by companies that use technology to make instant offers on homes.Some research has shown that homeowners may lose money by selling to an iBuyer.
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  Results=80% for 50% extraction

What Impeachment Could Mean for the Stock Market

Investors with long memories have every right to be afraid of what President Donald Trump's impeachment could do to the stock market. That's because impeachment proceedings against Richard Nixon and Bill Clinton were each associated with an equity bear market. In Nixon's case, the S&P 500 fell 23.7% from the date of the Watergate break-in in 1972 to the day he resigned in August 1974. The bear market in Clinton's case was shorter-lived, at least according to the bear market calendar maintained by Ned Davis Research. That decline lasted for six weeks between mid-July and the end of August of 1998, during which the S&P 500, on an intraday basis, fell 21.0%. During that six-week period, the historians among you will recall, the investigation into Clinton's relationship with Monica Lewinsky went into full gear. Clinton was served with a subpoena during that time, for example, and he became the first sitting president to testify before a grand jury investigating his conduct. Investors harboring this concern about the impeachment proceedings against Trump must think that the current stock market is in denial. Far from falling as impeachment hearings have progressed against the president, the major stock market averages have rallied to new highs. On Tuesday of this week, for example, as formal articles of impeachment were introduced, the S&P 500 only fell by a miniscule 3.4 points, or 0.1%.

What's going on? To gain insight, I turned to a novel statistical approach that takes advantage of the electronic betting websites that allow you to bet on almost anything -- including a contract keyed to whether Trump will finish out his first term. This contract is priced in all-or-nothing terms, which means its price reflects the probability that he will complete his term. Its current probability, based on the latest price at the site PredictIt.org, is 81%. Note carefully that this contract keys off whether Trump is actually removed from office, which is different than whether or not he is impeached. The accompanying chart shows the price history of this PredictIt.org contract since January, when it first began trading. Notice that its trading range since then has been from a low of 65% probability to a high of 87%.

To an untrained eye, of course, it might look as though there is a meaningful correlation between the PredictIt contract and the S&P 500. That contract did fall markedly in late September and early October, for example, in the immediate wake of the whistleblower's complaint that set the whole impeachment drama in motion. And the S&P 500 also fell.

But notice also that the S&P 500 declined by a similar amount in May a well as in late July/early August, and during neither of those two periods did the PredictIt contract make a major move.

Fortunately, we can be more rigorous than simply eyeballing the data. We can instead calculate the correlation coefficient between changes in the odds of Trump remaining in office through his first term and changes in the S&P 500. I calculated three different correlation coefficients: One that focused on changes over the trailing trading session, another on the trailing week, and the third on the trailing month. I came up with nothing that would help investors trade the stock market based on the odds of Donald Trump being removed from office. One set of results that shows how little those odds help a trader is that the correlations were not always consistent: In some periods, heightened odds of impeachment were associated with higher stock prices, but in other periods, with lower stock prices. Overall, changes in the impeachment contract price could explain next to none of the corresponding changes in the S&P 500. I also looked to see if the coefficients became stronger since late September, which was when the whistleblower's complaint became public and impeachment proceedings on Capitol Hill took center stage. Once again there were no consistent results; correlations became stronger than they were before September when calculated based on a trailing period of one length but weaker when calculated based on a period of different length. The bottom line? Whether you take these results to be good or bad news depends on whether you're bullish or bearish on the stock market -- and your politics. You of course can continue to predict what you think the stock market will do if and when the odds of President Trump being removed from office rise or fall markedly from current levels. You just can't base your prediction on how the stock market has reacted over the last year to changes in those odds.

Summary provided by Atchuthan

- That's because impeachment proceedings against Richard Nixon and Bill Clinton were each associated with an equity bear market.
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- During that six-week period, the historians among you will recall, the investigation into Clinton's relationship with Monica Lewinsky went into full gear.
- Clinton was served with a subpoena during that time, for example, and he became the first sitting president to testify before a grand jury investigating his conduct.

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- Once again there were no consistent results; correlations became stronger than they were before September when calculated based on a trailing period of one length but weaker when calculated based on a period of different length.

Results=60% for 50% extraction

Alibaba Stock Still Has Lots of Room to Rise. Analyst Sees a 44% Gain.

citigroup's Alice Yap initiated coverage of Alibaba's Hong Kong shares with a Buy rating and a target price of 284 Hong Kong dollars. Citigroup's Alice Yap initiated coverage of Alibaba's Hong Kong shares with a Buy rating and a target price of 284 Hong Kong dollars.. The Chinese e-commerce giant Alibaba Group Holding still has huge room to grow, and both its Hong Kong stock and American depositary shares are set to fly, according to Citigroup analyst Alicia Yap. The back story. In one of the largest stock offerings of 2019, Alibaba raised $13 billion through a listing in Hong Kong on Nov. 26, making it possible to trade the company in Asia, rather than only via American depositary shares, or ADS, on the New York Stock Exchange. Only the initial public offering of Saudi Aramco last week raised more, bringing in a reported $29.4 billion. Despite the protests and violence in Hong Kong, a slowing Chinese economy, and the U.S.-China trade war, there was strong demand for Alibaba's new shares. Investors remained bullish on China's largest internet retailer. The Hong Kong shares (ticker: 9988.HK) rose 12.2% from the listing price of 176 Hong Kong dollars (US$22.48) to HK$197.50 as of the close of trading on Friday. Alibaba's ADS (BABA)—traded on the NYSE since 2014—have rallied 47% year to date versus the S&P 500's 26% gain. What's new. In a Monday note, Citigroup's Yap initiated coverage of Alibaba's Hong Kong shares with a Buy rating and target price of HK$284. That is about 44% higher than last Friday's close. Yap also raised her target price for Alibaba's ADS—each representing eight ordinary shares in Hong Kong—to US$284 from the previous US$230. The depositary shares closed at US$201.89 on Friday. "Evolving from a 'data-technology-driven ecosystem' that synergizes business units within the Ali family, Ali management three years ago envisioned a path to the 'Ali Digital Economy' with the announcement of five breakthrough trends," she wrote, "Three years later, as we head into 2020, Ali has extended its commerce addressable market to New Retail, and is working with industry partners to transform and digitize their operations via the Alibaba Business Operating System (ABOS)." Yap says Alibaba can leverage its technology and other innovations to continue achieving its near- and long-term visions. The company has been focusing on opportunities in globalization and domestic consumption, as well as the use of big data, powered by cloud computing, in a push to transform the digital economy in China. Within the next five years, Alibaba is looking to serve more than one billion Chinese consumers per year and facilitate more than $10 trillion yuan ($1.42 trillion) of consumption. The company aims to serve two billion consumers a year world-wide by 2036 and create 100 million jobs. Looking ahead. Yap forecasts that Alibaba will increase its total revenue by 36.5% in fiscal 2020 to reach 514.5 billion yuan, or US$73.1 billion. Earnings before interest, taxes, depreciation, and amortization are expected to increase by 32% to 161.4 billion yuan. She valued the company at 30 times its expected earnings for fiscal 2021, plus Alibaba's 33% equity stake in Ant Financial Services Group, formerly known as Alipay.

Summary provided by Vijinthiny

- citigroup's Alice Yap initiated coverage of Alibaba's Hong Kong shares with a Buy rating and a target price of 284 Hong Kong dollars.
- The Chinese e-commerce giant Alibaba Group Holding still has huge room to grow, and both its Hong Kong stock and American depositary shares are set to fly, according to Citigroup analyst Alicia Yap.
- The back story. In one of the largest stock offerings of 2019, Alibaba raised $13 billion through a listing in Hong Kong on Nov. 26, making it possible to trade the company in Asia, rather than only via American depositary shares, or ADS, on the New York Stock Exchange
- Only the initial public offering of Saudi Aramco last week raised more, bringing in a reported $29.4 billion.

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- Yap says Alibaba can leverage its technology and other innovations to continue achieving its near- and long-term visions.
- The company has been focusing on opportunities in globalization and domestic consumption, as well as the use of big data, powered by cloud computing, in a push to transform the digital economy in China.
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- The depositary shares closed at US$201.89 on Friday.

- Yap says Alibaba can leverage its technology and other innovations to continue achieving its near- and long-term visions.
- The company has been focusing on opportunities in globalization and domestic consumption, as well as the use of big data, powered by cloud computing, in a push to transform the digital economy in China.
- Within the next five years, Alibaba is looking to serve more than one billion Chinese consumers per year and facilitate more than $10 trillion yuan ($1.42 trillion) of consumption.
- The company aims to serve two billion consumers a year world-wide by 2036 and create 100 million jobs.
- Earnings before interest, taxes, depreciation, and amortization are expected to increase by 32% to 161.4 billion yuan.

Results = 60% for 50% extraction.

Walmart Beats Earnings, Stock Fails at a Risky Level

Retail giant Walmart Inc. (WMT) extended its winning streak with its seventh consecutive beat of earnings per share estimates in its report released on Nov. 14. The stock set its all-time intraday high that day at $125.38 but then closed below its quarterly and monthly pivots at $123.15 and $121.04, respectively. Weakness has held the 50-day simple moving average, which ended last week at $118.63. The weekly chart is showing a warning and will be negative if the stock ends November below its five-week modified moving average at $118.29. Walmart stock, which is a component of the Dow Jones Industrial Average, has a gain of 28.1% year to date and is in bull market territory at 39.1% above its Dec. 24 low of $85.78. The stock is 4.8% below its Nov. 14 high of $125.38. Fundamentally, the stock is not cheap, as its P/E ratio is 24.12 with a dividend yield of 1.77%, according to Macrotrends. Walmart earnings beat estimates, and its holiday outlook was positive, but sales fell slightly versus estimates. Online sales are on the rise thanks to grocery items, but the costs of online commerce are a drag on earnings due to acquiring brands and enhancing speed of delivery. The daily chart for Walmart shows that the stock has been above a "golden cross" since Sept. 17, 2018, when the 50-day simple moving average rose above the 200-day simple moving average to indicate that higher prices lie ahead. This positive signal and was still in play when the stock set its Christmas Eve low of $85.78. Investors looking to buy at the 200-day simple moving average could have done so between Dec. 17 and Dec. 27, when the average was $90.82. The close of $93.15 on Dec. 31 was an important input to my proprietary analytics. The annual pivot remains at $103.41, which was a magnet between Feb. 19 and June 5 as this level was crossed several times. The close of $110.49 on June 28 was another important input to my analytics. Its second half semiannual value level is $101.88. The close of

$118.68 on Sep. 30 was an input that calculated the quarterly risky level at $123.15. The close of $117.25 on Oct. 31 was an input that resulted in a monthly pivot for November at $121.04.

The weekly chart for Walmart

The weekly chart for Walmart is neutral, with the stock above its five-week modified moving average of $118.29. The stock is well above its 200-week simple moving average, or "reversion to the mean," at $86.91, last tested during the week of July 14, 2017, when the average was $73.34. The 12 x 3 x 3 weekly slow stochastic reading is projected to end this week declining to 71.07, down from 83.18 on Nov. 15. At its Nov. 14 high, this reading was above the 90.00 threshold as an "inflating parabolic bubble," which typically is followed by a 10% to 20% decline.

Trading strategy: Buy Walmart shares on weakness to the annual and semiannual value levels at $103.41 and $101.88, respectively, and reduce holdings on strength to the quarterly risky level at $123.15.

How to use my value levels and risky levels: Value levels and risky levels are based upon the last nine monthly, quarterly, semiannual, and annual closes. The first set of levels was based upon the closes on Dec. 31, 2018. The original annual level remains in play. The close at the end of June 2019 established new semiannual levels, and the semiannual level for the second half of 2019 remains in play. The quarterly level changes after the end of each quarter, so the close on Sep. 30 established the level for the fourth quarter. The close on Oct. 31 established the monthly level for November.

My theory is that nine years of volatility between closes are enough to assume that all possible bullish or bearish events for the stock are factored in. To capture share price volatility, investors should buy shares on weakness to a value level and reduce holdings on strength to a risky level. A pivot is a value level or risky level that was violated within its time horizon. Pivots act as magnets that have a high probability of being tested again before their time horizon expires.

How to use 12 x 3 x 3 weekly slow stochastic readings: My choice of using 12 x 3 x 3 weekly slow stochastic readings was based upon backtesting many methods of reading share-price momentum with the objective of finding the combination that resulted in the fewest false signals. I did this following the stock market crash of 1987, so I have been happy with the results for more than 30 years.

The stochastic reading covers the last 12 weeks of highs, lows, and closes for the stock. There is a raw calculation of the differences between the highest high and lowest low versus the closes.

These levels are modified to a fast reading and a slow reading, and I found that the slow reading worked the best.

The stochastic reading scales between 00.00 and 100.00, with readings above 80.00 considered overbought and readings below 20.00 considered oversold. Recently, I noted that stocks tend to peak and decline 10% to 20% and more shortly after a reading rises above 90.00, so I call that an "inflating parabolic bubble," as a bubble always pops. I also refer to a reading below 10.00 as "too cheap to ignore."

Summary provided by Vijinthiny

- Retail giant Walmart Inc. (WMT) extended its winning streak with its seventh consecutive beat of earnings per share estimates in its report released on Nov. 14.
- The stock set its all-time intraday high that day at $125.38 but then closed below its quarterly and monthly pivots at $123.15 and $121.04, respectively.
- Weakness has held the 50-day simple moving average, which ended last week at $118.63.
- Walmart stock, which is a component of the Dow Jones Industrial Average, has a gain of 28.1% year to date and is in bull market territory at 39.1% above its Dec. 24 low of $85.78.
- Fundamentally, the stock is not cheap, as its P/E ratio is 24.12 with a dividend yield of 1.77%, according to Macrotrends.
- Walmart earnings beat estimates, and its holiday outlook was positive, but sales fell slightly versus estimates.
- Online sales are on the rise thanks to grocery items, but the costs of online commerce are a drag on earnings due to acquiring brands and enhancing speed of delivery.
- This positive signal and was still in play when the stock set its Christmas Eve low of $85.78. Investors looking to buy at the 200-day simple moving average could have done so between Dec. 17 and Dec. 27, when the average was $90.82.
- The 12 x 3 x 3 weekly slow stochastic reading is projected to end this week declining to 71.07, down from 83.18 on Nov. 15. At its Nov. 14 high, this reading was above the 90.00 threshold as an "inflating parabolic bubble," which typically is followed by a 10% to 20% decline.
- Value levels and risky levels are based upon the last nine monthly, quarterly, semiannual, and annual closes.
- My theory is that nine years of volatility between closes are enough to assume that all possible bullish or bearish events for the stock are factored in.
- To capture share price volatility, investors should buy shares on weakness to a value level and reduce holdings on strength to a risky level.
- My choice of using 12 x 3 x 3 weekly slow stochastic readings was based upon backtesting many methods of reading share-price momentum with the objective of finding the combination that resulted in the fewest false signals.
- I did this following the stock market crash of 1987, so I have been happy with the results for more than 30 years.
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Summary generated my model

- Retail giant Walmart Inc. (WMT) extended its winning streak with its seventh consecutive beat of earnings per share estimates in its report released on Nov. 14.
- Weakness has held the 50-day simple moving average, which ended last week at $118.63.
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- Online sales are on the rise thanks to grocery items, but the costs of online commerce are a drag on earnings due to acquiring brands and enhancing speed of delivery.
- The close of $93.15 on Dec. 31 was an important input to my proprietary analytics.
- The close of $110.49 on June 28 was another important input to my analytics.
- The weekly chart for Walmart is neutral, with the stock above its five-week modified moving average of $118.29.
- The 12 x 3 x 3 weekly slow stochastic reading is projected to end this week declining to 71.07, down from 83.18 on Nov. 15.
- At its Nov. 14 high, this reading was above the 90.00 threshold as an "inflating parabolic bubble," which typically is followed by a 10% to 20% decline.
- The original annual level remains in play.
- The close at the end of June 2019 established new semiannual levels, and the semiannual level for the second half of 2019 remains in play.
- My theory is that nine years of volatility between closes are enough to assume that all possible bullish or bearish events for the stock are factored in.
- To capture share price volatility, investors should buy shares on weakness to a value level and reduce holdings on strength to a risky level.
- A pivot is a value level or risky level that was violated within its time horizon.
- Pivots act as magnets that have a high probability of being tested again before their time horizon expires.
- There is a raw calculation of the differences between the highest high and lowest low versus the closes.
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- The stochastic reading scales between 00.00 and 100.00, with readings above 80.00 considered overbought and readings below 20.00 considered oversold.

- I also refer to a reading below 10.00 as "too cheap to ignore."

Accuracy 60% for 50% extraction

US STOCKS-Wall St at record levels after U.S. extends Huawei reprieve

Wall Street hovered around record levels on Monday after Washington's move to grant an extension for U.S. companies to do business with China's Huawei helped ease some concerns around U.S.-China trade relations. The benchmark S&P 500 and blue-chip Dow Jones indexes hit fresh record highs, while the Nasdaq was near its all-time level. The three main indexes had opened lower after CNBC reported that the mood in Beijing about a deal was pessimistic due to President Donald Trump's reluctance to roll back tariffs. Investors had turned optimistic over the weekend after Chinese state media said the two sides had held "constructive" trade talks, days after White House economic adviser Larry Kudlow said they were getting close to a deal. "This (CNBC report) shows that progress doesn't happen in a straight line and that is starting to frustrate people today. It feels very herky-jerky," said Scott Ladner, chief investment officer at Horizon Investments in Raleigh, North Carolina. Six of the 11 major S&P 500 sectors were higher. Technology shares reversed course to trade higher, while the Philadelphia Semiconductor index also gained 0.36%. However, defensives such as utilities, real estate and consumer staples - also known as bond proxies due to their high dividend yields - were the biggest gainers. Global stocks got a boost earlier in the day from a surprise cut in a key interest rate by China for the first time in more than four years. Attention this week turns to minutes from the Federal Reserve's latest policy meeting, where the central bank cut interest rates for the third time this year. Also on the radar are results from U.S. retailers, including Home Depot Inc, Kohl's Corp and Target Corp .

At 11:56 a.m. ET the Dow Jones Industrial Average was up 10.28 points, or 0.04%, at 28,015.17, the S&P 500 was up 0.30 points, or 0.01%, at 3,120.76 and the Nasdaq Composite was down 2.15 points, or 0.03%, at 8,538.68.

Shares of HP Inc fell 1.2% after the company rebuffed a $33.5 billion offer from Xerox Holdings Corp and said it was open to exploring a bid for the latter. Xerox dipped 0.4%. Coty Inc gained 1.3% after saying it would pay $600 million for a majority stake in Kylie Jenner's make-up and skincare businesses, as it looks to tap into the reality TV star's huge social media reach. Declining issues outnumbered advancers for a 1.21-to-1 ratio on the NYSE and for a 1.40-to-1 ratio on the Nasdaq. The S&P index recorded 35 new 52-week highs and no new lows, while the Nasdaq recorded 79 new highs and 103 new lows. (Reporting by Arjun Panchadar and Agamoni Ghosh in Bengaluru; Editing by Maju Samuel and Anil D'Silva)

Summary provided by Vijinthiny Prabakaran

- Wall Street hovered around record levels on Monday after Washington’s move to grant an extension for U.S. companies to do business with China’s Huawei helped ease some concerns around U.S.-China trade relations.
- The benchmark S&P 500 and blue-chip Dow Jones indexes hit fresh record highs, while the Nasdaq was near its all-time level.
- The three main indexes had opened lower after CNBC reported that the mood in Beijing about a deal was pessimistic due to President Donald Trump’s reluctance to roll back tariffs.
- Investors had turned optimistic over the weekend after Chinese state media said the two sides had held “constructive” trade talks, days after White House economic adviser Larry Kudlow said they were getting close to a deal.
- It feels very herky-jerky,” said Scott Ladner, chief investment officer at Horizon Investments in Raleigh, North Carolina.
- Technology shares reversed course to trade higher, while the Philadelphia Semiconductor index also gained 0.36%.
- However, defensives such as utilities, real estate and consumer staples - also known as bond proxies due to their high dividend yields - were the biggest gainers.
- Global stocks got a boost earlier in the day from a surprise cut in a key interest rate by China for the first time in more than four years.
- Attention this week turns to minutes from the Federal Reserve’s latest policy meeting, where the central bank cut interest rates for the third time this year.
- Coty Inc gained 1.3% after saying it would pay $600 million for a majority stake in Kylie Jenner’s make-up and skincare businesses, as it looks to tap into the reality TV star’s huge social media reach.

Summary generated my model

- The benchmark S&P 500 and blue-chip Dow Jones indexes hit fresh record highs, while the Nasdaq was near its all-time level.
- “This (CNBC report) shows that progress doesn’t happen in a straight line and that is starting to frustrate people today.
- It feels very herky-jerky,” said Scott Ladner, chief investment officer at Horizon Investments in Raleigh, North Carolina.
- Six of the 11 major S&P 500 sectors were higher.
- Attention this week turns to minutes from the Federal Reserve’s latest policy meeting, where the central bank cut interest rates for the third time this year.
- Also on the radar are results from U.S. retailers, including Home Depot Inc, Kohl’s Corp and Target Corp .

- ET the Dow Jones Industrial Average was up 10.28 points, or 0.04%, at 28,015.17, the S&P 500 was up 0.30 points, or 0.01%, at 3,120.76 and the Nasdaq Composite was down 2.15 points, or 0.03%, at 8,538.68.
- Coty Inc gained 1.3% after saying it would pay $600 million for a majority stake in Kylie Jenner's make-up and skincare businesses, as it looks to tap into the reality TV star's huge social media reach.
- Declining issues outnumbered advancers for a 1.21-to-1 ratio on the NYSE and for a 1.40-to-1 ratio on the Nasdaq.

Results: 45%

5 Discussion

5.1 Introduction

In the current world, research in the stock market investment is increasing as it gives a lot of profits to the industries and individuals. Though most of the research is based on the numeric stock data and identifying the sentiments of the people using stock text data, few researches have been done in the stock market investment news article in retrieving the significant benefits from them. So we focus on how these stock traders are reading the news articles to carry out their trading with the help of the domain experts and also from websites forum. From the information we gathered from the above, we focused on the keywords in the stock market and went on to summarize the stock market investment news articles base on the stock market keywords to identify how far the summarization of the stock market investment news articles will be helpful for the stock traders to carry out their trading activities. Main contribution of our research is, we have built a summarization tool which will be helpful for the stock traders to capture the significant content from the news articles effectively.

5.2 Discussion

In the study of identifying how far the summarization of Stock market investment news article is helpful for the stock traders, we have contributed through a summarization model for the future researchers and summarization desktop application for the stock market organization which carries out trading activities and individuals who carry out stock trading activites. We were able to obtain answers for our research question that we put forward at the beginning of the research and we were able to satisfy the requirements of the end users effectively by using the findings obtained from answering those questions.Throughout the research we were able to observe many things related to the summarization of news articles. Some of them are

- Stock traders use investment news articles to get **real time information about the organization** and also some **information about emerging organizations** in the stock.

- Summarization of stock market investment **will be helpful for the stock traders** to gain more information quickly for their trading activities.

- **Keywords related to stock market investment** play a major role in the summarization investment news articles.

- Graph analysis helps to identify the **relatedness between each and every sentence** which helps to analyse the relationship between each and every sentence.

- Use of graph analysis helps in **retrieving the salient sentences** for the summarization.

- Different stock traders read news articles differently, means some sentences are important to every trader but some sentences may not be important to traders which may be important for others.

Though many researches were done in the stock market investment news articles domain, still researchers did not involve more deeply in the financial news articles summarization. There is a lot of general research on summarization of articles but when it comes to a focus on a particular domain, we need to add some recipes to pick sentences which are relevant to a certain domain. We chose keyword based approach to retrieve the stock market related sentences, this approach made us achieve the requirements of our end users effectively for their trading activities.

5.3 Conclusion

Our main aim of the research was to identify how far the summarization of investment news articles will be helpful for stock traders to carry out their trading activities. We were able to achieve the aim of the research through the help of the domain experts who are involved in the stock domain and stock based keywords which we collected from the domain experts and websites.

"How to enrich the stock market investment domain in the text summarization?", questions have been answered through using the keywords related stock market while **"How to carry out the summary evaluation complying with stock market investment domain?"** , we gathered summaries from the domain experts and compared those summaries manually with the summaries generated from the model to find the accuracy of the model and also we evaluated how far the summary generated from our model has satisfied the requirements of the stock traders by giving our summary to some stock traders. **"How far summarized stock market investment news articles are helpful for stock traders?"**, this question was answered through the evaluation scores from the evaluation methods that we incorporated into our research methodology.

By exploring the answers for those research questions we were able to build the summarization model which would generate summary with **more than 55% usefulness for stock traders** and also summary generated from our model **has given 60% usefulness for stock traders.** With these evaluation scores, we could conclude that effective summarization which is expected by the stock traders for their trading activity can be obtained by applying summarization techniques.

Also we can conclude that graph based approach for the text summarization can give an effective result for the readers to gain significant contents from the document.

5.4 Future work

This research can be improved in the future to improve the accuracy and by some other alternative ways to make it more beneficial to users.Some future work which can be done are,

- Wordnet is commonly used in the English based common summarization to identify the synonyms and antonyms of the words, but if we need to find the similar financial related sentences, we need **financial ontology** like Wordnet.

- Our research is single document based summarization. In future **Multi document based stock market investment news article** summary generation can be done to provide significant information from different stock market investment news articles.

- As keywords play a major role in providing effective information to stock traders, in future these **keywords can be ranked and given different priority** or categorised based on priority on the importance and this can increase the accuracy of the summarization.

- Our summarization is based on the **abstractive based summarization**, in future this can be improved to abstractive summarization which can be helpful for any people to understand it without any prior knowledge on stock market domain.

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Appendix A Text summarization Work Flow

```python
import numpy as np
import nltk
nltk.download('punkt') # one time execution
import csv
import itertools
import networkx as nx
import math
from nltk.stem import PorterStemmer

#Read this documents
file = open("Evaluation/thenu3.txt", "r", encoding = "utf-8")

filedata = file.readlines()

stock_keywords = ['gain','annual', 'report', 'arbitrag', 'averag', 'down', 'bear', 'market'
                  , 'beta', 'sharehold', 'manag', 'strategi','sale', 'financi', 'solvenc',
                  'buy', 'sell', 'stock', 'invest', 'share', 'trade', 'price', 'stabl',
                  'dividend', 'fiscal', 'exchang', 'bourse', 'bull', 'broker', 'bid',
                  'close', 'execut', 'high', 'index', 'ipo', 'public', 'offer', 'leverag',
                  'low', 'margin', 'purchas', 'minimum', 'balanc', 'margin', 'account',
                  'open', 'order', 'portfolio', 'ralli', 'quot', 'sector', 'spread',
                  'volatil', 'volum', 'yield', 'bottom', 'line','perform','revenu','loss',
                  'profit', 'grow', 'increas', 'decreas', 'multipl', 'roe', 'roa', 'p/e',
                  'alpha', 'rel',  'nasdaq',  'msci', 'hangseng', 'world',  'indic',  'ep',
                  'quarterli', 'forward', 'contract', 'profit', 'take', 'equiti', 'market']

Multiple_keys = ['nikkei 225', 'forward P/BV', 'Dividend Yield', 'Penny stocks',
                 'Value stocks', 'Growth stocks', 'risk adjusted return', 'mean reverting',
                 'S&P 500', 'FTSE 100', 'MSCI Emerging markets', 'technical charts',
                 'moving averages', 'book value', 'EBITDA growth', 'EBITDA margin',
                 'all time high', 'all time low', 'price gains',
                 'Earnings exceeding forecasts', 'Last Twelve Months', 'intrinsic value',
                 'upside potential', 'stock futures']
from nltk.tokenize import sent_tokenize, word_tokenize
sentences = []
for g in filedata:
   sentence = sent_tokenize(g)
```

Figure 5.1: For the tokenization and Stemming purpose we used NLTK Python library.

```python
word_embeddings = {}
f = open('glove.6B.100d.txt', encoding='utf-8')
for line in f:
    values = line.split()
    word = values[0]
    coefs = np.asarray(values[1:], dtype='float32')
    word_embeddings[word] = coefs
f.close()

from nltk.corpus import stopwords
stop_words = stopwords.words('english')
nltk.download('stopwords')

def remove_stopwords(sen):
    sen_new = " ".join([i for i in sen if i not in stop_words])
    return sen_new
```

Figure 5.2: Stop words were obtained from Python NLTK library.

```python
def stockKey_calculation(sen):
    count = 0
    words = word_tokenize(sen)
    keys = []
    ps = PorterStemmer()
    stem_words = []
    for e in words:
        g = ps.stem(e)
        stem_words.append(g)
    for word in stem_words:
        if word in stock_keywords:
            count += 1
            keys.append(word)

    for kes in Multiple_keys:
        if kes in sen:
            count += 1
            keys.append(kes)
    return count

def calculate_keys(list_keys):
    total_count = sum(list_keys)
    ratio_keys = []

    if total_count == 0:
        return ratio_keys

    for stock_num in list_keys:
        ratios = stock_num/total_count
        ratio_keys.append(ratios)

    return ratio_keys
```

Figure 5.3: Calculate number keywords in Document.

```python
sentence_vectors = []
stockcounts = []
for i in clean_sentences:
  if len(i) != 0:
    v = sum([word_embeddings.get(w, np.zeros((100,))) for w in i.split()])/(len(i.split())+0.001)
    stockcounts.append(stockKey_calculation(i))
  else:
    v = np.zeros((100,))
  sentence_vectors.append(v)

sim_mat = np.zeros([len(sentences), len(sentences)])

from sklearn.metrics.pairwise import cosine_similarity

#Cosine similarities
for i in range(len(sentences)):
  for j in range(len(sentences)):
    if i != j:
      sim_mat[i][j] = cosine_similarity(sentence_vectors[i].reshape(1,100), sentence_vectors[j].reshape(1,100))[0,0]

ratio_keys = []
ratio_keys = calculate_keys(stockcounts)

mul_ratio_keys = [x * 10 for x in ratio_keys]

for val in range(len(clean_sentences)):
    sim_mat[val][val] = mul_ratio_keys[val]


G = nx.from_numpy_matrix(sim_mat)

```

Figure 5.4: Calculate similarity matrix

```python
def inverseRank_generator(g, smatrix):
    nodes_list = list(g.nodes)
    final_dict = {}
    for x in nodes_list:
        rank = 0
        for sim_value in nodes_list:
            rank += smatrix[x,sim_value]
        final_dict[x] = rank

    nx.set_node_attributes(g, final_dict, 'inverseRank')
    return g, final_dict

def summary_generation(g, rankDict, smatrix):
    key_max = max(rankDict.keys(), key=(lambda k: rankDict[k]))   #Find node which has maximum inverse rank
    g.remove_node(key_max)     #Remove node from the graph
    rest_rank = nx.get_node_attributes(g, 'inverseRank')  #get the inverse rank of the rest of the nodes
    key_max2 = min(rest_rank.keys(), key=(lambda k: rest_rank[k]))   #Find minimum inverse rank node
    connected_component = nx.node_connected_component(g, key_max2)    #Pick the suggraph whish has minimum inverse rank
    s = list(connected_component)   #Convert the set of nodes to list of nodes
    s_max = max(s)

    G_ex = nx.Graph()
    G_ex.add_nodes_from(s)
    G_ex.add_edges_from(itertools.combinations(s, 2)) #Generate graph from existing nodes and add weights
    new_matrix = np.zeros([s_max+1, s_max+1])
    for x in s:
        for y in s:
            new_matrix[x][y] = smatrix[x][y]
            G_ex.add_weighted_edges_from([(x, y, smatrix[x][y])])

    add_inverseRank, inverRank_dict = inverseRank_generator(G_ex, new_matrix) #find the inverse rank for the rest of the nodes
    return G_ex, inverRank_dict

clean_sentences = [remove_stopwords(r.split()) for r in sentences]
```

Figure 5.5: Iteratively eliminate the graph nodes.

```
add_inverseRank, inverseRank_dict = inverseRank_generator(G, sim_mat)
num_nodes = len(G)
summary_content = math.ceil(num_nodes/2)
iter_con = num_nodes
iter_G = G
rank_dict = inverseRank_dict
while(iter_con > summary_content):
    iter_G, rank_dict = graph_reduction(iter_G, rank_dict, sim_mat)
    iter_con = len(iter_G)

print(list(iter_G.nodes(data=True)))
summary = list(iter_G.nodes)
for summary_sen in summary:
    print(sentences[summary_sen])

with open('Edges.csv', 'w') as csvfile:
    fieldName = ['Source', 'Target', 'Weight', 'Type']
    theWriter = csv.DictWriter(csvfile, fieldnames= fieldName)
    theWriter.writeheader()

    for n1, n2, attr in G.edges(data=True):
        lines = [n1, n2, attr.get('weight')]
        if n1 == n2:
            continue
        else:
            theWriter.writerow({fieldName[0]:n1, fieldName[1]: n2, fieldName[2]: attr.get('weight'),fieldName[3]:'Undirected'})


    labels = dict((n, d['inverseRank']) for n, d in iter_G.nodes(data=True))
    nx.draw(iter_G, labels=labels, node_size=1000)
```

Figure 5.6: Generate Edges' information CSV file

```
s1 = 'Sent'
with open('Nodes.csv', 'w') as csvfile:
    fieldName = ['Id', 'Label']
    theWriter = csv.DictWriter(csvfile, fieldnames=fieldName)
    theWriter.writeheader()

    f = list(G.nodes(data=True))
    for node_label, attribute in f:
        linew = [node_label, attribute.get('inverseRank')]
        theWriter.writerow({fieldName[0]:linew[0], fieldName[1]:s1+str(node_label)})
```

Figure 5.7: Generate Nodes' information CSV file

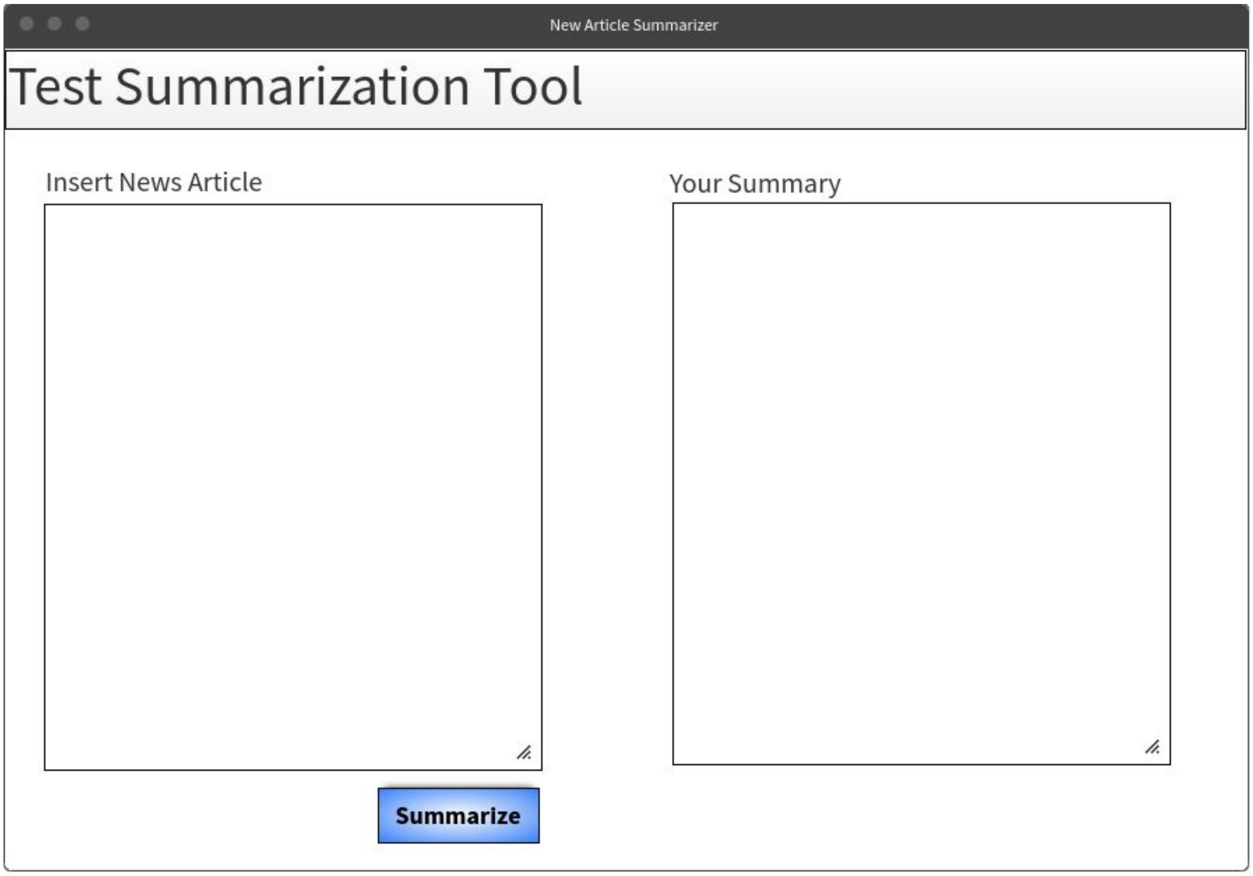

Figure 5.8 Summarization Tool