USING WEB SCRAPING IN SOCIAL MEDIA TO DETERMINE MARKET TRENDS WITH PRODUCT FEATURE-BASED SENTIMENT ANALYSIS

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Declaration

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Abstract

Customer product reviews are openly available online and they are now widely used for deciding quality of product or service and to determine market trends and influence decision making of users. Due to the availability of a massive number of customer reviews on the web, summarizing them requires a fast classification system. Compared to supervised and unsupervised machine learning techniques for binary classification of reviews, fuzzy logic can provide a simple and comparatively faster way to model the fuzziness existing between the sentiment polarities classes due to the uncertainty present in most of the natural languages. But the fuzzy logic techniques are not much considered in this domain. This thesis proposes a model which measures product market value by using sentiment analysis conducted on the reviews of online products which are collected from a well known ecommerce website “Amazon”. Fuzzy logic approach is used in calculating the final product market demand.

Hence, in this paper we propose a fine grained classification of customer reviews into weak positive, average positive, strong positive, weak negative, average negative and strong negative classes using a fuzzy logic model based on the most popularly known sentiment based lexicon SentiWordNet. By creating rules and relationships between fuzzy membership functions and linguistic variables, we can analyze the customer opinions towards online products. This proposed model provides the most reasonable sentiment analysis because we try to reduce all the problems from the related past researches. The outcomes can allow the business organization to understand their customer’s sentiments and improve customer loyalty and customer retention techniques in order to increase customer values and profits result. Fine grained classification accuracy approximately in the range of 74% to 77% has been obtained by experiments conducted on datasets of electronic products containing reviews of smart phones, TV and laptops.

Keyword- Sentiment analysis, Fine grained classification, Fuzzy Logic, SentiWordNet, Online reviews

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List of Abbreviations

Abbreviation	Description
POS	Part of Speech
NLP	Natural Language Processing

CHAPTER 1

Introduction

1.1 Prolegomena

The recent expansion of World Wide Web and the social media have dramatically changed the way that people express themselves and interact with others. People can now contribute their opinions and reviews about the products and services they use on the merchant sites and also can interact with others through various blogs, social networking sites and discussion forums. Online customer reviews have become an integral and huge source of valuable information for the product manufactures and the service providers to know and analyze the market value of their products which would greatly aid them to formulate strategies for their business and to monitor their reputation in the market. Also, individuals who wanted to purchase the product or use the service would be interested in knowing other's opinion about the product features, pros and cons of the service for decision making. Sentiment Analysis of online reviews has thus become an extremely important area of research today. This visibly emphasizes the motivation behind the need of this research. Sentiment analysis or opinion mining can be defined as sub discipline of NLP (Natural Language Processing), computational linguistics and text mining that focuses on computational study of opinions, sentiments and emotions expressed in text. It covers a wide range of potential applications which includes ecommerce, politics, movies, tourism, and social networking sites etc. Hence research has been taking place in this domain for so many years. Some research papers discuss the main research problems in this area and the techniques adopted so far to solve different levels of sentiment analysis problems [1]. In our everyday life, we use qualifiers like "good quality", "excellent quality" or "poor quality" to express different degrees of qualification due to the ambiguity rooted in the natural language. In the literature, most of the works concentrate on binary classification of customer reviews rather only very few works have been done for fine grained classification of reviews. Also fuzzy techniques have been less explored. This paper therefore makes an attempt to explore a fuzzy logic model based on the most popularly used lexicon in the field of sentiment analysis, the SentiWordNet for fine granular classification of the reviews into weak positive, average positive, strong positive, weak negative, average negative and strong negative classes. The remainder of this paper is structured as follows. In Section 2, the existing research works done in the field of sentiment analysis so far has been discussed briefly. In Section 3 and Section 4, the proposed model has been explained in detail. Experiments and results' analysis are tabulated and discussed in Section 5. The conclusion and the future scope for improvement are presented in section 6.

1.2 Aims and Objectives

The goal of the research is to come up with an efficient way to measure product market by using the Fuzzy logic approach.

This research aim to redefine the issues related to Sentiment analysis (SA) structure. The purpose is to identify and modify the rules and results that have been used in former research. Also reviews are interpreted in a better way that will help us to achieve the goals in a more precise way in the field. The aim of this paper is to improve the efficiency of using the SentiWordNet in the task of sentiment classification for the reviews and evaluate product market demand with help of fuzzy logic approach.

Analyzing product market demand is becoming the most important and common issue in today's business. People are continuously shifting towards other products. So, it becomes difficult to retain your customers. Sentiment analysis can used to help out the business in their critical situations. It is type of appropriate mining of text which extracts Subjective imitations only, not facts. After the sentiment analysis the demand is not fulfilled accurately. So for this purpose we use Stanford Core NLP. This technique filters the reviews which are in the form of text, split them, remove stop words, tokenize the text and apply POS (Parts-Of-Speech) tagger on them. By using POS tagger grammatical rules, it becomes very easy to extract customer sentiments. We also prefer SentiWordNet software for further analysis because it gives values between 0-1 and provides three possibilities Which are POS(), NEG() and NEU(). By using all these techniques we can understand the reviews of customers and use another technique to find whether your customer is loyal towards your product or not. For this purpose, we use fuzzy logic which tells us the truth values of Yes/No. It creates linguistic variables to membership functions and gives them values between 0 and 1. This process classifies the customer reviews into various sentiments. In this process we have formulated an approach which consists of two phases. The first is to assign expressive (positive and negative) scores to the words; SentiWordNet Interpretation phase. The second phase is to apply fuzzy rules on reviews to classify those using words scores from first phase. By using these two phases, we can achieve useful results. It can save time and energy as well.

In order to reach this aim, we have defined the following objectives,

- Critical reviews of sentiment analysis based research on social media and define the research problem.
- In depth study of technology used in web scraping.
- Design and develop social media data scraping and analysis solution.
- Evaluate web scraped consumer reviews and improve recommender system using sentiment analysis and fuzzy logic based solution.

1.3 Background and Motivation

Some authors did researches on product review sentiment analysis and proposed to extract features from the review and categorize them into negatives, positives and neutral category using sentiment analysis and classification method. Before applying the sentiment classification method the pre-processing was done by removing noise, extracting features and isolating parallel descriptors. Then it was expanded to comprehend the consequence of fuzzy functions and linguistic obstructs to mimic the outcome of modifiers, dilator sand concentrators as well. This method was tested and the aftermath showed the accuracy of fuzzy logic in SA which was impressive [2]. Some authors have used the techniques of unsupervised Machine Learning, fuzzy sets, and a sentiment vocabulary which have been used and enhanced by SentiWordNet. A Hybrid Standard Classification (HSC) was implemented and upgraded to an approach: Hybrid Advanced [3]. It combined semantic ranking of linguistic polarity which is given by the fuzzy sets. The polarity (classification category) of any sentence that was presented as review was calculated with the help of new opinion mining technique. Other authors worked on another method to analyze the reviews of people on social networking sites. The author took to user's influence on several messages exchanged in social network along with the authorship of those messages. The result obtained was then used to study the reviews on some product and was then employed for the development of the analytics tools [4]. Some other authors determined a way to retain decision makers and city planners to spread awareness on issues related to city such as environmental, security and mobility. They used Fuzzy logic and the Cognitive Maps for the accomplishment of the goals. To establish the relationship between the two fuzzy sets, they had taken signatures and different signatures got assembled to mark a field. In addition to this, the authors preferred the factual concept of (FCS) Fuzzy Cognitive Map along with the implementation of if-then analysis [5]. After experimenting the outcomes were found to be persuasive and created a good consciousness on the quality of urban areas which actually created an effect on the issues that are associated to the city. Some authors proposed different model for fuzzy clustering for scanning posts or reviews that relate to the sentiments of a specific field or brand. They used the actual dataset of containing 12 months data. An analysis via comparison was produced with the process of K-Means clustering and partitioning technique and alongside Expectation Maximization algorithms were used [6]. The execution time, metric precision accuracy was used. The approach built up was tested and was found to give outstanding twitter result of sentiment analysis. Some authors put forward a method to retrieve the opinions about the product from manufacturers and customers through Naïve Bayesian classifier and presented a more realistic value of opinions obtained through fuzzy method [7]. Sentiment classification was performed and SentiwordNet and fuzzy method were used to calculate the value of opinion. Fuzzy rules magnified the effect of opinion describing the imprecise information and its varying degree of value.

1.4 Problem definition

In this specific area of research, there are many problems which researchers are already facing. Now-a-days the main problem people are facing is “Trust” issues, people do not trust any social media website and this issue cause a decrease in the rate of online shopping. Due to many fake sites people becomes conscious and starts to avoid online shopping. Then it come another important issue which is customer sentiments which are just taken as optional or a cause of promotion. Many business websites do not take customer reviews seriously because it consume much time to read and understand each and every review. These reviews contain hundreds of words and emotions and it is very challenging to recognize the tone of emotions only by reading some series of words. Another issue is parsing in which we do not know that which review refers the verb and/or adjective and what is the subject and object of the review. There are few more issue regarding to this research, some are discussed here. The most important problem is ambiguous or complex conditions. For example: The mobile shop is located at the first floor right by the entrance”. Is this sentence is positive, neutral or it’s negative? The answer is possibly different for different people. Another issue is Anaphora Resolve - The problem of identifying, what a pronoun, or a noun, phrase is actually trying to refers? "They went to park and also went for a dinner; it was awesome." We do not know that “What does "It" mentions?” The most important and common issue is sarcasm. It means we don’t understand user/customer’s

feelings behind their words. If we don't identify the source of author, we don’t judge whether 'good' means bad or good.
Customer loyalty has become a major issue in today’s business. Many business are falling down only because of customer turnover rate is increasing. Customer satisfaction of products is the vital for business as customer loyalty is gained by customer satisfaction. We need to focus on customer trust and understand their feelings in online product market. For this reason many ecommerce sites introduce online surveys which are actually very useful and as well as save the time and energy of customers. Despite all these arrangements, businesses were not achieving the actual goal of customer satisfaction because collections of online reviews are very easy but reading them all is difficult for them. It takes so much time and energy and they still could not understand them completely because of some extra words and emotion symbols. So businesses do not reaches their peak positions just because they read top few reviews and comments and try to make their business models according to them. After considering all the problems regarding this research, several techniques were used to overcome this problem but they have not achieved any reasonable results. However we introduce simplest technique: the use of sentiment analysis. This proposed technique fulfills our requirement as well as save the cost and time on the other useless techniques. Through this technique, the physical energy of the person who reads the reviews and understands them one by one is reduced as the work is done by the computer.

1.5 Fuzzy based Sentiment Analysis Solution

The fuzzy logic based sentiment analysis model classifies customer reviews into weak positive, average positive, strong positive, weak negative, average negative and strong negative classes. The model uses scores from the popularly known sentiment based lexicon, SentiWordNet instead of manual scoring which is time consuming and laborious task.

The final step is to evaluate sentiment scores of reviews of online products. By using this technique of sentiment analysis, we can easily evaluate product market demand. Fuzzy membership function and Fuzzy rules approach used here helps in achieving more reasonable and accurate results.

1.6 Resource Requirements

- Web Scraping tool

A web scraping tool is used which is capable of collecting information about target products from online e-commerce websites. The software is implemented in Python using BeautifulSoup.

- Python Libraries
  - NLTK , SentiWordNet and WordNet.
- Matlab Fuzzy logic toolbox

Matlab Fuzzy logic toolbox is used implement fuzzy rules and membership functions and evaluate them.

1.7 Structure of the Thesis

In this research, we do sentiment analysis of customer reviews towards online products. We used many different techniques for accurate and efficient results. We read the past papers and their weakness in this approach and tried to overcome it. We mainly used two approaches sentiment analysis and fuzzy logic in order to find the market demand of ecommerce products. The following terms used in this research are shown as follows:

- Customer sentiment

It is based on the feelings, moods and emotions that your customers feel when they involve with your business. When a customer buy something from you, then mentions you to a family, friend or relatives or give a review about your products, they are showing their emotions or we say a sentiments. Customer sentiment includes a variety of emotions like pleasure, eagerness, loyalty, satisfaction, grief, dissatisfaction, rage, and many more.

- Stanford POS tagger

This is to convert a simple sentence into the easiest and grammatical form in order to understand by a computer easily which is known as POS tagging (Parts-Of-Speech tagging). The purpose of Core NLP is to provide easy tools for language analysis. It is an open source library and extremely modifiable and flexible in design. Here we use a POS tagger which is written by The Stanford Natural Language Processing Group in Java language.

- Sentiment Analysis

It is also known as Opinion Mining which represents the customer's opinion about the product, goods, services etc. It defines the method of writing either it is positive, negative or neutral. Sentiment Analysis is actually to determine the feeling of people about specific matter. We can easily understand the meaning of Sentiment Analysis by the word

“Sentiment” which means feelings, Attitudes, Emotions and Opinions. It also helps to understand the social opinion of products and services in the form of online reviews which are beneficial for businesses.

- Fuzzy Logic

The fuzzy logic works on the levels of possibilities of input to achieve the definite output. It deals only with truth values and is called many valued logic. The value of truth varies from all the values in between 0 and 1. These truth values can encompass all the numbers between 0 and 1. It does not hold only with both true and false values like Boolean algebra. The membership functions organize these truth values and provide approximate reasoning. It does not provide accurate results but gives acceptable reasoning. It generally consists of three main working steps.

- Fuzzy Inference Engine
- Fuzzy membership functions
- Defuzzification

Chapter 2 contains related work which defines the past work, techniques and researches which are used by the other related papers and topics. It helps us to understand our research more efficiently and also clarify the weakness of the previous work.

Chapter 3 contains proposed methodology which describes the approaches we used in our thesis. We used different approaches to evaluate customer loyalty of online products. We perform sentiment analysis on the reviews and comments of customers on specific product. Then apply soft computing technique-Fuzzy logic in order to obtain the desired values.

Chapter 4 contains the implementation of the approaches described in Chapter 3.

Chapter 5 contains results. This chapter shows the results we obtained by applying different approaches. We take products of three domains and analyze their customer loyalty.

Chapter 6 contains conclusions and future work. The conclusions show the results we obtained from the proposed work. It justified that our results are according to the techniques used in our works. The future work shows that if anyone wants to expand this research, one may use some more techniques and research for this purpose.

1.8 Summary

This chapter presented an introduction to sentiment analysis and aims and objectives of this research. Research background and motivation is identified to define the research problem. Then Fuzzy based sentiment analysis solution and resource requirements for this solution is identified.

CHAPTER 2

Fuzzy Based Sentiment Analysis – Developments and issues

2.1 Introduction

Research and experiments have been done in the field of sentiment analysis since many decades. Researchers have proposed many different techniques for classifying reviews into either positive or negative. Techniques like supervised or unsupervised machine learning or semantic orientation approaches are used to solve the problem of sentiment analysis. Some brief descriptions of the work done in this field are described in this chapter. Bo Pang Lee [2] [3], C.Whitelaw [4], Alistair Kennedy [5] and Wen Fan, Shutao Sun and Guohui Song [6] have proposed supervised machine learning approaches with different features sets for binary classification of customer reviews into positive and negative classes. The features extracted include unigrams, bigrams, combination of unigrams and bigrams, adjectival appraisal groups, bag of words and POS based features. Different machine learning approaches have been applied in each of the works which include Naive Bayes Classifier, Maximum Entropy Classifier support vector machines and multiple classifiers algorithms namely, Bagging and Boosting. Experiments have been performed on various benchmark and home built datasets consisting of reviews on topics like movies, automobiles, travel destinations, news articles and electronic products namely digital cameras, DVD player, kitchen appliances, cellular phone. Accuracy in the range of 81% to 90% has been obtained and most of the previous works have proved to show better results while using SVM classifier.

A model has been built using support vector machines for binary classification of reviews to identify the best combination of features by extracting different features [7]. A research done by Peter D. Turney has proposed a simple unsupervised learning algorithm by estimating the semantic orientation of the phrases in the review using Pointwise Mutual Information (PMI) and Information Retrieval (IR) algorithms achieving an average accuracy of 74% [8]. A distance measure to determine the semantic orientation of adjectives using WordNet has been proposed by Jaap Kamps [9]. Osgood's theory of semantic differentiation, which yields a value between -1 and +1, was applied to measure the semantic orientation of the adjectives. A system for feature based summarization of reviews was proposed by Minqing which extracts noun and noun phrases as product features and adjectives as opinion words [10]. Semantic orientations of the opinion words were measured and final summary was produced with an accuracy of 84% [11].

Three scoring mechanisms for scoring the adverb adjective combination have been proposed by Benamara and Farah [12]. Tim O'Keefe, Irena Koprinska and Yan Dang proposed sentiment feature based on the SentiWordNet to train SVM Classifier [13]. Feature weighting methods using the SentiWordNet were compared with standard feature weighting methods namely frequency, presence and Term Frequency – Inverse Document Frequency (TF-IDF). An accuracy of 87.15% was obtained using Proportional Difference as feature selector and presence as feature weighting mechanism using less than 36% of features when tested on benchmark movie review dataset. Gang Li and Fei Liu introduced clustering based sentiment analysis approach which is a new approach to sentiment analysis [15]. An acceptable and stable clustering results using K-means clustering algorithm has been obtained with less human participation with accuracy in the range 77.17% to 78.33%.

The machine learning techniques are proposed in the previous works performs binary classification of customer reviews, that is, into positive and negative classes. But due to the ambiguity present in the natural languages, there is a need to perform still fine grained classification of reviews. Also instead of just restricting to classification of reviews, determining the sentiment of individual product characteristics will be very useful for the end customers to take decision before purchasing the product. This can be achieved by implementing fuzzy logic techniques together with natural language processing techniques. Those research works that have been done based on fuzzy logic techniques are briefly discussed. Guohong Fu and Xin [16] Wang presented a fuzzy set theory based approach to Chinese sentence-level sentiment classification since it provides a straightforward way to model the intrinsic fuzziness between the sentiment polarity classes. Word level, morpheme level and phrase level polarity were determined to calculate the sentence sentiment polarity. Three fuzzy sets were defined to represent three sentiment polarity classes positive, negative and neutral Rise Semi-Trapezoid, Semi-Trapezoid and Drop Semi-Trapezoid membership functions were built to indicate the degree of the opinionated sentence in the different fuzzy sets. By applying principle of maximum membership, final polarity was determined. Samaneh N Adali, Masrah Azrifah Azmi Murad and Rabiah Abdul Kadir [17] proposed a fuzzy logic model to perform semantic classification of customer reviews into very weak, weak, average, very strong, strong subclasses by combinations of adjective, adverb and verb to increase the holistic accuracy of the lexicon approach. Manual scores were assigned for all the words. Triangular membership function was used to model three fuzzy sets namely low, average and high. Elton Ballhysa and Ozcan Asilkan [18] proposed a novel approach for discovering the underlying opinion of reviews in Albanian Language by formulating a number of related fuzzy measures and aggregating to yield a resulting score. Relevance measure, Positivity measure, negativity measure and Obscenity measures were calculated using the proposed algorithms. Classification accuracy close to 80% was obtained when experimented on 1000 blog entries. Animesh Khar [19] has proposed a supervised method combining text mining approaches with fuzzy approximation techniques for product C Priyanka et al. / International Journal of Engineering and Technology (IJET) ISSN : 0975-4024 Vol 7 No 4 Aug-Sep 2015 1454 ranking by measuring the strength of individual product features. Experiments have been done with reviews on seven different models of digital cameras and a good accuracy has been obtained in predicting product ranking. Wei Wei [20] has also proposed a fuzzy based model to evaluate the quality of Chinese product reviews under the proximity membership principle based on three defined fuzzy sets. Experiments have shown promising performance for this method. Amit Pimpalkar [21] has proposed a fuzzy based technique for comparative analysis of two products. Sentences from product review are first categorized as subjective and objective using rule based system and dictionary and then the objective sentences are considered for analysis. While analyzing opinion words/phrases are checked with SentiWordnet to obtain semantic score. In fuzzy analysis weights are assigned considering 4 cases e.g. good, very good, not good, not very good etc. (Weight is assigned to (word, its POS tag)). Smileys in reviews are also compared with dictionary and finally the overall score of review is calculated to classify the review. Md. Ansarul Haque [22] implemented a java based application to search tweets from Twitter on any interested field or topic and analyze the sentiment of the same. The application is designed to handle tweets of different languages other than English by using Microsoft translator. The required preprocessing of the tweets is done and finally SentiWordNet is used to determine the score for each word in the tweet. Classification into six different classes namely, Strong Positive, Weak Positive, Positive, Strong Negative, Weak Negative, Negative is done based on total score of the tweet. Duc Nguyen Trung [23] proposed and implemented a practical system called Tweet Scope based on fuzzy propagation modeling for sentiment analysis of Twitter tweets. Here, twitter data with tweet, re-tweets, user, timestamp etc. are analyzed to find relationship between sentiment words and information propagation in social media. Tweets with similar diffusion pattern are grouped to obtain dependence between information propagation pattern and sentiment words. Mita K. Dalal [24] has proposed an opinion mining system extending feature based classification approach to incorporate the effect of various linguistic hedges. Fuzzy functions have been defined accordingly to emulate the effect of modifiers, concentrators and dilators. Evaluations have been done on dataset containing reviews of four electronic products of different brands. Based on the study it is evident that the fuzzy logic techniques are less explored in the domain of sentiment analysis. Also, most of the previous works on fuzzy logic have been done by manually assigning scores by human experts which is laborious and time consuming. Also, no understandable model is presented so far which completely make available fuzzy logic techniques in sentiment classification. All the work reported so far have been utilized the partial knowledge of fuzzy theory without reasoning and explanation. This research gap has been attempted and presented in this research work. This is the first attempt of its kind to discuss detailed fuzzy based model in sentiment analysis by combining the standard lexicon to imitate close to human behavior for fine grained classification of reviews. This proposed work has attempted to develop a fuzzy based straightforward model using the scores from a popularly used sentiment based lexicon SentiWordNet for fine grained classification of reviews into weak positive, average positive, strong positive, weak negative, average negative and strong negative classes

2.2 Problem definition

Lack of product feature usage in identifying sentiments of user product reviews has been a research challenge. When a consumer provides feedback about different features of a product, classifying a single review as either positive or negative may overlook valuable information contained within it. Based on this study we define the research problem as inadequate research in aspects such as product features when analyzing sentiment of product reviews.

Researches done on fuzzy based sentiment analysis for analysis of customer reviews have used a limited set of rules. Therefore, it is important to develop an extended fuzzy-based SA system for the analysis of customer feedback and satisfaction for the efficient classification of customer sentiment of a product. Thus overcoming the limitations of the aforementioned prior studies, a fuzzy-based SA scheme is proposed in this study that uses an extended fuzzy rule-set for the fine-grained SA of customer feedback and satisfaction.

2.3 Summary

This chapter contains related work which defines the past work, techniques and researches which are used by the other related papers and topics. It helps us to understand our research more efficiently and also clarify the weakness of the previous work.

CHAPTER 3

Approach

3.1 Introduction

In chapter 2, we discussed the technologies that can be used to solve our research problem of determining market trends by product feature based Sentiment Analysis. We have come up with a Fuzzy based Sentiment Analysis solution to address the above problem. The new approach is inspired by numerous evidence of the application of Fuzzy Logic for similar projects. Rest of the chapter has been structured with the subheading hypothesis, input/output, process, users and features.

3.2 Hypothesis

The hypothesis of this research is that latest market trends can be determined by product feature based Fuzzy based Sentiment Analysis solution using social media reviews.

3.3 Input

The input for this system is web scraped product related contents and reviews from social media. Amazon is selected as the most applicable platforms for web scraping based on the number of product reviews.

3.4 Output

This research produces the output as a new sentiment score for a product, which allows us to obtain rankings for products according to product features.

3.5 Process

- Web Scraping API collects product related contents and reviews from social media.
- Natural language processing (NLP) techniques, including text data mining, and clustering techniques are used to identify features of product reviews.
- Obtain a new sentiment score based on the sentiment score (feature review) given by a SA tool and fuzzy logic.

3.6 Users

The users of this system will be customers who will be selecting a product or service through web based merchant sites and manufactures and the service providers for these sites.

As online customer reviews are an integral and huge source of valuable information for the product manufactures and the service providers, they can analyze the market value of their products which would greatly aid them to formulate strategies for their business and to monitor their reputation in the market. Also, individuals who wanted to purchase the product or use the service will be benefitted in knowing other's opinion about the product features, pros and cons of the service for decision making.

3.7 Features

In this system, Sentiment Analysis is used to determine the feeling of people about specific products.

Fuzzy Inference Engine is used for approximate reasoning/thinking to convert Rule-based knowledge which consists of IF-THEN-ELSE rules. It gives conclusions on the given inputs.
Defuzzification converts the given output into a crisp value. It transforms the output gained by the inference engine into non-fuzzy values. It gives measurable results.

3.8 Summary

This chapter contains proposed methodology which describes the approaches we used in our thesis. We used different approaches to evaluate customer loyalty of online products. We perform sentiment analysis on the reviews and comments of customers on specific product. Then apply soft computing technique-Fuzzy logic in order to obtain the desired values.

CHAPTER 4

Implementation

4.1 Introduction

The high level design for the model is given in Figure 4.1. The working of each block in the high level design is described in subsequent subsections.

A. *Preprocessing Based On NLP Techniques*

Web crawled reviews are unorganized and contains noisy data which has to be preprocessed. Steps that are followed for data pre processing to eliminate theses noisy and incomplete information are listed here. The four preprocessing steps and the three NLP steps performed in this research work are as follows.

- Substitution of words having apostrophe.
- Substitution of repeating characters.
- Substitution of misspellings.
- Substitution of short hand words like “hve for have” etc.
- POS Tagging.
- Lemmatization.
- Stemming.

The preprocessed reviews needs to be POS tagged with appropriate part of speech tags in order to extract opinion information. The POS tagging of the preprocessed sentences is performed using the Stanford POS Tagger. A word can take many forms for e.g. the word “perform” can take forms like “performed”, “performing”. It is not possible for all word form to appear in the SentiWordNet. Lemmatization and stemming is performed in case the word in the review is not found in SentiWordNet. Stemming is the process for reducing

such inflected words to their stem, base or root form. WordNetLemmatizer is used for lemmatization and Lanchester stemming algorithm is used for stemming. Following example shows the raw data and the preprocessed sentence. The text has been carried forward in different steps in the order as specified. The corrected words in the preprocessed sentence have been underlined for clear understanding.

English Sentence: “Excellenttttttt fone !!!!!. Lot of good and useful features, it's very fast and have very good screen of high resolution .loveeeeeee it!“ is transformed into

Preprocessed Sentence: “Excellent phone !!!!!. Lot of good and useful features, it is very fast and have very good screen of high resolution. love it!".

POS tagged output :"Excellent_JJ phone_NN !!!!!_NNP Lot_NN of_IN good_JJ and_CC useful_JJ features_NNS ._. it_PRP is_VBZ very_RB fast_JJ and_CC have_VBP very_RB good_JJ screen_NN of_IN high_JJ resolution_NN ._. love_NN it_PRP !_."

B. *Extraction Of Opinion Information*

All words in customer review sentences are not providing opinion information about the products or their features. The nouns and noun phrases in the sentences are likely to be the features or product that customers comment on. The adjectives/adverbs that are used to qualify the nouns and express customer feelings are mainly taken as opinionated words. If POS tagged customer reviews matches with any of the patterns given in Table 4.1 two or three of those consecutive words are extracted. Example opinion phrases for all the specified patterns are shown here. For instance, the opinion phrases conforming to pattern 2 (Adverb, Adjective) are "slightly bad" and "extremely worst". Preprocessed reviews can be used to extract phrases similar to these examples thereby extracting all the opinion information.

Table 4. 1 Extracted phrase patterns and example opinionated phrases

Pattern No.	Pattern(First Word, Second Word, Third Word)	Opinionated Phrases
1	(Adverb, Adverb, Adjective)	(very very good) (not very good)
2	(Adverb, Adjective)	(slightly bad) (extremely worst)
3	(Adjective)	(good) (excellent) (poor)
4	(Adverb, Adverb, Verb)	(too nicely built) (not poorly performing)
5	(Adverb, Verb)	(perfectly working) (highly recommend)

C. *Crisp Inputs from SentiwordNet*

The Adjectives, Adverbs, Verbs, which are the linguistic variables for the fuzzy inference system, should be given assigned scores which are crisp inputs.In SentiWordNet, how objective, positive, and negative the terms contained in the synset are described by associating each synset of the English lexicon WordNet to three numerical scores Obj(s), Pos(s) and Neg(s). The process of extracting the score for adjective, adverbs and verbs consists of steps which are depicted in Figure 4.2. SentiWordNet is searched to find the required word. Lemmatization and stemming is performed if the word is not found in SentiWordNet.

Stemming algorithms WordNetLemmatizer3 and Lanchester Stemmer algorithms4 are used here.If the output of WordNetLemmatizer is not found in SentiWordNet, output of Lanchaster stemming algorithm is applied. Positive words will get high positive scores and the negative words will get alow positive scores. Similarly negative words will get high negative scores and positive words get low negative scores. Therefore the positivity and negativity of the word is measured based on positive and negative scores respectively. The manipulation can be done by extracting either positive or negative scores since both convey the same information. After lemmatization and stemming, if the word is not found in SentiWordNet then the word is objective and has no sentiment.Hence a default value of 0 is assigned for both positive score and negative score of the word. After word is found in the SentiWordNet, the positive scores corresponding to the word are extracted. The final score for the word will be the maximum value of this list. Interpretation from the membership function plot becomes difficult here as the SentiWordNet scores range from 0 to 1.Therefore, for scaling purposes, the final score of the word is multiplied by 10 and assigned as the crisp input for the input linguistic variables. The crisp input for the found word is the scaled value of the positive score of the word directly extracted from SentiWordNet.

This crisp input should therefore be converted into fuzzy sets by applying suitable membership functions which are explained in the below respective sections.

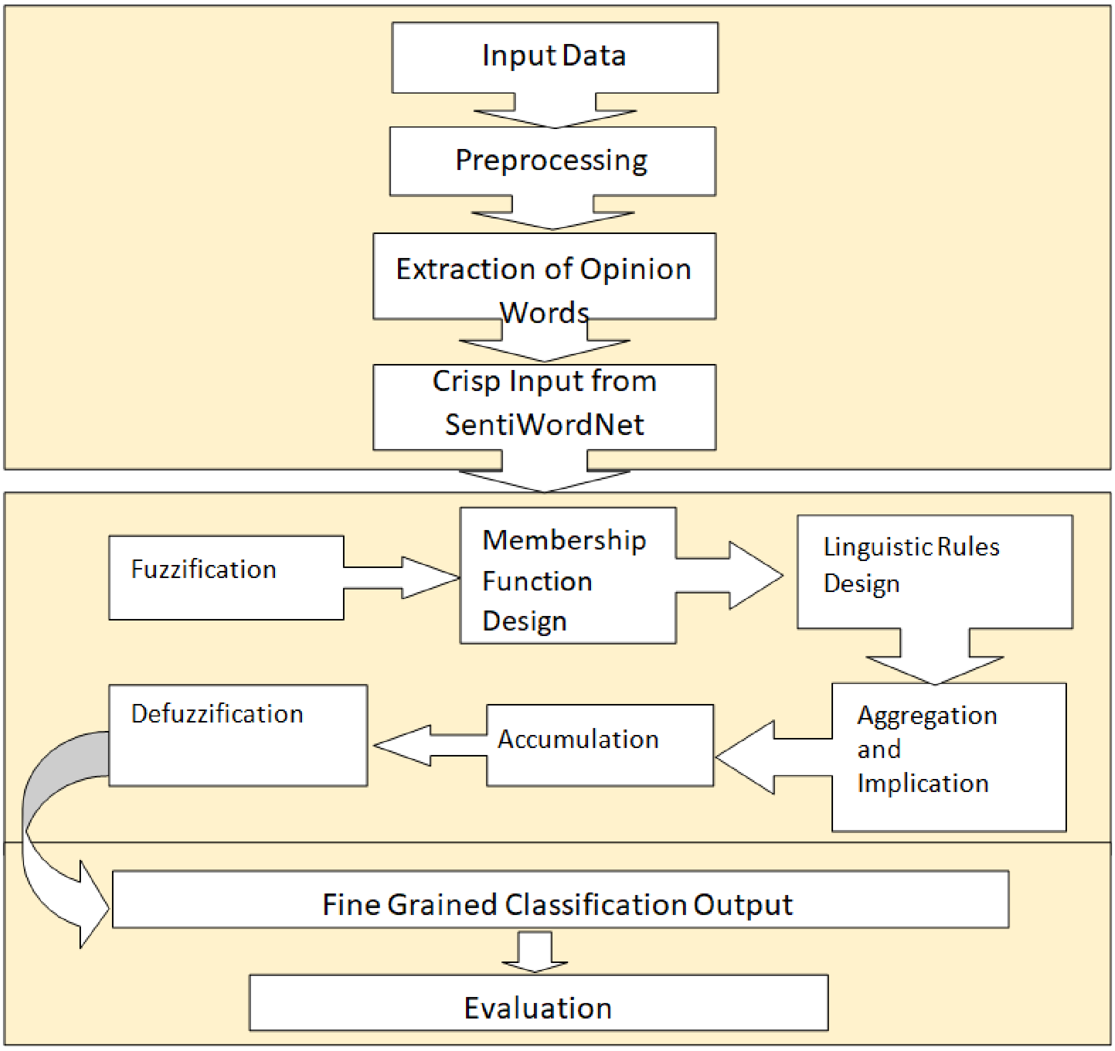

Figure 4. 1 High Level Diagram of the proposed Methodology

D. Fuzzification

The first step in a fuzzy system includes the identification of input and output linguistic variables. In this work, “Verb”, “Adverb” and “Adjective” are taken as input linguistic variable as sentiment information is mostly provided by verbs and adjectives and the adverbs covey the intensity of the sentiment. The proposed fuzzy model aim to classify the reviews into polarity classes, for e.g. Weak Positive, Average Positive etc. The output linguistic variable will be the “Degree of Polarity”. The input and the output variables for the system are designed to accept values of REAL data type.

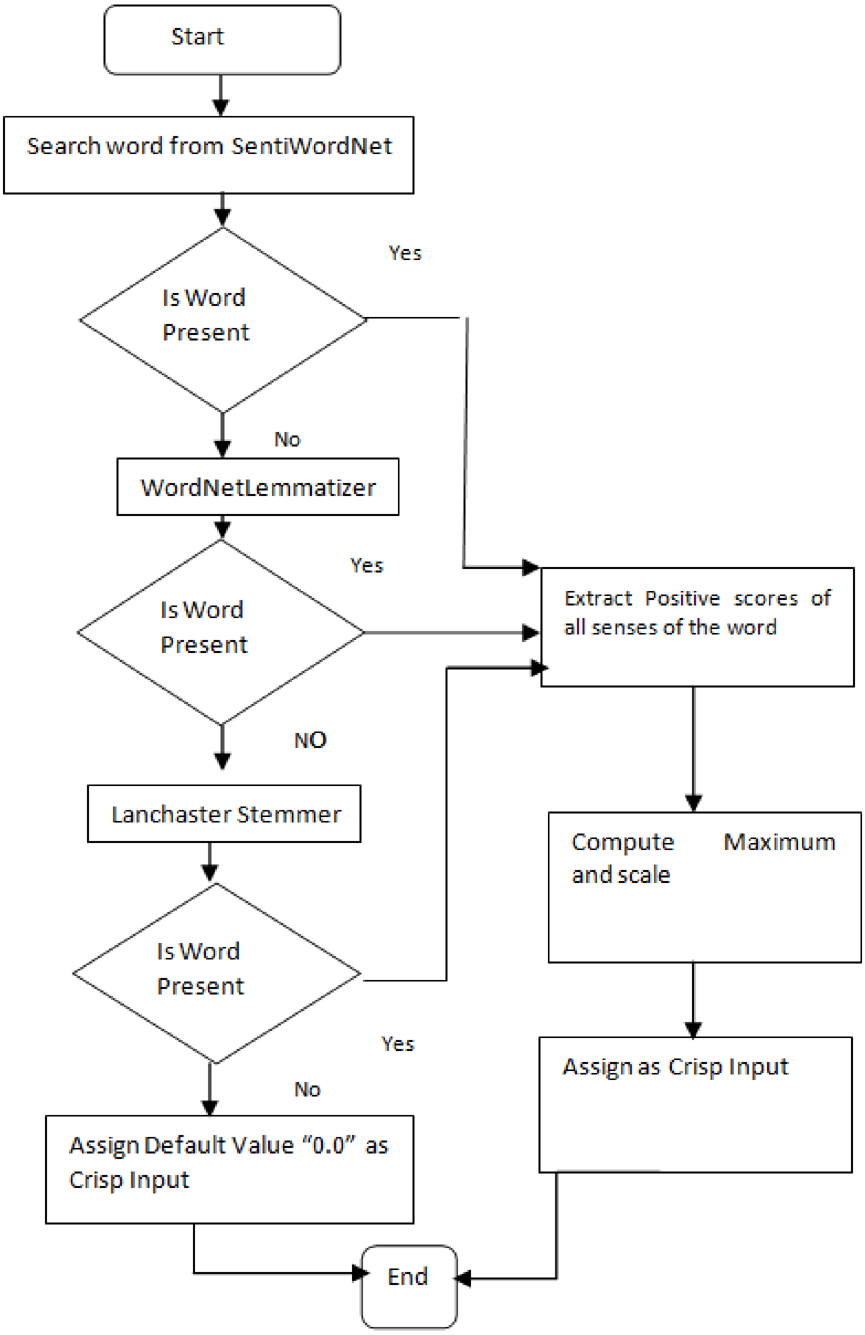

Figure 4. 2 Extraction of Crisp Input from SentiWordNet

Fuzzy sets are named accordingly as it is easy for us to imagine the fuzzy sets of the input and output variables as linguistic terms instead of numbering. The first stage in a fuzzy system is fuzzy partition and fuzzification. Here linguistic variables are divided into suitable fuzzy sets (linguistic terms) by partitioning of each variable. Then a membership function is applied over each fuzzy set (partition). The fuzzy sets defined for the input and output linguistic variables for this work are shown in Table 4.2. All the fuzzy sets are given respective notations in braces and in all the rules the respective notations are used. In most cases the opinion is conveyed by the adjectives and verbs. So there are 6 fuzzy sets defined for Adjective and Verb. Partitioning them into many classes will be easier for final classification of the reviews. Only three fuzzy sets for adverbs are defined as only the strength of the opinion is conveyed by adverbs.

Thus based on these two input linguistic variables, the output fuzzy set is determined which conveys the degree of polarity of the review.

Table 4. 2 Linguistic Variables and Fuzzy Sets

<table>
<tr><td colspan="2">Input</td></tr>
<tr><td>Linguistic Variable</td><td>Fuzzy Sets</td></tr>
<tr><td>Adjective</td><td rowspan="3">High Negative (HN), Average Negative(AN), Low Negative (LN),
Low Positive (LP) , Average Positive (AP), High Positive (HP),
Low (L), Average (A) , High (H)</td></tr>
<tr><td>Verb</td></tr>
<tr><td>Adverb</td></tr>
<tr><td colspan="2">Output</td></tr>
<tr><td>Linguistic Variable</td><td>Fuzzy Sets</td></tr>
<tr><td>Degree of Polarity</td><td>Strong Negative (SN), Average Negative (AN), Weak Negative (WN),
Weak Positive (WP), Average Positive (AP), Strong Positive (SP)</td></tr>
</table>

D. *Membership Function Design*

The Crisp Values of the Linguistic Variables are converted to the given fuzzy sets by a function called Membership Function [27]. For the partitions of linguistic variables as linguistic term sets or linguistic values, the inputs are mapped into the degree of membership by suitable membership functions. There are many different forms of membership functions. Generally, the membership functions can be drawn linearly or non-linearly such as triangular, trapezoidal, bell-like, or Gaussian forms. Vertical axis (y) shows the results of the membership function $\mu(x)$. The horizontal axis shows the crisp quantities, as support. The quantity on the horizontal axis is the base variable and represents the universe of discourse; while the quantity on the vertical axis is the membership degree to the fuzzy set. One of the important parts in a fuzzy system is the selection of suitable membership functions for fuzzy sets. By analyzing the scores of the lexicon provided in SentiWordNet, Triangular, Semi-Trapezoidal and Piece-wise Linear Membership Functions are used for respective fuzzy terms.

Fig.3 shows the elected fuzzy sets and the corresponding membership function, defined by translating the variable “Adjective” into six linguistic terms {“High Negative”, “Average Negative” , “Low Negative” , “Low Positive” , “Average Positive”, “High Positive”}: positivity increases as they shift towards the left. Shifting towards the right direction indicates the increase in negativity. For the fuzzy set ‘Average Positive’, a triangular membership function is chosen. It is defined with end points as (4.5, 0) and (7, 0) and high point as (6, 1) in (1). In a similar fashion, Semi Trapezoidal membership function is chosen for the fuzzy set “High Positive” and shown in (2). In the same way, for the other fuzzy sets membership functions are defined by selecting appropriate end points as depicted in the plot shown in Fig 3. The Semi Trapezoidal function “High Positive” is defined with end points (6.8, 0) and (9, 1). Six fuzzy sets are formed for “Verb” namely {“High Negative”, “Average Negative”, “Low Negative”, “Low Positive”, “Average Positive”, “High Positive”} and by analyzing the scores from SentiWordNet , suitable membership functions are defined for all the fuzzy sets. For instance, the triangular membership function is chosen for the fuzzy set ‘Low Positive’. It is defined with end points as (1.25, 0) and (3, 0) and high point as (2, 1) in (3). In a similar fashion, semi Trapezoidal membership function is chosen for the fuzzy set “High Positive” and shown in (4). Membership functions are defined in same manner for the other fuzzy sets by selecting suitable end points and they are depicted in the plot shown in Figure 4.2. The Semi Trapezoidal function “High Positive” is defined with end points (4.5, 0) and (7, 1).

FUZZY SET	MEMBERSHIP FUNCTION
High Negative	Piece-wise Linear
Average Negative	Triangular
Low Negative	Triangular
Low Positive	Triangular
Average Positive	Triangular
High Positive	Semi - Trapezoidal

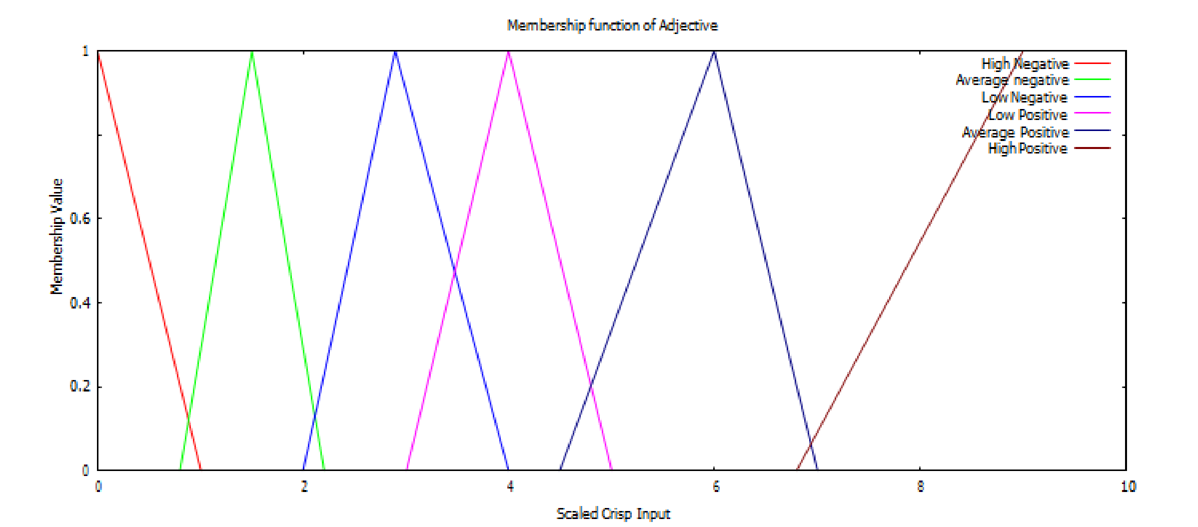

Figure 4. 3 Membership Function for Adjective with Six Linguistic Terms

The intensity enforced on adjectives by adverbs is in the range of low to high. The three fuzzy sets low, average and high and their respective membership functions are shown in Figure 4.3. The Triangular and Semi- trapezoidal function are defined for the three "Adverb" fuzzy sets.

E. Linguistic Rules Design

The fuzzy sets formed in the previous step are used in rules-making, either by expert rule or by data-based rule. The rule block contains fuzzy operators to combine all fuzzy sets of linguistic variables per rule. Simple and straightforward operators are used such as OR (maximum) or AND (minimum). The result of this step is used determine the degree of polarity of the customer reviews. The general form of the fuzzy rule can be expressed as: If x1 is ADV AND/OR x2 is ADV AND/OR x3 is ADJ/VERB THEN x4 is DEG where, ADJ/VERB is a set containing the fuzzy sets of the input linguistic variable "Adjective" and "Verb". ADV is a set containing the fuzzy sets of the input linguistic variable "Adverb". DEG is a set containing the fuzzy sets of the output linguistic variable "Degree of polarity".

x1, x2, x3 represent the fuzzy variables which are the opinion words of the opinion phrases extracted from the customer reviews. x4 represents the fuzzy variable “Degree of Polarity”. The ADJ/VERB, ADV and DGE sets are discussed in Table II. The minimum operator “AND” is used between the antecedents variables in the rules defined in our fuzzy inference system. Table 4.3 shows sample rules of the IF– THEN rules designed for the developed fuzzy inference system to determine the degree of polarity of the customer reviews.

FUZZY SET	MEMBERSHIP FUNCTION
High Negative	Piece-wise Linear
Average Negative	Triangular
Low Negative	Triangular
Low Positive	Triangular
Average Positive	Triangular

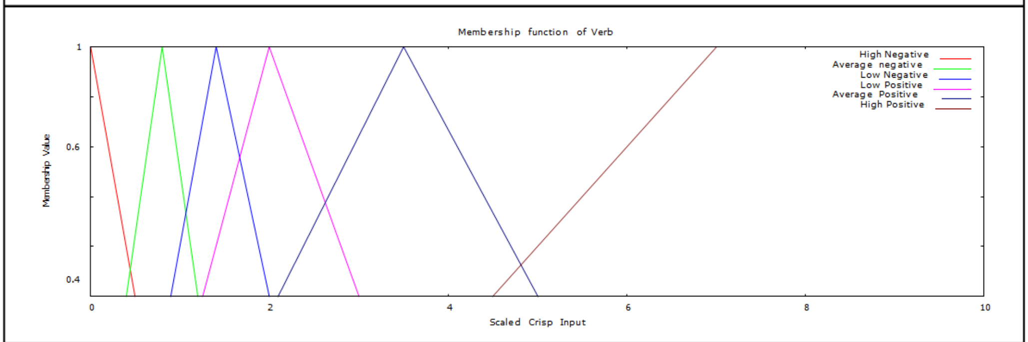

Figure 4. 4 Membership Function for Verb with six Linguistic Terms

FUZZY SET	MEMBERSHIP FUNCTION
Low	Piece-wise Linear
Average	Triangular
High	Semi - Trapezoidal

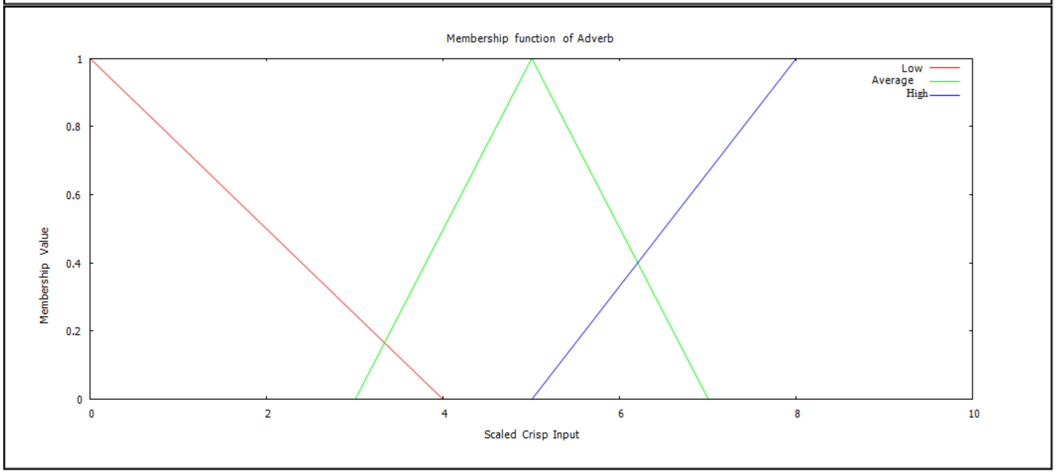

Figure 4. 5 Membership Function for Adverb with Three Linguistic Terms

Table 4. 3 Sample If – then Rules

S.No	Rules
1	IF (adverb1 IS L) AND (adverb2 IS L) AND (adjective IS LN) THEN (degree IS SN);
2	IF (adverb1 IS L) AND (adverb2 IS L) AND (adjective IS AN) THEN (degree IS WN);
3	IF (adverb1 IS L) AND (adverb2 IS L) AND (adjective IS HN) THEN (degree IS average_neg);
4	IF (adverb1 IS L) AND (adverb2 IS L) AND (adjective IS LP) THEN (degree IS WP);
5	IF (adverb1 IS L) AND (adverb2 IS L) AND (adjective IS AP) THEN (degree IS WP);
6	IF (adverb1 IS L) AND (adverb2 IS L) AND (adjective IS HP) THEN (degree IS AP);
7	IF (adverb1 IS L) AND (adverb2 IS M) AND (adjective IS LN) THEN (degree IS SN);
8	IF (adverb1 IS L) AND (adverb2 IS M) AND (adjective IS AN) THEN (degree IS AN);
9	IF (adverb1 IS L) AND (adverb2 IS M) AND (adjective IS HN) THEN (degree IS AN);
10	IF (adverb1 IS L) AND (adverb2 IS M) AND (adjective IS LP) THEN (degree IS WP);
11	IF (adverb1 IS L) AND (adverb2 IS M) AND (adjective IS MP) THEN (degree IS WP);
12	IF (adverb1 IS H) AND (adverb2 IS L) AND (adjective IS LN) THEN (degree IS AN);
13	IF (adverb1 IS H) AND (adverb2 IS L) AND (adjective IS HN) THEN (degree IS SN);
14	IF (adverb1 IS H) AND (adverb2 IS M) AND (adjective IS LN) THEN (degree IS AN);

IF_THEN rules that can support all possibilities are in total of about 324. In this work, rules that are irrelevant are pruned out and a total of 78 rules have been defined. Consider for example the IF THEN rule from Table III, IF (adverb1 IS L) AND (adverb2 IS L) AND (adjective IS LN) THEN (degree IS SN).

Here, if the adverb1 belongs to the fuzzy set "Low", adverb2 belongs to the fuzzy set "Low" and adjective belongs to the fuzzy set "Low Negative", then degree of polarity of the corresponding opinion phrase belongs to the fuzzy set "Strong Negative". Similarly, other rules are also interpreted in the similar way and are fired one after the other.

F. *Aggregation and Implication*

The first step is to take the crisp inputs of the input linguistic variables "Adjective" and "Adverb" and through their respective membership functions find the degree to which they belong to each of the appropriate fuzzy sets. The input is always a crisp numerical value (in this case the interval between 0 and 10) and output is a fuzzy degree of membership in the qualifying linguistic set (always between 0 and 1).

After the fuzzification of inputs, the degree to which each part of the antecedent is satisfied for each rule can be found. In this work, 3 types of rules have been defined: antecedent with one part, two parts and three parts. The logical fuzzy operator "AND" is applied to the antecedent of the rules having more than one part in order to obtain one single number that represents the result of the antecedent for that rule. The fuzzy "AND" operator simply selects the minimum of the values. This is the process of aggregation. Now after aggregating, implication process is implemented for each rule. The implication process reshapes the consequent of the rule using the single number given by the aggregation of the antecedent, and the output is a fuzzy set. The implication method used here is same as the "AND" method: minimum, which truncates the output fuzzy set which is the Degree of polarity of the POS pattern.

G. *Defuzzification and Output*

In this step, to calculate a final score for the extracted POS pattern, we map the fuzzy values into crisp. In this stage, the Centre of Gravity (CoG) defuzzification operator is used which returns the centre of area under the curve and is given in " Eqn (5) ". The accumulated fuzzy rules outputs are converted to a single crisp value which represents the degree of polarity for each of the POS based pattern extracted. Five fuzzy terms are defined for the output linguistic variable Degree of Polarity, and all are represented by triangular membership functions as shown in the plot given in Figure 4.6. The Centre of gravity defuzzification is defined in Eqn (5) as, Where, z* is the defuzzified value and µC (z) is the accumulated output of the list of output functions returned by the applying implication process for each rule.

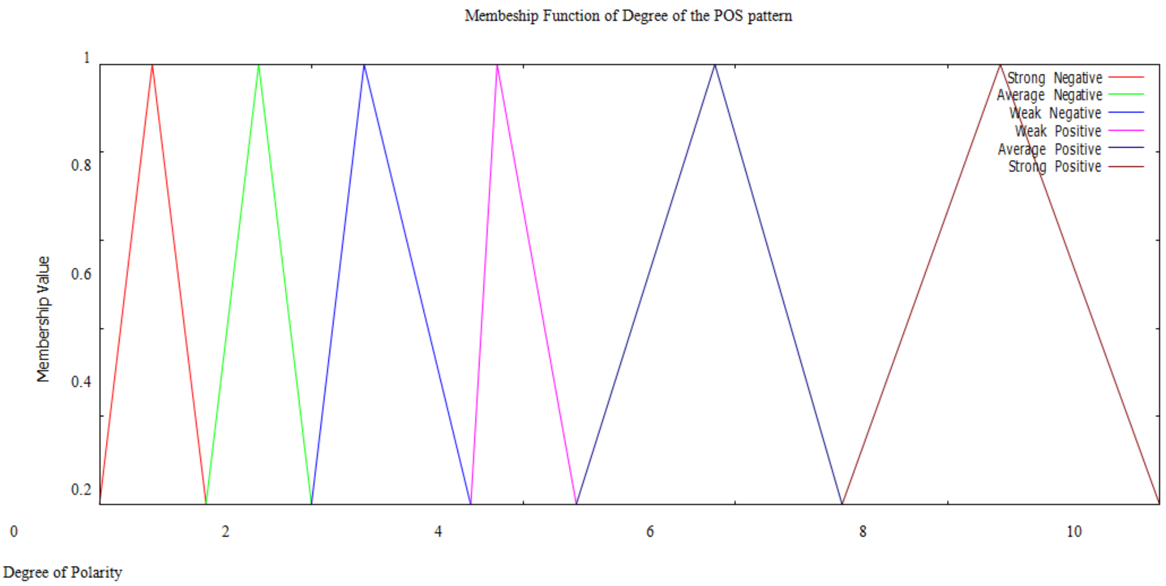

Figure 4. 6 Membership Function for Output with Six Linguistic Terms

For instance, the triangular membership function for the fuzzy set 'Strong Positive' is defined in (6). The function is defined with end points as (7, 0) and (10, 0) and high point as (8, 1). In the same way, triangular membership functions are defined for the other fuzzy sets by selecting suitable end points and high point.

A crisp score is determined using the fuzzy logic model based on the fuzzy sets defined for the input linguistic variables for each of the POS based pattern that is extracted. Now to determine the degree of polarity of the entire customer review is, the average of all the scores provided for each of the POS pattern extracted from the review is calculated which is shown in Eqn (7).

$$\text{Fine Grained Score} = \frac{\sum_{i=1}^{n} D_i}{N} \tag{7}$$

Where, Di is defuzzified output of the i^{th} extracted pattern and N is the total number of POS patterns extracted from a review. The fine grained score ranges from 0 to 10. The degree of polarity can be identified from the patterns extracted from a review. The fine grained score ranges from 0 to 10. The degree of polarity can be identified from the score with the help of the plot shown in Figure 4.5. As we move towards right in the graph indicates positivity and as we move towards left indicates negativity. The range for each degree of polarity is pre-defined and hence the class to which the customer review belongs to can be determined from this final fine grained score. In this stage, the Centre of Gravity (CoG) defuzzification operator is used which returns the centre of area under the curve and is given in " Eqn (5) ". The accumulated fuzzy rules outputs are converted to a single.

4.2 Summary

This chapter contains the implementations of the approaches described in Chapter 3.

CHAPTER *5*

Evaluation

5.1 Introduction

The experiments performed to prove the advantage of the proposed fuzzy based model is discussed here. The Stanford Part of Speech tagger developed by Stanford University has been used to tag the reviews. The PyFuzzy-0.1.05, a python based fuzzy logic module has been used for implementation of the proposed model in which the required coding is done in Python 3.0 programming language. The results and analysis have been furnished in order to demonstrate the usefulness of the proposed model.

A. Corpus Statistics

Reviews have been collected from Amazon and experiments have been conducted on three datasets containing reviews of electronic products namely smart phones, TV and laptops. They are annotated manually based on the star rating provided in the website. The reviews that are rated 1-2 are considered as negative and 4-5 are considered as positive. The star rating information has not been used anywhere in the proposed fuzzy model but this information helps us to calculate the binary classification accuracy of our proposed model. The detailed statistics of the three data corpus is presented in Table 5.1. The reviews have been chosen in such a way that average word count per review ranges from 42 to 82 approximately. This proposed model has been therefore tested on reviews irrespective of the nature of the review in terms of its length. The total number of reviews in each dataset ranges from 800 to 1200 approximately. Therefore, the experimental results obtained reveal that the proposed fuzzy based model can be applicable to any dataset containing electronic products' reviews irrespective of the dataset size as well as the review length.

Table 5. 1 Corpus Statistics

Review Dataset	**# of reviews**	**Avg word count per review**	**Avg sentence count per review**
Domain : Smart Phones			
Positive Review	538	42.69	2.95
Negative Review	580	49.52	2.91
Domain : Laptops			
Positive Review	585	67.50	3.78
Negative Review	592	81.94	4.02
Domain : TV			
Positive Review	580	70.34	3.05
Negative Review	510	75.19	4.39

B. *Experimental Results and Analysis*

For the evaluation of efficiency and usefulness of the proposed model, the model has been tested on many opinion phrases of different degrees of polarity extracted from the customer reviews of the corpus given in Table 5.1. The defuzzified output of some of the opinion phrases has been tabulated in Table 5.2. There is significant difference between the scores of the phrase “Bad” and “Good” which is 2.689 and 5.766 respectively. Similarly in the phrases “Very Good” and “Very Excellent”, the adverb “Very” has been used to intensify the positive polarity of the words “Excellent” and “Good”. Hence scores are also relatively high compared to the other phrases which are 8.3333. Also from Table 4, it is clear that the system is able to show significant difference between the opinion phrases containing verb. The scores of the phrases “Not Working” and “Badly Working” are 1.5 which is relatively low compared to the score of the opinion phrase “Working” which is 5.068. This clearly shows that the two former phrases are negative compared to the latter one. Similarly the model provides for the phrases “Nicely Working” and “Excellently Working” a higher score of 6.772 and 8.389 respectively thereby proving the positive polarity of these phrases. Thus the scores provided by the proposed model for the opinion phrases given in the Table 4 clearly confirms that the proposed fuzzy logic model is able to capture the intrinsic fuzziness between the polarity classes using the scores from the lexicon SentiWordNet.

The average of all the defuzzified output scores of the opinion phrases extracted from a customer review has been used to calculate a final output score for the review as per the Eqn(7). This score determines the final class to which the review belongs to. To classify the reviews into positive and negative classes based on this score, cut off value which partitions the entire set into two classes has to be fixed. Experiments have been performed with different cut off values and the accuracy in (%) for binary classification of reviews into positive and negative classes for those different cut off values has been determined and plotted in Figure 5.1. Binary classification accuracy ranges from 74% to 77%. It is evident from the graph that better classification accuracy can be obtained with the cut off value of 3.2. Similar experiments have been performed in order to determine the cut off values for all the six classes of fine grained classification. Based on the results of those experiments, the range for each class is computed and tabulated in Table VI. The results of the fine grained classification for all the three datasets have been tabulated in Table 5.2. The accuracy of fine grained classification ranges from 74% to 76%.

Table 5. 2 Results of sample opinion phrases

Product Opinions	Defuzzified Output	Product Opinions	Defuzzified Output
Not bad	3.9166	Not Very Good	5.766
Very bad	1.5	Very Worst	1.5
Bad	2.689	Fantastic	5.7574
Slightly Bad	3.9567	Very Excellent	8.333
Not Good	2.6666	Excellent	5.766
Very Good	8.333	Not Working	1.5
Good	5.766	Badly Working	1.5
Slightly Good	3.484	Nicely Working	6.772
Worst	2.689	Excellently Working	8.389
Slightly Worst	3.9567	Working	5.068
Very Very bad	0.5		

The experiments thus performed are sufficient to evaluate the efficiency and advantage of the proposed fuzzy based model. The results tabulated in Table 5.1 and Table 5.2 has been analyzed and the findings have been listed below.

It can be seen from the Table 5.2 that the defuzzified output values of the phrases “Slightly Good” is 3.484, “Not Good” is 2.666, “Good” is 5.766 and “Very Good” is 8.333. It is clear from these values that the scores have been assigned for the phrases by the model according to its degree of polarity. The phrase “Slightly Good” has a score little higher than the phrase “Not Good” and the Phrase “Good” has a score little higher than the other two “Slightly Good” and “Not Good”. The phrase “Very Good” has a score higher than all the other three phrases. Logically, the sentimental meaning of the phrases and the assigned scores are hand in hand with each other.

Table 5. 3 Range for the six classes

Class	Range
Strong Negative	(0 – 1)
Average Negative	(1 – 2)
Weak Negative	(2 – 3.5)
Weak Positive	(3.5 – 4.5)

Average Positive	(4.5 – 7)
Strong Positive	(7 – 10)

Table 5. 4 Evaluation results for fine grained classification

Domain	**Accuracy (%)**
Smart phones	76.5%
Laptops	75%
TV	74.3%

- It can also be seen from Table 5.4 that the scores that have been assigned by the proposed model for the opinion phrases containing verb according to their degree of polarity. The defuzzified output value for the phrases “Not Working” and “Badly Working” are very less which implies that they bear negative sentiment. In the same way, the output value for the phrases “Nicely Working” and “Excellently Working” are higher which implies that they bear positive sentiment. Also there is significant difference between the scores of the phrases “Nicely Working” and “Excellently Working” which clearly indicates the degree to which each of the phrases is positive.
- Experiments have been performed with numerous opinion phrases in order to know the real advantage of directly using the scores of the lexicon SentiWordNet for proposed fuzzy based model. It is found that the scores provided in SentiWordNet for most of the adjectives can be used directly and only scores for few adjectives require revision.
- The defuzzified output values for some of the opinion phrases containing verb show less satisfactory results. Analysis of these output values reveals that the scores provided by SentiWordNet for a quiet larger number of verbs are not that suited for direct usage in our proposed fuzzy model. Revision of these scores either manually or through automatic approaches may be required to obtain more satisfactory results which will also lead to significant improvement of the final classification accuracy results.
- The accuracy in (%) ranges from 74% to 77% for binary classification of reviews into positive and negative classes. Comparing the accuracy (%) with respect to the

different cut off values for all the three datasets, it is evident that fixing the cut off value to 3.2 would give better binary classification accuracy.

5.2 Summary

This chapter shows the results we obtained by applying different approaches. We take products of three domains and analyze their customer loyalty.

CHAPTER 6

6.1 Conclusion and Further Work

In this paper, a fuzzy logic based sentiment analysis model is proposed for in-depth classification of customer reviews into weak positive, average positive, strong positive, weak negative, average negative and strong negative classes. The model has been designed in such way that the scores from SentiWordNet have been effectively used instead of manual scoring which is a time consuming task. Experimental results have shown to produce accuracy in the range of 72% to 75% when tested on three datasets containing reviews of electronic gadgets. This model does not require any kind of labeled data which is expensive with lot of prior human effort. It is also computationally less intensive and less time consuming. Also, instead of restricting to only classification of reviews, determining the sentiment of each product feature from the reviews was very beneficial. This was achieved by combining natural language processing techniques and fuzzy logic model.

We can achieve more reasonable and accurate results in this research in the future by applying some techniques in this process. In future work, few revisions in the scores of SentiWordNet, either manually or through automated approaches by analyzing data from different datasets, can also lead to significant improvement in the final results. By using voice recognition feature, one could easily understand the feelings behind the review, but it also needs to be added into the SentiWordNet dictionary as well, and this spans a very vast range. Modifying the membership functions of the defined fuzzy sets also has scope for enhancement of the final accuracy results.

6.2 Summary

This chapter contains conclusions and future work. The conclusions show the results we obtained from the proposed work. It justified that our results are according to the techniques used in our works. The future work shows that if anyone wants to expand this research, one may use some more techniques and research for this purpose.

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