Aspect Based Sentiment Analysis Using the Deep Learning Convolutional Neural Networks

Thesis submitted in partial fulfillment of the requirements for the award of degree of

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Submitted by

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CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, "*Aspect Based Sentiment Analysis Using the Deep Learning Convolutional Neural Networks*", in partial fulfillment of he requirements for the award of the degree of Master of Technology in Computer Science and Applications submitted in Computer Science and Engineering of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of Dr. Husanbir Singh Pannu and refers other researcher's work which is duly listed in the reference section.

The matter presented in the thesis has not been submitted for award of any degree of this or any other University.

(Ravindra Kumar)

This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

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(Ravindra Kumar)

ABSTRACT

Sentiment Analysis is also known as Opinion Mining, is the computational study of unstructured textual information. It might be in regard to a person's perspective, attitudes, feeling and emotions toward an event or an entity in the form of a piece of text. Sentiment analysis has become an important task for automatically classifying a piece of text as positive, negative or neutral. It helps to explore meaningful information from the data over the internet. Three important aspects are presented. The first one is creating ontologies for the extraction of semantic features. It gives effective information about domain in our case. Overall score for opinion is calculated by using these features and further we label the dataset. Second aspect involves *word2vec* for conversion of processed corpus. *Word2vec* is an unsupervised neural network, which is used to extract feature vector used by deep learning algorithm. The third and final aspect is Convolutional neural network (CNN) for training and testing. In this thesis, the proposed framework can be expressed as combination of Ontology, Word2vec and CNN. Ontology is a technique for knowledge representation and association between different entity and attributes of a specific domain. Experiments show that the use of CNN along with Ongology is an efficient approach for opinion mining. As a classifier, it achieves 88.5%, 94.3% and 81.8% in accuracy, precision and recall respectively making it more efficient compared to other state of art algorithms such as compare to SVM, Random Forest, Decision Tree, Maximum Entropy, Generalized Linear Model, Stabilized Discriminant Analysis.

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ABBREVIATIONS

WOM	Word of Mouth
VOV	Voice Of Voters
VOM	Voice Of Mouths
BRM	Brand Representation Management
CNN	Convolutional Neural Networks
ReLU	Rectified Linear Unit
SVM	Support Vector Machine
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative

CHAPTER 1

INTRODUCTION

Sentiment analysis is always a challenging task in the field of natural language processing. It is the process of finding opinion attached with a piece of text by evaluating whether it is positive, negative or neutral. It also finds the degree of polarity (high, mild or moderate) well known as opinion mining. It analyzes the feeling, thought, attitude from collecting opinion as review on various web sites. Opinion mining can be done mainly by two approaches, first one is machine learning approach and the second one is a lexicon based approach. Further machine learning based approach is divided into two parts, supervised and unsupervised.

There are three ways to perform sentiment analysis. First one is Document level. The least demanding of the three fore specified methodologies is unquestionably the first and this concept is followed by most of current opinion mining approaches right now (essentially grouping docu-ments or posts like tweets as positive and negative). It doesn't consider the diverse points of the archive, however it can have moderately great outcomes particularly in cases, where we are intrigued just in discovering which records does a particular client need to peruse (Antoniou, 2012).

At Sentence level, The sentence level grouping considers each sentence as a different unit and expect that sentence ought to contain just a single supposition. Sentence level examination has two undertakings as subjectivity characterization and estimation grouping.

In Phrase level, also known as aspect level aspect. The objective of performing classification at feature level, is to create a component based perspective outline of different surveys. It has basically three undertakings. The primary assignment is to recognize and extricate question includes that have been remarked on by a conclusion holder (e.g. "picture", "battery life"). The second job is to decide the extremity of viewpoints on different classes of features: positive, negative and impartial.The third job is identified with the gathering words equivalent to features.

The contents present on the internet in the form of literature, review, blogs are increasing day by day. This data is available as structured data and unstructured data. Structured data comprises of numeric data, transactional data and information that is gathered and stored in well mannered form by enterprises. Further, such data is used to access, perform query so as to help in taking important decisions by organizations. Unstructured data includes data that is present in the form of text documents, PDF files, SMS, e-mail, customer comments, review about an entity, social post, audio and video.

1.1 Foundation

Extraction of information from text content is always required for NLP tasks. Thus it becomes necessary to analyze the text content. Finding sentiment polarity attached with sentence, document, literatures is always a challenging task. Continuous effort have been made by the researchers to identify the perspective of writers regarding a specific topic. Various machine learning approaches like SVM, Naïve Bayes, LDA, Random Forest has been in use to get the best result. Recently, deep learning has included and achieved remarkable results in computer vision and speech recognition. It provides better results in field of opinion mining as well. Inspired by the success of Convolutional Neural Network, sentiment analysis of hotel review using deep learning is proposed as a methodology to accurately classify the reviews. Ontology is used for aspect based analysis and to label the complete review as positive or negative. Word2vec is used to convert the processed review to vector form and finally CNN is applied for training and testing of reviews.This dissertation work is focused on aspect based sentiment analysis.

1.2 Aspect Based Sentiment Analysis of Hotel Review

Aspect based sentiment analysis takes the reviews and learn the aspects present inside it. For every aspect score is provided and on the basis of these score polarities for complete sentence is calculated. After this review are classified as training and testing and then the model is trained. Training of the model makes it capable to find out the polarity of new review.My working model is shown in below Figure1.1:

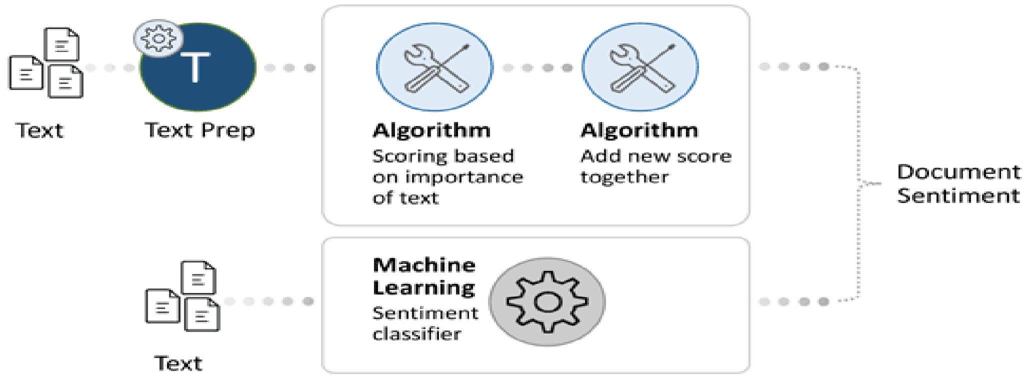

Figure 1.1: An Aspect Based Sentiment Analysis Model [31].

Whole work is completed in five phase data collection, data preprocessing, ontology creation, Word2vec representation and CNN implementation. These phases are shown in Figure 1.1.

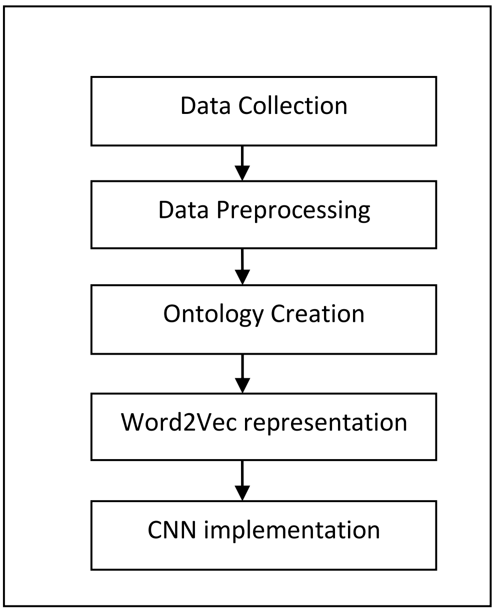

Figure 1.2 : Phases of Aspect Based Sentiment Analysis.

1.2.1 Data Collection

In this phase reviews are collected by using web scrapping technique. With the help of scrapy, large numbers of hotel reviews were fetched from booking.com. These reviews were already divided into two parts positive and negative contents. It makes the task easy and helps to easily identify different aspects with positive and negative views.

negative_content	positive_content	score	tags	title
The rooms showed there	Upon arrival we checked into our two-	10		Large rooms, perfect for family trips!
The problem is that the front desk is aloof and can be rude.They		6.3		The problem is that the front desk is aloof and can be rude.
Additional charges. Taxes	Bathroom, and the bed is extremely cc	5		Poor value for money.
very dirty wallpapers in th	nice for large group gathering (in the s	7.9		Good stay for Times square/Central park area
The restaurant was extrer	The location was really the only positi	5		A bit disappointing...
The carpets everywhere a	The large and clear room, the double s	7.1		Fine but will not return.
The entrance hall needs a	Comfortable quite clean	7.5		Comfortable quite clean
I do wish that they offere	I have been staying at the London for t	9.6		The London is spectacular! like a vacation even though I'm working
The staff was not up to pa	24 hour room service.	6.3		24 hour room service.
Shabby room. Booked the	View amazing. Comfortable beds and l	5		Great location - great square footage for NYC - needs some tlc
I had many issues at the r	The hotel location is amazing and very	7.5		Comfortable Rooms ..
Nothing	Large, beautiful and modern apartmen	10		Large, beautiful and modern apartments, excellent service...
No view whatsoever.	Overall, very good. Only reason why c	7.5		Great location!, but will try other hotels next time.

Figure 1.3: Raw Reviews.

1.2.2 Preprocessing

In this phase reviews collected as raw data format is converted into processed informational data. Raw reviews collected using scrapy contains empty rows and empty cells. By using Panda library these data are cleaned and left with useful data only.

1.2.3 Ontology Creation

An ontology can be defined as an ‘‘explicit, machine-readable specification of a shared conceptualization’’ (Studer, Benjamin, & Fensel 1998). The most important goal of ontology is to facilitate knowledge about a particular domain in such a format that can be easily understood by developers as well as machines. Ontology is created by using positive and negative content of a particular review and score is provided for different aspects of hotel reviews[2].

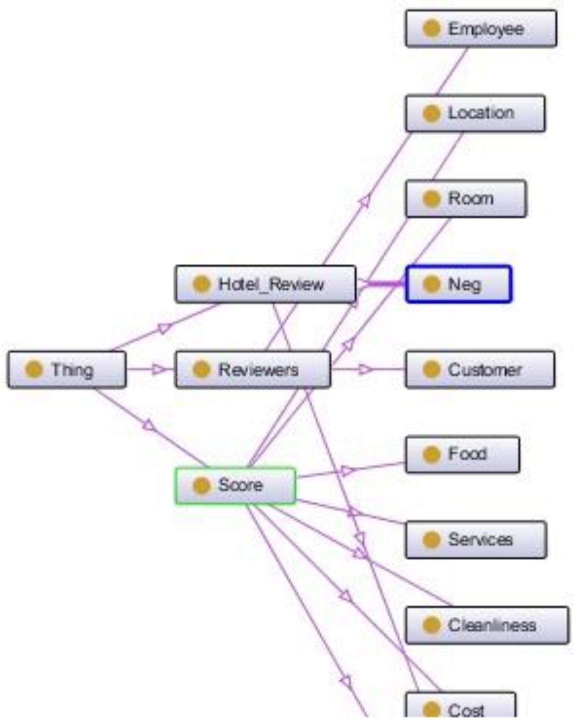

Figure 1.4: Ontology for Positive and Negative Content and Different Aspects.

1.2.4 Word2Vec Representation

Since machine learning model work on numerical value so for working with text first of all we have to convert the text into a numerical value by using TF-IDF value or Word2Vec representation. For this word embedding is produced by using word2vec which is grouped of models. It is neural networks having two layers are trained to generate the linguistic context of words. Due to this order of words is taken care as compared to bag of word model[13].

1.2.5 CNN Implementation

In this phase CNN model is implemented in deep learning of reviews and finding the sentiment attached with the text. Whole data are divided into two parts testing and training set. The training set is used to train the model and testing set is used to find out the accuracy of trained model.

1.3 Ontology

It defines the relationship among various entities and also tells about the entities related to interest to the domain. Interoperable operation on data between different applications becomes easy due to the information retrieval capability of ontology. Different facilities are being provided by different ontology languages. The latest developed standard ontology is OWL language from the World Web Consortium (W3C). An OWL comprises of three things Individual, Properties and class. An object of a particular domain of interest is defined as Individuals. 'Instances of classes' are also known as an individual. A binary relation to individuals is known as property. For example the property areBrothers might link Suresh and Ram or the property hasChild might link John and Bekham. Properties can be limited to only one value. It can be reversed as well. Classes of OWL are a collection of individuals in the form of sets. In place of the word concepts sometimes class is used. The class defines some constraint, individuals must follow that to be part of the class.

1.4 Supervised Learning

It is a mechanism by which machine generates a function from well labeled training data. The training data samples comprise generates e collections of of examples related to target domain or topic. For supervised learning machine must have previous knowledge of dataset. Due to this given training data must be in the form of pairs of input vector and target output. On the basis of these training data a function is deduced which is used to work with unknown or unlabeled data and classify them according to their class.

- Random Forest
- Maximum Entropy
- Support Vector

1.4.1 Random Forest

This is an ensemble learning technique for regression, classification and other machine learning tasks that works by analyzing the various features at the training time. Features analysis is much important as a result their priority is decided and according to these priority multitudes of decision tree is constructed. Output of this tree is mode of the class (for classification type problem) or mean prediction of individual tree in the case of regression problems. Each tree in random forest has capability to influence the whole decision since each tree is designed on the basis of importance of features and finally results of all tree is aggregated to find out the target result.

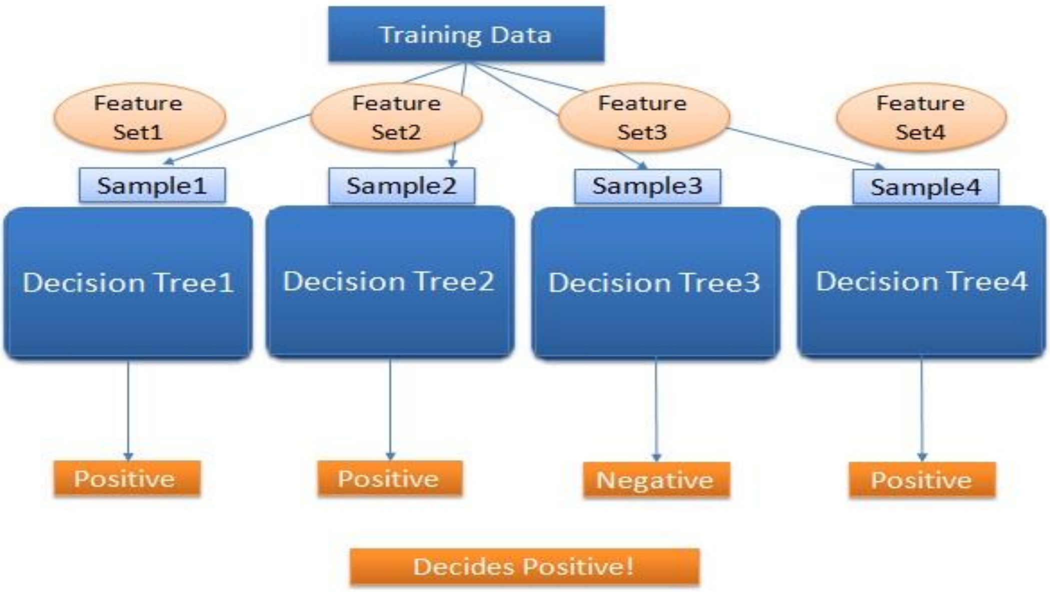

Figure 1.5 : Random Forest [32].

1.4.2 Maximum Entropy

This classifier comes under the category of probabilistic classifier belongs to an exponential mode class. In this classifiers feature are not considered independent of each other as in Naïve-Bayes classifiers. It follows the principle of maximum entropy and whichever model fits our training data from this one which has highest entropy is selected. This model is used to solve the various problems like classification of topics, detection of language, sentiment analysis and many more. Maximum entropy classifier makes the minimum assumption due to this whenever we have no prior knowledge of distribution we use this model or when it is not safe to work with the assumption. If we cannot assume the conditional independence of features we can use this classifier. Mostly used in text classification since in the text documents words are related to each other.

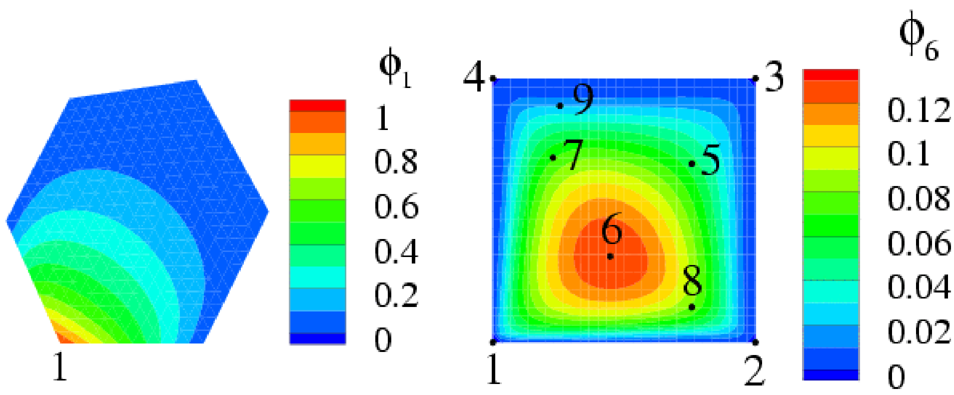

Figure 1.6: Maximum Entropy Classifier[33].

1.4.3 Support Vector Machine(SVM)

SVM is a supervised machine learning approch used for both type of problems classification as well as regression. But most of the time it is used to solve classification problems. SVM are directed machine learning techniques utilized for characterization, relapse and identification models. SVM are more successful for high dimensional space. SVCs are able for multi-class order. SVC and NuSVC are comparable while, LinearSVC depend on direct bits.

All these SVCs take two info cluster: an exhibit X of size [samples, features] and cluster Y of size [samples]. NuSVC executes 'one-against-once' plot for multi-class, henceforth it gives predictable interface different classifiers. While, LinearSVC execute 'one-versus rest' plot.

NuSVC implementation is based on 'libsvm' library, whereas LinearSVC implementation is based on 'liblinear' library. A SVM classification, regression and other tasks are done with the help of hyperplanes. These hyper-planes or set of hyper-planes are contructes in high dimensional space. Thus, from hyper-planes we can understand, a good separation is achieved by those that have the maximum distance to the nearest data points of any class which is called functional margin. It is concluded that larger the margin lower the generalization error of multiclass classifier. An example of hyper-plne use is shown in Figure 1.7.

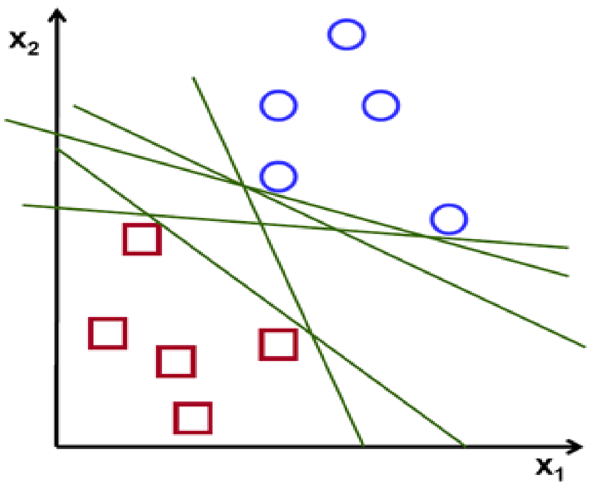

Figure 1.7 : All Possible Classification Hyperplane [36].

Every line illustrated in above figure which is separating our training data into two classes couldn't be the best solution. Thus only the hyperplane that maximizes the margin of trainining corpus or data is chosen as opyimal solution shown in figure 1.8

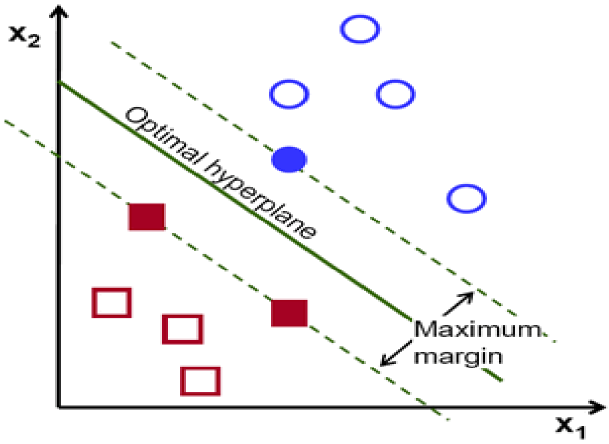

Figure 1.8 : Support Vector Machine Hyperplane that Maximizes the Margin [36].

1.5 Need for Doing Sentiment Analysis

Sentiment analysis is a rapidly evolving research area with the emergence of social networking websites like Twitter, Facebook, Instagram. It plays an important role in the analysis of the opinions specified by the users regarding different domains like industry products, movies hotel etc.

1.5.1 Industrial Development

The qualitative data is more important than quantitative data.Since today is the world of big data so every company has a big collection of structured and unstructured data.To work perfectly in this scenario it becomes necessary to identify which document has what type of information such that only those data will be kept that is solely for the development of organization. This can be find out by doing sentiment analysis it will provide opportunity to the industries to gain their value hiher and higher and finding their target audience easily .Any of the company which has deals with customer can get benefit, whether it Mobile customer, restaurants, hospitalitality, retail or travel agency.

1.5.2 Research and Development Work

Another reason behind the sentiment analysis is researchers demand. Whatever solution present today that is evolving rapidly, the main focus is to reduce the manual work that is required to discriminate the document. Also assists in improvisation of research being conducted in the field of computer desciplines like NLP, Machine learning, topic modeling, automatic content analysis, language translation etc.

1.5.3 Decision Making

For company, organization or any individual making a decision is not an easy task. Any task like purchasing or selling the product cannot be taken spontaneously, it must be done after proper analysis in which sentiment analysis plays an important role.

1.5.4 Understanding Contextual

Day by day, human language is becoming more complex and it creates a problem for machines to understand these languages. Slangs, sort form, misspelled word, nuances and different cultures main reason for such complexity. Hence there is a need to develop such system which can handle this scenario.

1.5.5 Internet Marketing

We can say internet marketing has high dependency on their customer demand, behavior, pattern of purchasing and their review regarding the purchased product. So it is necessity of an organization to analyze these characteristics properly and according to that target the customers.

1.6 Sentiment Analysis Application

In natural language processing, sentiment analysis has a number of applications. Due to continuous enhancement of internet a huge collection of information is generated on social networking websites, blog, etc. Most of the companies doing sentiment analysis on these data for the overall development of the company. Major application of sentiment analysis is mentioned as follows:

1.6.1 Word of Mouth (WOM)

Word of mouth is used to pass the information from an individual to others. Earlier for when the reviews were not available online at that it is the main source to get knowledge of the product by asking person to person for taking decisions. At present views or opinions are available online and system is also designed to find out the polarity of favored or against that makes the user's task easy in making decision about the product.

1.6.2 Voice of Voters (VOV)

To do effective complain and getting the best result depends on best analysis of person's suggestion, review and their opinion for the party. Here Sentiment analysis plays an important role not only for politicians but also for news channel and their analyst in determining the winning chances of political parties. Since most people active on the social networking websites and post their feeling or attitude for different parties.

1.6.3 E-Commerce

E-commerce relates to a transaction that is made for the purpose of selling or purchasing product or services online. On the internet a plenty of sites are available which achieved huge success in online business and dealing with customers' demands by analyzing their attitude and opinions related to their product and recommending the user according to their like or dislike or on the basis of their product purchase pattern.

1.6.4 Voice of Market(VOM)

Sentiment analysis makes us capable to choose the best product. Since companies always take care about our thought for their product so first they launch beta version to learn about the customer opinion. After analyzing customer demand product is reconstructed or modified and then launch the original version of the product to best fit the customers.

1.6.5 Brand Reputation Management (BRM)

BRM concerned with the reputation of company brand in the market.Online communities are available that focus on the company status and on the product for achieving the best position among other competitors. This can be done by sentiment analysis. If once company lost its faith of customer about their services in the market, then it would take too much time to regain its ranking, So on the regular basis company track the pros and cons of their product for maintaining the graph of their development.

1.7 Issue Related to Sentiment Analysis

Sentiment analysis is gaining popularity increment exponentially and last few years and is being used for tracking the customers reaction, monitoring the competitor ranking, anticipating the election results, forecasting the future investment by learning trends, predicting the box office collection of movies. It deals with all these things, but there are some issues which can degrade the performance of sentiment analysis models are as follows:

1.7.1 Sarcasm

It is one of the most difficult task to understand the sentiment attached to the sarcasm sentence by using automatic tracking to interpret properly. Example: "I am trying to understand with your personality."

1.7.2 Navel Gazing

While tracking social media it starts to pick most items related to someone's own's promotional efforts, then such type of content should be filtered out for better sentiment analysis.

1.7.3 Neutral Sentiment

Neutral sentiment is just like swinging voters in an election, we cannot make any expectation of these people. In the same manner, moderate statements are not very useful that's why we divide it further for deep analysis.

1.7.4 Relative Statement

Relative statements have always talked about with respect to any entity. In that case it may be good for one entity, but not for others. Example:"I have purchased a Lenovo laptop" good for Lenovo but bad for Dell.

1.7.5 Multidimensional or Compound Statement

When someone expresses their feeling including positive and negative aspect, it increases the complexity in this scenario it must be cared. Example “I love Gehraiyaan episode, but hate its climax.”

1.7.6 Conditional Statement

Sentiment attached with conditional statement is not clear it depends on the situation so not easy to determine. Special care must be taken to determine these sentiments. Example:”The customer is not worried now about the product, but says he will if the owner doesn’t reply against his complain”.

1.7.7 Positive Issue But Not Relating to the Core Issue

Most of the time people talk about the actors in a positive manner, but focus is their personal life but not their acting skills.

1.7.8 Negative Opinion Doesn’t Mean Negative Factor

It talks about the negative publicity. Sometimes all things happened wrong, but the result is positive. A criminal comes on the stage in the mid of the live show for anchoring as a result, people start posting the negative comments but it droves the high rating.

1.7.9 Ambiguous Word

The context which sentence belongs must be understood before doing sentiment and tagged accordingly. Example:”That Dance step was so sick” is actually a positive statement.

1.7.10 Word Related to Trends

For representing feeling and emotion we follow the trends like short form, abbreviation, lack of capitals, poor spellings, poor punctuation, poor grammar to deal with these aspect everyone involved in doing sentiment analysis must take care.

1.8 Capital Structure

In Chapter 2 it will be described briefly what work has been done till now in the area of sentiment analysis. Also an effort will be taken to explore the literature's strength and weakness. Significance of current work will be justified by finding the gap.

In Chapter 3 Problem statement is described. Further in Chapter 4 Sentiment analysis model and its complete architecture is explained in detail. In Chapter 5 Result and their analysis is discussed. It provides evidence that strengthen my thesis work. In Chapter 6 conclusion and possibilities for future extension is mentioned.

CHAPTER 2

LITERATURE SURVEY

In this Chapter, a summarized literature survey of the research work done in the domain of sentiment analysis is represented.Efficiency for a system is achieved by using data structure optimization, query technique optimization and parallel processing optimization. As a whole designed model perform well on capacity concurrent users, response rate and expandability.

Wei et al. (2010) designed a system based on ontology to analyze the product review. A sentiment ontology tree is formulated to represent the knowledge in hierarchical relation of product features and sentiment attached to it. The analysis of human labeled data assures to provide better accuracy. The future work that can develop this model is to automate the feature or attribute extraction. It can reduce the manual effort, but there may probability in little loss in accuracy [1].

Kontopoulos et al. (2013) this paper proposed the implementation of real ontology based deployment technique for more effective sentiment analysis of twitter tweets. The proposed model uses the ontology technique in more efficient manner to analyze the twitter not only giving the score for complete tweets but anazes every hidden aspects of tweets then procide score for a particular tweets that makes feature engineering process more accurate to achieve high level of accuracy [2].

Cric et al. (2013) proposed a framework for doing sentiment analysis of twitter tweets. In this work multiple machine learning model is used to perform opinion mining and their assembling is done to provide better results. Obtained results with different approach is compared properly for providing detailed analysis [3].

Behrainian et al. (2013) has proposed a hybrid model for target based sentiment analysis of twitter tweets. It is shown that hybrid approach outperforms other approach and also shows high performance with various features and functionality [4].

Freitas et al. (2013) has proposed a model in which feature extraction is done by using ontology technique and data sources are Movie review and Hotel review dataset.Sentiment analysis by using ontology is highly effective in their experiments nd achieved high performance and accuracy [5].

Zhao et al. (2013) proposed an approach to work on chineese language and achieved a better perfornce than earlier model. It achieve high accuracy [6].

Bakliwal et al. (2013) implemented a model in which 3-class sentiment classification was done Iris Genral electronics tweets. Uaing supervised learning approach and Subjectivity laxicon based score was used and achieved accuracy 61.6% [7].

K. M. Sam et al. (2013) work concern about generalized model that analyzes the customer reviews about the electronincs products available on social networking websites. The extraction of keyword and the ontologies designing of electronics product deals in understaning the behavior of online customers [8].

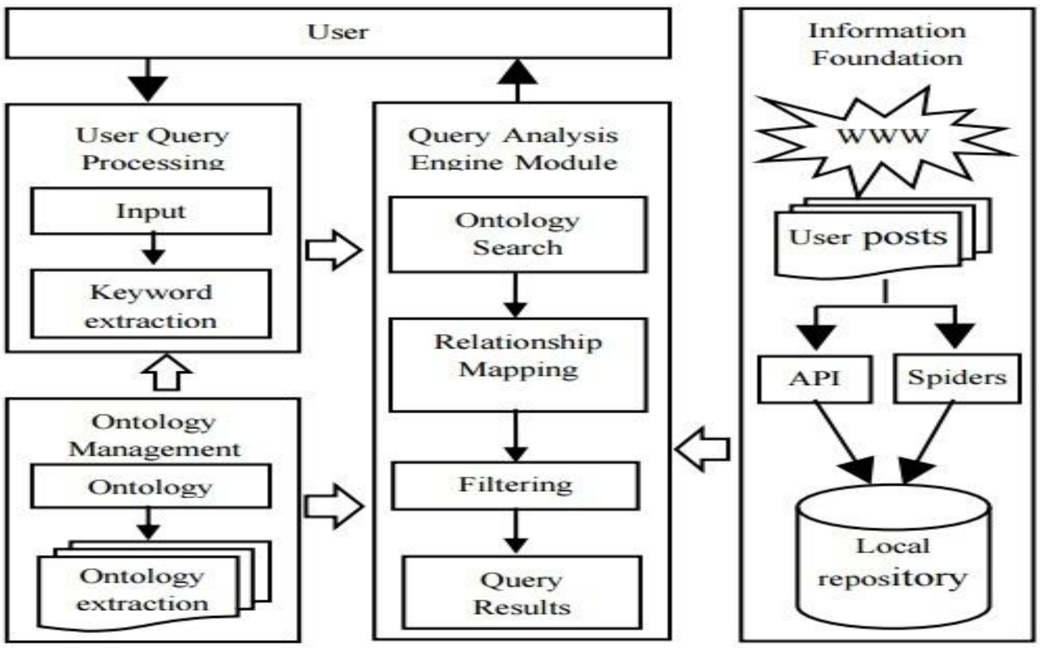

Figure 2.1 : Ontology Model[8]

Yoon Kim (2014) reported a series of experiments with convolutional neural network (CNN) trained on top of pretrained word-vector for sentence-level classification tasks. In this a simple CNN with little hyperparameter tuning and static vectors achieves excellent results on multiple benchmarks. It is implemented with single convolutional layer architecture [9].

Stojanvaski.et al.(2015) proposed a model by using the deep Convolutional neural network. In this work pre- trained word vector embedding is obtained by implementing unsupervised learning on large corpora. The data set used belongs to SemEval 2015 and result supports the Twitter SemEval 2015 benchmark and no handcrafted features was utilized in this framework. The measuring F1 score was 64.85%. Future Scope for this framework is this whole framework can be reconstructed by using twitter based corpora that can enhance the performance of discussed model [10].

Ouyang et al. (2015) proposed a framework consist of Word2Vec and CNN. In this architecture, 3 pair of Convolutional layer and maxpooling layer was used. This was the first time that seven layer framework model was applied using word2vec and CNN to find out the sentiment of the sentence. Parametric Rectifier Linear Unit with normalization and dropout technology. Publicly available movie review data was used with five different label negative, somewhat negative, neutral, somewhat positive and positive. The network had acquired test accuracy of 45.4% [11]. The discussed framework is well described by below figure:

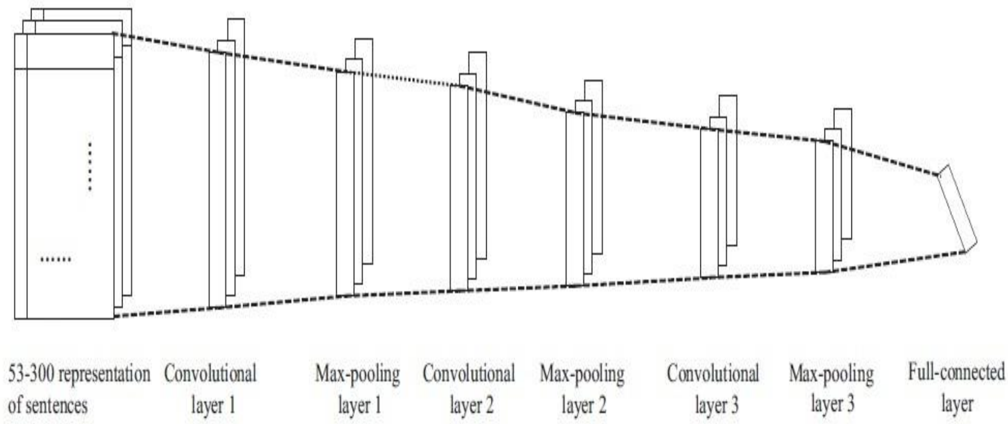

Figure 2.2 : 3-Pair Convolutional Model [11]

Jindal et al. (2015) designed a system an image, sentiment identification framework was built with a deep Convolutional neural network. This framework was retrained on large data for object recognition and transfer learning.The dataset used to be Flicker labeled images [12].

Yang et al.(2016) presented a different neural network model that using a Convolutional neural network with tree bank information for performing sentiment analysis task. This model uses a number of aspects like syntax information, structure information that works better than the other single aspect model.Static word embedding is used which can be improvised by defining what kinds of sentence architecture can express the opinion in a better manner. It is also mentioned that the prefix and suffix knowledge for the sentiment extraction can be given [13].

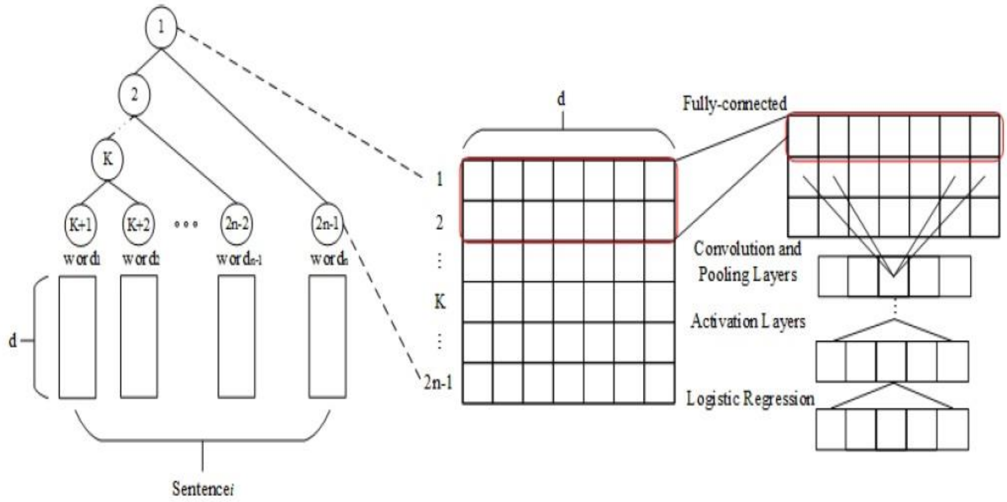

Figure 2.3: The Structure of Model TrCNN [13].

Bouazizi et al. (2016) designed a framework to do sentiment analysis of twitter tweets with specific capability of detecting sarcastic statements that enhance the performance of opinion mining. Its capability to detetect saracastic tweets result as better accuracy level. Sarcasm when user transmits message under message [14].

Deriu et al. (2016) implemented a model for sentiment analysis in which sentiment of the Italian Twitter message is used as training and testing purpose. This system uses two layer Convolutional layer architecture with multi-task training. This system was represented in the EvalItalia-2016 competition and proved its accuracy and outperformed all other approaches [15].

Gao et al. (2016) proposed a framework in which sentiment polarity detection has done by CNN. Multiple implementation of the Convolutional neural network is done with different filter size and different no of filter size and then adaboost is used to combine the different implementation of CNN to find the polarity of sentiment in the given sentence. Datasets used in this work are IMDB and Rotten Tomatoes movie reviews already divided into two classes positive and negative. The future scope of the framework is it can be developed by using more than one layer of Convolutional that may result better than current accuracy [16].

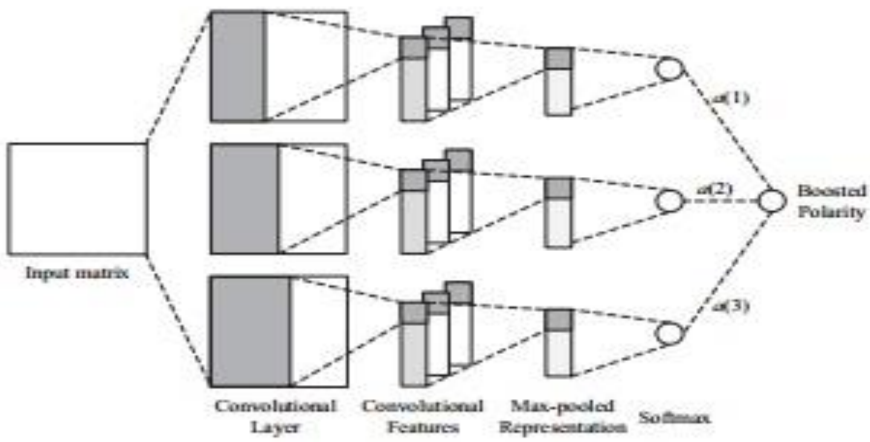

Figure 2.4: Adaboost Convolutional Neural Network [16].

Wu et al. (2016) implemented a model which studies Aspect based opinion summarization (AOS) of reviews on a specific product. This approach, which maps each sentence with predefined aspect. The discussed model consists of two CNN based methods, cascaded and multitask. Level 1 deals with aspect mapping and a single CNN at level 2 deals with sentiment classification. For training purpose dataset used is Amazon smartphone reviews [17].

Poriya et al. (2017) proposed a framework for the extraction of emotion for video content.Multiple kernel learning architecture is implemented to combine audio, visual and textual modularities. The proposed framework achieved accuracy in multimodal sentiment analysis with a margin of 10-13% and 3-5% accuracy in polarity detection and emotion identification. The future scope of this framework is to focus more on extracting relevant feature from visual content.This can be implemented by using 3D CNN implementation for automatic feature extraction [18].

Kim et al. (2017) Song designe a system which is indepent of language and easily adapt with language. The fine grained opinion mining model is divided into two parts one is Sentiment classification and other one is aspect extraction. The sentiment classifier is implemented by using a three level architecture for classification approach and the aspect extractor is made by using extended biterm topic model(eBTM), an extentended approach of LDA topic model for extension for small text. Dataset used belongs to multiple language dataset and movie review dataset was used. Achieved accuracy is 98% [19].

Kontopoulos et al. (2013) this paper proposed the implementation of real ontology based deployment technique for more effective sentiment analysis of twitter tweets. The proposed model uses the ontology technique in more efficient manner to analyze the twitter not only giving the score for complete tweets but anazes every hidden aspects of tweets then procide score for a particular tweets that makes feature engineering process more accurate to achieve high level of accuracy [20].

Table 2.1 : Sentiment Analysis Based on Ontology and CNN

Title	Authors	Methodology	Result
Sentiment Learning on Product Reviews via Sentiment Ontology Tree[1]	Wei Wei, Jon Atle Gulla	HL(Hierarichical Learning)-SOT(Sentiment Ontology tree) approach	NA
Sentiment Analysis and Classification Based On Textual Reviews[30]	Ms.K.Mouthami, Ms.K.Nirmala Devi, Dr.V.Murali Bhaskaran	Sentiment Fuzzy Classification algorithm with parts of speech tags	NA
Sentiment Analysis Using Convolutional Neural Network[11]	Xi Ouyang, Pan Zhou, Cheng Hua Li, Lijun Liu	a 7-layers architecture CNN model is applied using word2vec to analyze sentences	45.5 %Accuracy
Image Sentiment Analysis using Deep Convolutional Neural Networks with Domain Specific Fine Tuning[12]	Stuti Jindal and Sanjay Singh	An image sentiment prediction framework is built with Convolutional Neural Networks (CNN) pretrained on a large scaling data and CNN for object recogntion pretrained on a large scaling data and CNN for object recognition	53.5 %Accuracy
Tb-CNN: Joint Tree-bank information for sentiment analysis using CNN[13]	Tao Yang, Yang Li, Quan Pan, Lantian Guo	convolution neural network with the tree bank information	94.7%(BinaryClassification accuracy), 49.9%(Fine Grained Accuracy)
Twitter Sentiment Analysis Using Deep Convolutional Neural Network[10]	Dario Stojanovski, Gjorgji Strezoski, Gjorgji Madjarov and Ivica Dimitrovski	CNN with multiple filters with varying window sizes ,2 fully connected layers with dropout and a softmax layer	F1 score 64.85 %

Table 2.2 : Supervised Algorithm Performance Measurement

Title	Authors & Publication	Methodology	Result
Opinion Mining Using Decision Tree Based Feature Selection Through Manhattan Hierarchical Cluster Measure[32]	Authors: Jeevanandam Jotheeswaran, Dr. Y , S. Kumaraswamy Publication Journal of Theoretical and Applied Information Technology(2013)	Naïve Bayes	79%(Accuracy)
Sentiment Analysis: Measuring Opinions[33]	Author: Chetashri Bhadane, Hardi, Dalal, Heenal Doshi	SVM	78%(Accuracy)
Twitter Sentiment Mining Framework Based Learners, Emotional State Classification And Visualization For E-Learning System[34]	Author: M.Ravichandran G.Kulanthaivel Publication: Journal of Theoretical and Applied Information , Technology, 2014	SVM,Maximum Entropy	95%, 95%(Accuracy)

2.1. Data Source and Tools Available for Opinion Mining

For sentiment analysis data source is the most important part.Since the enormous amount of data is present on the web but which is the right one to determine we have to face lots of problems so in this paper information regarding data sources and tools are given.

2.1.1 Data Source Available for Opinion Mining

There are various data sources like blogs, micro blogging sites, social networking sites, online post, news feeds, forum, review sites etc.

Table 2.3 :Data Resources to Perform Sentiment Analysis

Data Sources	Respective Sites /Sources
Blogs	http://indianbloggers.org/, hubspot.com/https://wordpress.com/ http://www.digitaltrends.com/, http://www.bloggersideas.com/, http://thoughts.com/free-blog,http://blog.com/,
Review Sites	http://www.sitejabber.com/, http://www.toptenreviews .com/, http://www.businessedge.com/, http://www.websitemagazine.com/ http://www.trustedreviews.com/, https://in.pinterest.com, , http://www. yellowpages.com
Micro Blogging	/(Jaiku),http://www.qaiku.com/(Quiku),https:// www.identi.ca/(Identica),http://www.spotjots.com/(S potjots),http://www.meetme.com/(Meet me)https://tumblr.com/(Tumblr),http://friendfeed.com/(Fr endfeed),http://www.plurk.com/top/(Plurk), https://twitter.com/(Twitter),http://www.jaiku.com
Online Posts	https://www.linkedin.com/(Linkedin), https://diasporafoundation.org/(Diaspora),https://plus. google.com/(GooglePlus),https://www.whatsapp.com /(Whatsapp),https://www.snapchat.com/https://www.facebook.com/(Facebook),https:/ /myspa ce.com/(MySpace),http://www.skype.com/en/ (Skype),

2.1.2 Tools Available for Opinion Mining

Main difficulty is extraction of emotions, structure of text, from unstructured data i.e. image or text, the language used on internet for communication is vary from every individual person or status to status. So here are some ready to use tools for opinion mining for various purposes like data preprocessing, classification of text, clustering, opinion mining, sentiment.

Table 2.4 : List of Available Tools to Perform Sentiment Analysis

Tools	Uses
STANFORD CORENLP	Sentiment analysis, Bootstrapped pattern learning ,POS tagging, Named entity recognizer, Parsing, Coreference resolution system
WEKA	Classification, Regression, Clustering, Association rules, Visualization , Data pre-processing, Machine learning, algorithm for Data Mining
NLTK	Tokenization, Provides lexical resources such as WordNet Classification , Parsing, Semantic reasoning, Stemming, Tagging
APACHE OPENNLP	Parsing, Coreference resolution, Tokenization, Part-of speech tagging, Chunking, Sentence segmentation
LING PIPE	Classification Entity extraction., POS tagging, Clustering.

CHAPTER 3

PROBLEM STATEMENT

Sentiment analysis is research area that is evolving rapidly with the emergence of social networking websites like Facebook, Twitter etc. It plays an important role in the analysis of the opinions specified by the users regarding different domains like industry products, movies, hotels and services etc. Analyzing these opinions accurately using data mining and machine learning approachs is always a challenging task. Since it has been observed that there is no single machine learning model that is appropriate for every data mining problem. The same holds also for sub problems like opinion mining. It is an experimental process. That is the reason that we compared lots of different schemes to find the most suitable for classifying reviews into specific ontologies and after that give a rating to each different aspect that is contained into them.

The present work focuses on the ontology base feature extraction which includes the semantic information of the domain. It is then used to make classifier model by using a convolution neural network. The CNN model is trained by using these features and is validated by *10*-fold cross validation. Semantic features and multi-layer convolution neural network which improves the training and testing accuracy of model and the result is better than other model.

CHAPTER 4

ONTOLOGY GUIDED FEATURE EXTRACTION FOR OPINION MINING BY USING DEEP LEARNING CONVOLUTION NEURAL NETWORKS

In the current work, first of all data is collected by using web scrapping. Python is used to design web scrappy. Then preprocessing is done for getting clear or valuable data from raw data. After this ontology model is prepared, data is fed into the classifier model is done. Further the semantic features are extracted from the given domain. Overall score is calculated on the basis of initial features extracted from the ontology model. Then word2vec is created for given processed corpus by using unsupervised neural network. Finally a vector form of used corpus is trained through the Convolutional neural network classifier. Then classification is performed and k-fold cross validation is done for getting better accuracy. Development stages of Sentiment analysis model is shown in Figure 4.2.

4.1 Data Collection

One of the prerequisites of sentiment analysis is real time data that makes research work more authenticated. This makes it necessary to design web scrappy with the help of monkeylearn website.By using this live review of customer are extracted from Booking.com where customers have given review as positive and negative aspects of hotels. It makes task easy. There is possibility of getting duplicate data, empty rows reviews and empty cells reviews. It means there is some missing value so to handle all these unwanted characteristics, We have to perform preprocessing on the extracted reviews explained in the next section

negative_content	positive_content	score	tags	title
The rooms showed there	Upon arrival we checked into our two-	10		Large rooms, perfect for family trips!
The problem is that the front desk is aloof and can be rude.They		6.3		The problem is that the front desk is aloof and can be rude.
Additional charges. Taxes	Bathroom, and the bed is extremely cc	5		Poor value for money.
very dirty wallpapers in th	nice for large group gathering (in the s	7.9		Good stay for Times square/Central park area
The restaurant was extrer	The location was really the only positi	5		A bit disappointing...
The carpets everywhere a	The large and clear room, the double s	7.1		Fine but will not return.
The entrance hall needs a	Comfortable quite clean	7.5		Comfortable quite clean
I do wish that they offere	I have been staying at the London for t	9.6		The London is spectacular! like a vacation even though I'm working
The staff was not up to pa	24 hour room service.	6.3		24 hour room service.
Shabby room. Booked the	View amazing. Comfortable beds and l	5		Great location - great square footage for NYC - needs some tlc
I had many issues at the r	The hotel location is amazing and very	7.5		Comfortable Rooms ..
Nothing	Large, beautiful and modern apartmen	10		Large, beautiful and modern apartments, excellent service...
No view whatsoever.	Overall, very good. Only reason why c	7.5		Great location!, but will try other hotels next time.

Figure 4.1 : Collected Data.

4.2 System Model

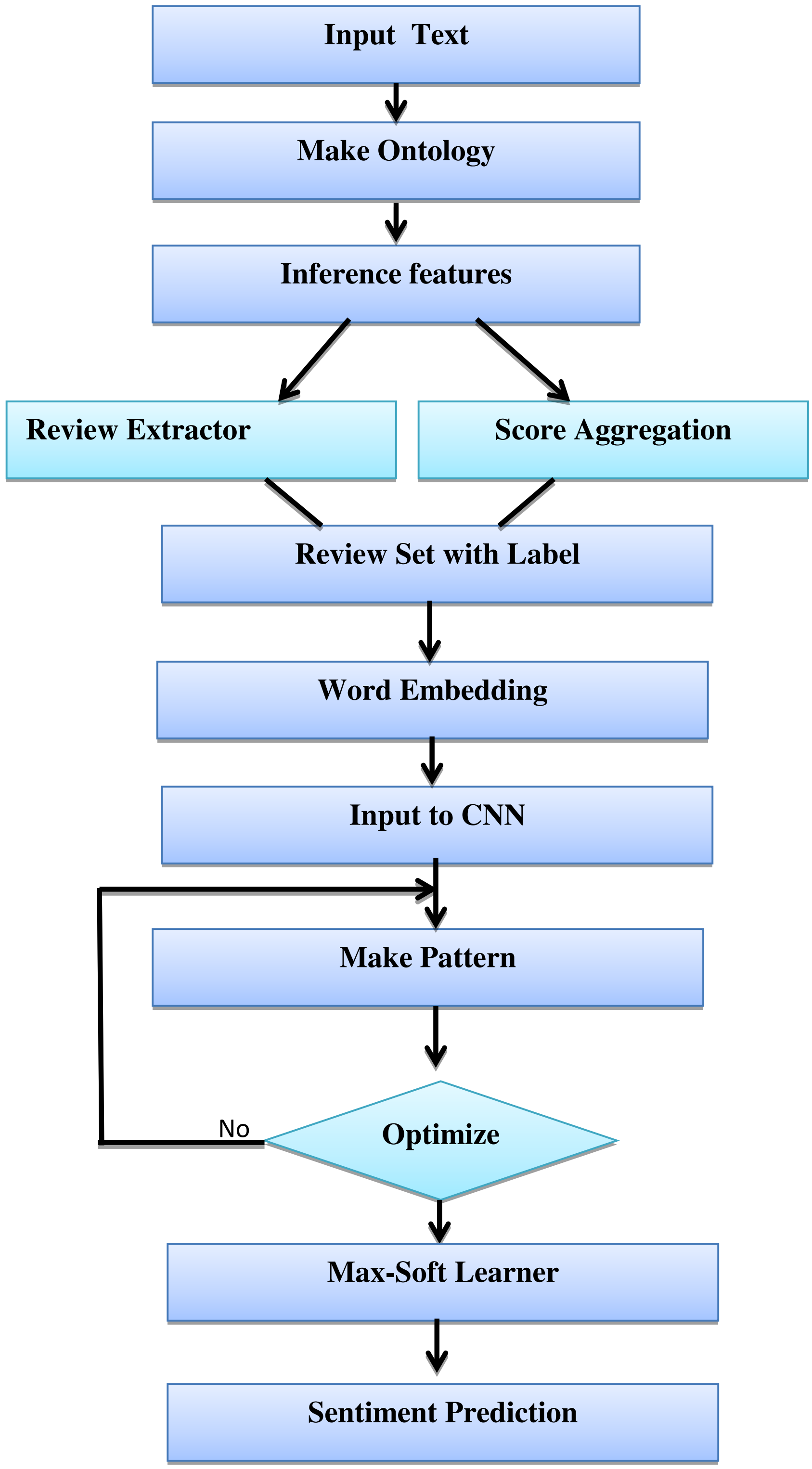

Figure 4.2 : System Model.

4.3 Data Preprocessing

Collected data by using web scrappy may contains duplicate data ,empty rows and most of the time raw data comes with empty values to implement analysis this type of data is not appropriate so we have to perform some preprocessing to get processed informative data with valuable information. For completing preprocessing task we have to use pandas library. Using this we can easily process the data and with applying constraint we can easily remove empty rows, empty cells data from CSV reviews files. Duplicate rows can be removed with panda library. Since a huge dataset as CSV file is extracted so it's become necessary to get balanced data for that purpose removal of neutral is done. Finally a dataset with balanced review is achieved.

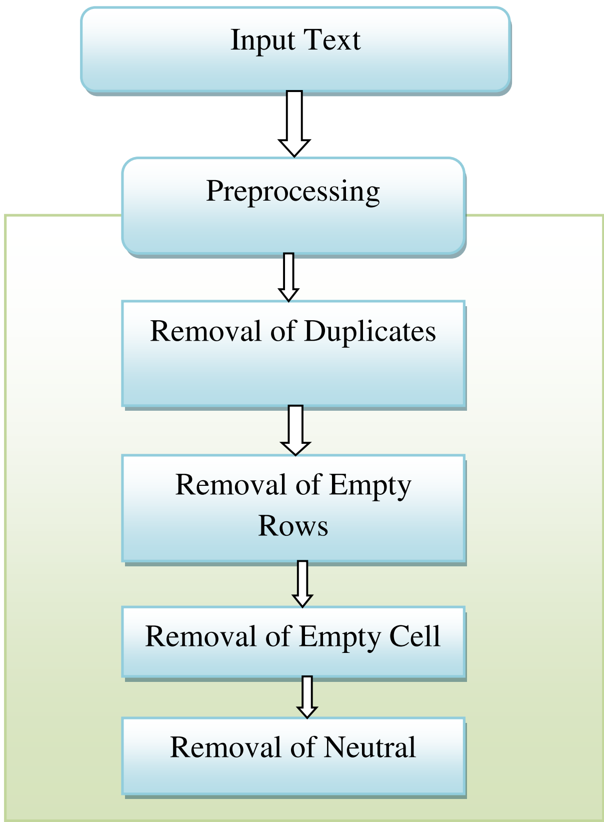

Figure 4.3: Preprocessing of Data.

4.4 Data Preparation

The hotel reviews are reused, which were analyzed manually in our experiment during development of ontology and the dataset comprises of hotel review that are grouped into negative and positive categories. Ontology is designed by parsing the reviews. The final data set is prepared by combining positive and negative part of reviews with the help of SPARQL query. This query is executed on the prepared hotel ontology.

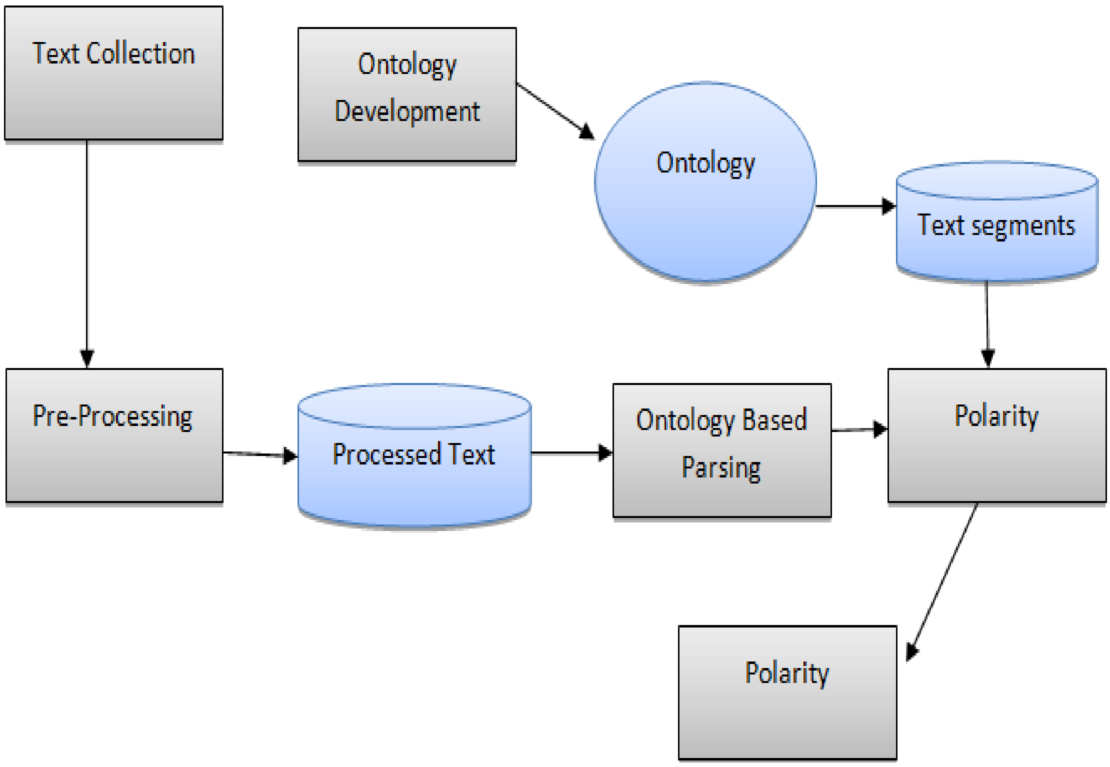

Figure 4.4 : Ontology Architecture

4.5 Aspect Based Ontology Framework

Ontology has a large history referring to the existence subject. In knowledge management context, ontology is defined as some domains shared understanding that conceives often an entities set, functions, instances, relations and axioms. Ontology is used for knowledge reuse and representation. Nowadays, higher is the requirement in the fields of tools development, integration, standardization, and users' adoption. For the requirement satisfaction, a strategy has been developed for software applications which utilize Web Technology. A web-based system can avail some audit outcomes.

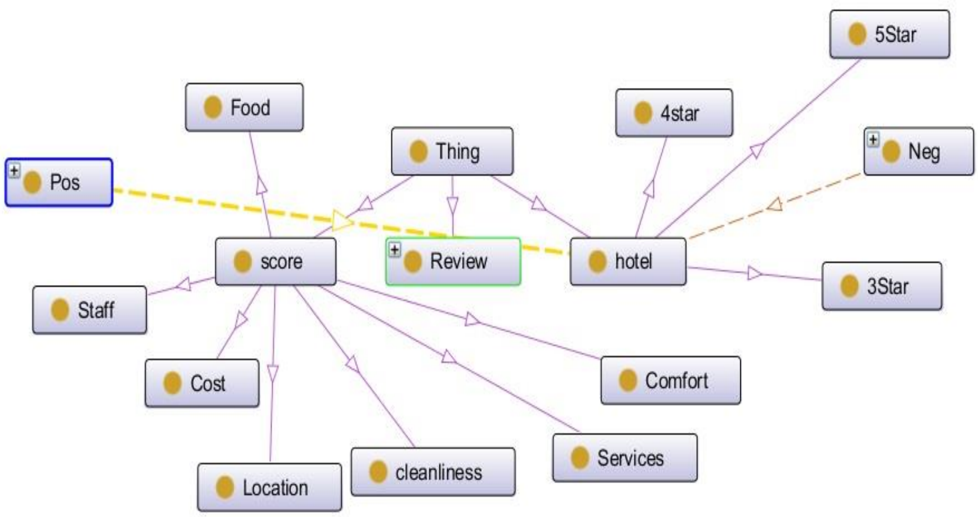

Figure 4.5 : Hotel Ontology Model

A semantic web vision is centered in the next step of development from this viewpoint. The semantic web main goal is to assist the human users' online activities on the daily basis. A shared domain understanding is provided by the ontology in a web context. Ontology used in the ontological approach for managing and representing the contents and containers of the organizational knowledge. The organizational knowledge representation is allowed by this technique in such a way that it facilitates reuse and sharing of knowledge among organizational agents. Knowledge Management System needs to be capable of supporting discovery, storage, application, generation, capture and distribution of knowledge of a wide variety through knowledge based related services. Further, a capability is required by the knowledge based management for interoperating with existing information systems.

For satisfying requirements, knowledge management systems needs to have the capability of knowledge representation which ontology languages can provide and various kinds and forms of organizational knowledge specification can be allowed, and organizational entity abstract representation is carried out which supports interoperability between various organizational and systems areas.

4.6 Algorithm For Review Label

ReviewLabel (Input Text Corpus)

Input: Dataset of hotel reviews.

Output: Review with proper label as positive or negative upon testing.

Step 1: Positive and Negative content of each review is parsed by using Ontology.

Step 2: Rating for each predefined Features (Cleaniliness, Services, Location, Cost etc) are extracted from review.

Step 3: Summation of ratings of each feature is calculated.

Step 4 : Summation is compared with predefined threshold value if summation value is

greater than threshold value ,review will be labeled with positive tag.

Else If: Summation is smaller than threshold value review will be labeled with negative tag . Else: Neutral reviews will not be considered.

Step 5: End

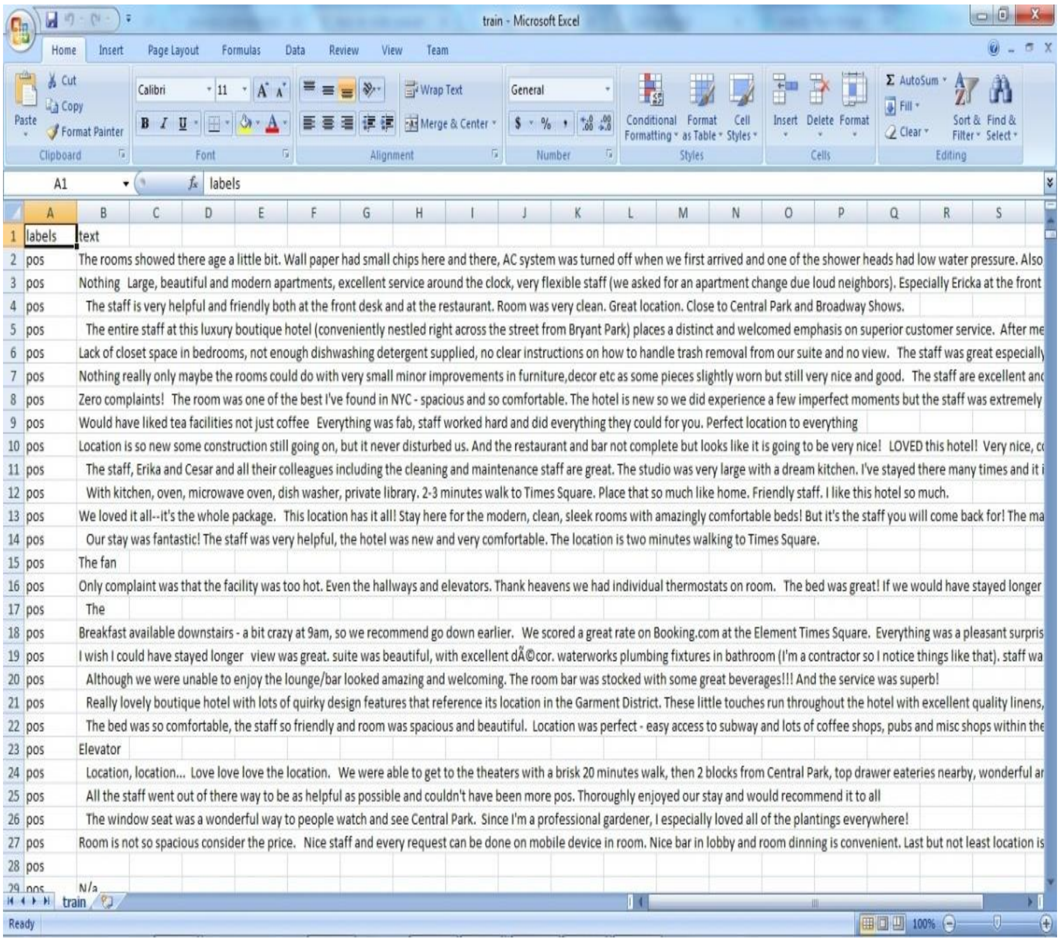

Figure 4.6 : Ontology Parsed Data

4.7 Convolutional Neural Network

For a given sentence, sentiment label is created by analysing score. For scoring a sentence, the words sequence in the sentence is taken as input in a network and it passes through layers sequence in which extraction of features with increased complexity level. The feature extraction of network can be done from the sentence level and character level. The main network architecture novelty is two convolutional layers inclusion that allows it to handle any size sentence and words.

4.6.1 Feature Extraction

The network first layer converts words into feature vectors of real-value (embedded) which captures syntactic, semantic and morphological information about words. The word vocabulary of fixed size v^{word}, and considering the words comprises of characters from character vocabulary of fixed size v^{char}. Given sentence comprises of n words {W_1, W_2,………W_n}, and converting the W_n(each word) into vector V_n=[r^{word}, r^{wchar}], that consist of two sub-vectors: the embedding word level $r^{word} \in R^{d^{word}}$and the embedding character level $r^{wchar} \in R^{d_n^0}$. The embedding of word level are meant for capturing semantic and syntactic information and embedding of character level meant for capturing shape and morphological information.

4.6.2 Word Level Embedding

Column vectors encode the word level embedding in an embedding matrix $w^{word} \in R^{d^{word}} \times [v^{word}]$. The embedding of word level corresponding each column $w_i^{word} \in R^{d^{word}}$of i^{th}vocabulary word is generated. A word W transforms into embedding of word level by utilizing product of matrix-vector:

$r^{word} = v^w w^{word}$

where

$v^w \leftarrow$vector size of $|v^{word}|$ having 1 value at index w and 0 in other positions

The w^{word} matrix is a parameter for learning, and the embedding word level size d^{word} is the user choosing the hyper-parameter.

In current work Word2vec is used to perform word level embedding.

4.6.3 Word2Vec

Word2vec is a tool provided as open source by Google in 2013 under the license of Appache License 2.0. It extract features from the given text corpus without any intervention from the human side. Most important thing is that it will perform very well even the text size is too small or an individual word. By giving a large corpus context and uses Word2vec makes appropriate word's meaning. It will run faster with big datasets too. In deep learning, meaning of words is one of the most important aspect that is completely fulfilled with use word2vec for classifying larger entities.[11]

In this work I have used pre trained vectors trained by using Google News dataset (about 100 billion words). The vector can be found easily on the URL https://code.google.com/p/word2vec/. The model contains 3 million combinations of words and phrases with 300 dimensional representations. We can achieve precise relation by using such a huge corpus. In the below figure I have tried to explain the relationship among words by using word2vec conversion. It is showing the similarity between them.

bad	terrible 0.682861	horrible 0.670260	lousy 0.664764	crummy 0.567782	horrid 0.565169
good	great 0.729151	decent 0.683735	nice 0.683609	excellent 0.644293	fantastic 0.640778
awful	horrible 0.759767	terrible 0.747892	dreadful 0.721818	horrendous 0.697003	horrid 0.672018
beautiful	gorgeous 0.835300	lovely 0.810064	wonderful 0.685409	fabulous 0.670007	loveliest 0.661258
terrible	horrible 0.924392	horrendous 0.846727	dreadful 0.802277	awful 0.747891	horrid 0.717903
fantastic	wonderful 0.804792	great 0.793521	amazing 0.778987	marvelous 0.768760	fabulous 0.760597

Figure 4.7: Similarity Representation[11].

In figure 2 diffusion network is being represented to visualize the relationship among different words in the Google news dataset.

Figure 4.7 : Diffusion Network of Word2Vec[11].

The edge width represent similarity and node represent the word. Now it can be easily visualize the similarity so words with same sentiment labels have same vector.

4.6.4 Character Level Embedding

The robust methods for extracting shape and morphological information from words taken into all characters consideration of the word and selecting the important feature for task. For instance in the sentimental analysis task of twitter data, and appearing important information in different hash tag parts (e.g., "#ilikeit") and various adverb information endings having suffix "ly" (e.g., "badly"). The local features are produced by Convolutional approach around word's each character and further max operation are utilized for combining them for creating embedding character-level of fixed-size word.

Given words composed of m character $\{k_1, k_2, \ldots\ldots\ldots\ldots, k_m\}$, each character k_m is transformed into embedding character r_m^{char}. Column vectors encode the embedding character in the matrix embedding $w^{char} \in R^{d^{char}} \times |v^{char}|$. Given k character, the matrix-vector product obtains its embedding r^{char}:

$r^{char}=v^k w^{char}$

where

$v^k \leftarrow$ vector size of $|v^{char}|$ having 1 value at k index and 0 in other positions.

The convolution layer input is the embedding character sequence $\{r_1^{char}, r_2^{char}, \dots\dots\dots.., r_n^{char}\}$. The matric vector operation is applied by convolution layer for each window having size k^{char} of the sequence of successive windows. Consider the defined vector as $x^m \in r^{char} R^{d^{char}}$ which is a embedding character concatenation n, having its left neighbors $(r^{char}-1)/2$, and its right neighbors $(r^{char}-1)/2$:

$$x^n = (k^{char}_{n-\frac{(r^{char}-1)}{2}}, \dots\dots\dots, k^{char}_{n+\frac{(r^{char}-1)}{2}})^T$$

The vector $k^{char} \in R^{c_u^0}$ having j^{th} element computed by convolutional layer that is the w embedding character-level as follows:

$$[k^{wchar}]_j = \max_{1<n<N} [w^0 x_n + a^0]_j$$

where

$w^0 \in R^{c_u^0 \times d^{char} r^{char}} \leftarrow$ Convolution layer weight matrix

The local feature is extracted using same matrix around each window character in a given word.

4.7 Sentence Label Analysing

A sentence x is given with m words $\{w^1, w^2, \dots.w^m\}$ and converting that to word level joint and embedding level character $\{u^1, u^2, \dots.., u^n\}$, SCNNchar next step comprises of representation of sentence-level extraction r_x^{st}. A sentence-wide extraction of feature set method deals with two issues:

- Different sizes of sentences
- At any position in the sentence appears the important information

These issues are tackled with the use of convolutional layer for computing the feature vector of wide sentence r^{st}. The convolutional neutral network architecture second convolutional layer operates in a similar way as the layer used for character level feature extraction. Local features are produced in this layer around each word and they are combined after which utilizes max operation for creating feature vector of fixed-size for sentence.

A matrix-vector operation applied by second convolution layer for each window size of k^{word}in successive window sequence $\{u^1, u^2, \ldots, u^n\}$. The vector $x_m \in R^{(d^{word}+c_u^0)k^{word}}$ as sequence concatenation of embedding k^{word} in n^{th} word centralization:

$$x_m = (u_{m-\frac{(u^{word}-1)}{2}}, \ldots\ldots\ldots, u_{m+\frac{(u^{word}-1)}{2}})$$

The j^{th}element is computed by convolutional layer having vector $r^{st} \in R^{c_u^1}$ as follows:

$$[r^{st}]_j = \max_{1<m<M}[w^1_{x_m} + a^1]_j$$

Where

$w^1 \in R^{c_u^1 \times (d^{word}+c_u^0)k^{word}}$ ←Convolutional layer weight matrix

Finally, r_x^{st}vector having feature vector "global" of x sentence which is processed with the two neural network layer uses that extracts one more representation level and each sentiment label $\tau \in T$ score is computed:

$S(x)=w^3h\ (w^2 r_x^{st} + a^2)+a^3$

Where learning parameter matrix and vectors,

$w^2 \in R^{h_u \times c_u^1}$, and $w^3 \in R^{|T| \times h_u}$

h(.)←Hyperbolic tangent

4.6.7 Network Training

A negative probability is minimized in the network training over training set A. A sentence x is given having parameter set θ in the network is computing each sentiment label $\tau \in T$ score$S_\theta(x)_T$. These scores are transformed into given labels conditional probability distribution of the sentence and network parameter set θ, and applied a softmax operation over $\tau \in T$ score:

$$P(\tau|x,\theta) = \frac{e^{S_\theta(x)_i}}{\sum_{\forall_i \in T} e^{S_\theta(x)_i}}$$

The stochastic Gradient descent (SDG) for minimizing the negative log gradient:

$$\theta \mapsto \sum_{(u,v)\epsilon A} -\log P(v|x,\theta)$$

Where (u, v) is the sentence corresponding in the corpus training A and v represents a respective label.

4.8 Layer of CNN

Architecture of CNN is formed by the distinct layer stack which transforms input volume to output (e.g. the class score holding) through a function that is differential. The various layer of convolutional neural network utilized in our research work are:

- Convolution Layer
- Max-Pooling Layer
- ReLU Layer
- Back Propagation Layer

4.8.1 Convolutional Layer

The CNN core building block is the convolutional layer. A learnable filter set comprises in the layer's parameters that are having smaller receptive field, and extends through full input volume depth. Convolving each filter during the forward pass across the input volume height and width, and the dot product among the input and filters entries are computed and then, filter's 2-dimension activation map is produced.Result would be the network learning filters which activates when some special feature type is detected at some spatial input position.

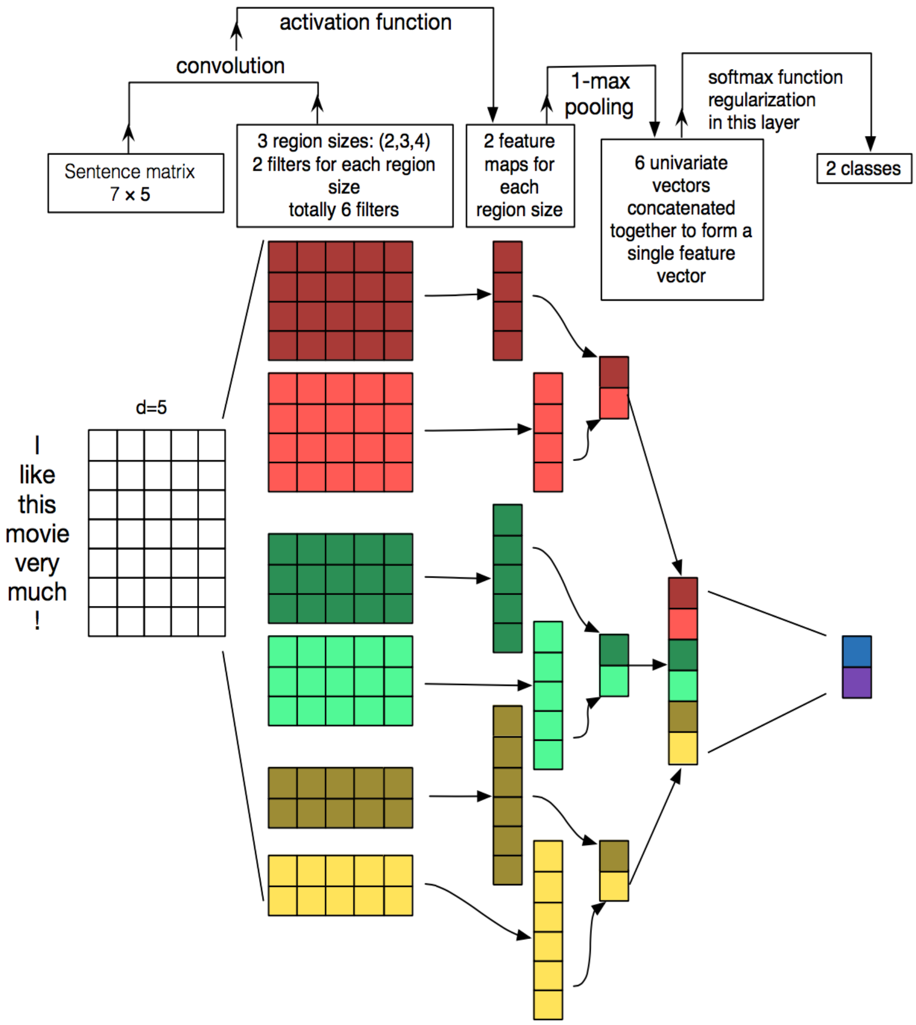

Figure 4.9 : Convolutional Neural Network [35]

4.8.2 Max Pooling Layer

CNN having another important concept and that is pooling that is in down-sampling non-linear form. Several non-linear functions are there for implementation of pooling and among which the most common is max pooling. The input image is partitioned into non-overlapping rectangles set and maximum is the output for such each sub-region. The exact feature location is least important its relative rough location for other features. The spatial representation size is reduce progressively by serving pooling layer and also for reducing the parameters utilized and computation amount in the network and for over-fitting control also. Commonly, the pooling layer can be inserted periodically in the CNN architecture among the successive Convolutional layers. An invariant translation form is provided through pooling operation.

4.8.3 ReLU Layer

ReLU (Rectified Linear Units) is a neurons layer which applies the activation non-saturating function f(n) = max(0,n).The decision function non-linear properties of the overall network increases without affecting the convolution layer receptive fields. For increasing the non-linearity utilizing other functions, such as hyperbolic saturation tangent f(n)=tanh(n), f(n)=|tanh (n)| and sigmoid function f(n)=(1+e^{-n})$^{-1}$. In comparison to various other functions, the ReLU usage is more preferable because of its result showing its several time faster without any difference significantly for accuracy generalization.

4.8.4 Back Propagation Layer

This process importance is that in network training, the intermediate layer having neurons organizes itself in a manner that various neurons learn organizing various total input space characteristics. While an input arbitrary pattern is present containing noise after training, then the hidden layer having neurons will respond with output actively in case, a pattern is contained in the new input which resembles the feature that is learned by individual neurons for recognition during their training.

4.9 Training and Testing Using Ten Fold Cross Validation

In the classification model of CNN we have used 30 number of Epochs in which we have implemented validation logic. The output of this logic shows the training accuracy and validation accuracy.Validation with highest accuracy is saved as model that can be used for testing purpose in future use. In each epoch the whole data is scanned two times and k-fold testing is being implemented. For the k-fold whole data set is divided into k parts. K-1 part is used for training purpose and one part is used for testing.

CHAPTER 5

EXPERIMENTAL RESULTS

As per discussion in last Chapter 4, we have implemented sentiment analysis model by using deep learning.Apart from this different models has implement to show the strength of implementemodel and and it outperforms with respect to other model.The different metrics for model validation are Accuracy, Precision, Recall, F1-Score.

5.1 Confusion Matrix

A tabular representation of prediction which provides information whether they are exactly matched with original data or not.

Table 5.1 Confusion Matrix

		Predicted Sentiment	
		Negative	**Postive**
Actual Sentiment	**Negative**	TN	FP
	Positive	FN	TP

i. **True Positive** : Correctly classified as the class of interest.
ii. **True negative**: Correctly class as not the class of interest.
iii. **False Positive** : Incorrectly classified as the class of interest.
iv. **False negative**: Incorrectly classified as not the class of interest.

- **Accuracy :** It is the ratio of correct prediction to the total prediction.
  Accuracy = (TP+TN)/(TP+TN+FP+FN)
- **Precision :** Proportion of positive samples that are truly positive.
  Precision=TP/(TP+FP)
- **Recall :** The proportion of positive that were classified correctly:
  Recall=TP/(TP+FN)

- **F-Measure :** The harmonic mean of precision and recall.
  F-Measure = (2*precision*recall)/(recall+precision)

Table 5.2 Result of Experiments

Model	Accuracy(%)	Precision(%)	Recall(%)	F-Measure(%)
Aspect based Analysis with CNN model using ontology	88.5	94.3	81.8	86
Dictionary Based Approch using positive and negative word dictionary	82	92.7	70.8	80.2
SVM	85.56	86.2	85	85
Random Forest	83.62	86.1	80.6	83.2
Decision Tree	66.69	65.6	71.8	68.5
Maximum Entropy	81.25	82.2	80.3	81.2
Genralised Linear Model	83.5	82.3	85.8	84
Stabilized Linear Discriminant analysis	70.31	72.6	66.2	69.2

5.2 Detail result of CNN Model with aspect based analysis

	A	B	C	D	E	F	G	H	I
1	Number of data-points	1600							
2	Number of labels	2							
3	Accuracy	88.50%							
4									
5	Label	neg							
6	F-score	89.21%							
7	TP	761	FP	145	TN	655	FN	39	
8									
9	Label	pos							
10	F-score	87.68%							
11	TP	655	FP	39	TN	761	FN	145	
12									
13									
14									

Figure 5.1 : Represnting the Result of CNN.

	A	B	C	D
1	probabilit	y_predict	y_actual	tweets
2	0.999984	neg	pos	While the room in general was adequately clean, there was a sizable amount of dust and other dirt such as hair between the mattress and the bed. Good facilitie
3	0.999948	neg	pos	Drinking
4	0.999907	neg	pos	Avoid
5	0.999828	neg	pos	Room was very hot and heat through radiator was strong. Could not be controlled. There was a/c unit in window thankfully and I often had it cranked up. It was n
6	0.999827	neg	pos	I only
7	0.999807	pos	neg	Roof top bar
8	0.999707	neg	pos	Old rooms with stains on carpet and sofa Heated indoor pool, great staff
9	0.999706	neg	pos	Small moan but carpet and floor could be cleaner. Room very small but fine got us on this short stay Location fab, breakfast just right, staff very helpful and beds
10	0.999642	neg	pos	There was a stain on the desk chair; probably nail polish. I reported it. I slept well and was surprised to have a t.v. in the room. It was like a hotel.
11	0.999637	neg	pos	The facility was listed as mixed "dorm style" which I interpreted as a room of males and a room of females on the same floor. I did not realize individual rooms w
12	0.999621	neg	pos	Heating
13	0.99961	neg	pos	hallway were not vacuumed very well / much, shower pull down knob was messed up, but a good sized room for the nightly rate Very Good value for the $87.00
14	0.999378	neg	pos	Unbeknownst to us there is a garage right next door. We parked blocks away - we should have been told there is a next door garage. There is almost no accommo
15	0.999255	neg	pos	Slow elevator. TV reception bad. location.location,location. Low priced room with an acceptable rating. Expect a small room though. Pleasant staff.
16	0.998938	neg	pos	Very cold in the room. To make it warmer - turn on air con to 26.5 C it helped, but the air con is really noisy There is everything in the room that you need - fridge
17	0.998876	neg	pos	Poor Wi-
18	0.998779	neg	pos	Apparently, the Mgmt. was not culpable and was working to resolve the problem...but the breakfast was a joke. Arranged through the pizza joint next door, the
19	0.998494	neg	pos	Hostel is situated near Central Park and all the transportation is really close. Free coffee is nice option, but it was surprise for me that there is no any kitchen, or c
20	0.998351	neg	pos	Carpets were pretty dirty in the hallway (where we wore shoes, so not really a big deal). That's the only negative I could come up with, we loved it! Room size w
21	0.998312	pos	neg	Our ac broke and they didn't do anything about it. I made sure some money was refunded. An awesome cappuccino machine and a 15 second walk to 5th ave
22	0.998097	neg	pos	The hotel does not have central A/C and the window units are noisy. The Cable TV is SD only - no HD which is rather old fashioned in 2016. Location is excellent.
23	0.997997	neg	pos	TV was
24	0.997879	neg	pos	Room quite small but adequate for 4 night stay, breakfast area also small for amount of people using. But Oscaf got everyone fed and watered as quick as he coul
25	0.997657	neg	pos	Thermost

Figure 5.2 : Representing Misclassified Result by CNN With Ontology.

probabilit	y_predict	y_actual	tweets
1	neg	neg	Hotel
1	neg	neg	Room is
1	neg	neg	Dirty floor, dirty bed, noise from room above, no mention to 100 USD deposit in beforehand, unfriendly staff, no breakfast. One of the staff members complained that
1	neg	neg	Front
1	neg	neg	False
1	neg	neg	Very noisy building, gaps in door so all noise heard in hallways & cleaning staff very loud in mornings. Tiny rooms & no onsite facilities. Shower very poor pressure witl
1	neg	neg	Old
1	neg	neg	The condition of the room was very poor, furniture is torn out and everything need updating. Not very clean, dust all over the place and hair in the bathroom. Not wort
1	neg	neg	They charge a $20 deposit .. They need to say that online and not when you get there. Small bed and tiny room . Place looks dusty old and dirty nothing special. I didn't
1	neg	neg	The
1	neg	neg	This hotel is not really a hotel. It is a former tiny apartment building with four rooms per floor of all different awkward shapes and sizes. tiny tiny tiny. For what we pai
1	pos	pos	Loved everything about the hotel, from the super friendly employees, to the amenities like free breakfast and evening wine/cheese. I was concerned about sounds be
1	neg	neg	There was no air conditioning in the hallways. The rooms looked NOTHING like the pictures! Our room was extremely outdated. The walls are yellowing. There was a T
1	pos	pos	Nothing Second visit for us, excellent location, all staff warm, welcoming and helpful. Excellent quality of room, large, lovely comfortable bed. Huge room with balco
1	neg	neg	Very
1	neg	neg	The room was very dated and in desperate need of renovation. The bed was very uncomfortable, tv vary old, carpet was old and dirty....also there looked to be mold c
1	neg	neg	Poor condition of hallway carpet -- dirty and stained. Air conditioning blowing loud and right at the bed. Terrible workout facility. The location
1	neg	neg	The stuff
1	neg	neg	Room is
1	neg	neg	Shower broken so could not use it. In this heat not being able to shower was awful. Very overpriced for such a tiny room and broken shower. Breakfast room very smal
1	neg	neg	the apathy of the front desk staff upon check in. his attitude and extremely rude manner in addressing us. the fact that we had to wait till 1 am for the extra bed to be s
1	neg	neg	The
1	neg	neg	Room is tiny but also for the price of $300/night, you don't even get free internet service and they don't clean the room daily or make the bed. Bathroom floor is dirty -
1	neg	neg	Old
1	neg	neg	Facility was not a 4+ star as rated on site, I usually use hot wire & plan on returning Bc there hotel ratings are right on the money. This room was very stained throughou
1	neg	neg	Horrible room, old and poorly maintained. Our floor and room were filthy, hair all over the bathroom, gross dirty walls, peeling wall paper, old dirty shower fixtures. V

Figure 5.3 : Representing Right Prediction of Models.

5.3 Dictionary Based Approch using CNN results

	A	B	C	D	E	F	G	H
	Number o	1600						
	Number o	2						
	Accuracy	82.69%						
	Label	neg						
	F-score	84.52%						
	TP	756	FP	233	TN	567	FN	44
	Label	pos						
	F-score	80.37%						
	TP	567	FP	44	TN	756	FN	233

Figure 5.4 : Dictionary based and CNN output.

	A	B	C	D
1	probabilit	y_predict	y_actual	tweets
2	1	neg	pos	No WiFi in the rooms and small tv The prices were great. Breakfast was good. Staff was pleasant.
3	1	neg	pos	I only
4	1	neg	pos	While the room in general was adequately clean, there was a sizable amount of dust and other dirt such as hair between the mattress and the bed. Good facilities
5	1	neg	pos	Room was very hot and heat through radiator was strong. Could not be controlled. There was a/c unit in window thankfully and I often had it cranked up. It was no
6	1	neg	pos	Limited control of room temp (had to run AC in winter to offset central heat), limited lighting (just one overhead light), and no place to hang clothes. Location, cle
7	1	neg	pos	Room quite small but adequate for 4 night stay, breakfast area also small for amount of people using. But Oscaf got everyone fed and watered as quick as he could
8	1	neg	pos	Paid parking and wifi. Paying for wifi just seems wrong in 2015. We got free wifi for signing up for the Mariott Rewards program. Oh my the parking was $70 per 24
9	1	neg	pos	Thermost
10	1	pos	neg	Roof top bar
11	0.999999	neg	pos	When I
12	0.999999	neg	pos	hallway were not vacuumed very well / much, shower pull down knob was messed up, but a good sized room for the nightly rate Very Good value for the $87.00 p
13	0.999999	neg	pos	No daily cleaning or replacement towels without a charge. Great value for the money. Good location and nice rooms.
14	0.999998	neg	pos	Poor Wi-
15	0.999998	neg	pos	Slow elevator. TV reception bad. location.location,location. Low priced room with an acceptable rating. Expect a small room though. Pleasant staff.
16	0.999998	neg	pos	Unbeknownst to us there is a garage right next door. We parked blocks away - we should have been told there is a next door garage. There is almost no accommoda
17	0.999998	neg	pos	Nothing to mention. Room and bathroom were cleaned everyday. Bath towel, bed light, hair dryer, room key are provided without any deposit. Bathrooms are al
18	0.999995	neg	pos	No room service. Restaurant not affiliated with the hotel. Take out sandwich was not very good. The room was well appointed. Linen was superior.
19	0.999993	neg	pos	some travellers did not abide the no smoking rule, but it's not the fault of the hotel. seriously i was concerned about it, but no, the beds were clean and rooms we
20	0.999987	neg	pos	There was a stain on the desk chair; probably nail polish. I reported it. I slept well and was surprised to have a t.v. in the room. It was like a hotel.
21	0.999984	neg	pos	Heating
22	0.99998	neg	pos	Carpets were pretty dirty in the hallway (where we wore shoes, so not really a big deal). That's the only negative I could come up with, we loved it! Room size was
23	0.999978	neg	pos	No wifi
24	0.999977	neg	pos	small room
25	0.999974	neg	pos	Bed was not comfortable. Location, Cleanliness, security and value for money.

Figure 5.5: Dictionary based misclassified results.

probabilit	y_predict	y_actual	tweets
1	neg	neg	Front
1	neg	neg	Room decor was shabby and there wasnt any mirror in the bedroom only in bathroom. Could have been more helpful at check in, no offer of maps or help with getting
1	neg	neg	Poor condition of hallway carpet -- dirty and stained. Air conditioning blowing loud and right at the bed. Terrible workout facility. The location
1	neg	neg	Dirty floor, dirty bed, noise from room above, no mention to 100 USD deposit in beforehand, unfriendly staff, no breakfast. One of the staff members complained tha
1	neg	neg	Very
1	neg	neg	Room is tiny but also for the price of $300/night, you don't even get free internet service and they don't clean the room daily or make the bed. Bathroom floor is dirty
1	neg	neg	The bed was broken. After a nightmare night, they changed the room, telling us to move the luggage from one room to another... The new room had the bathroom do
1	neg	neg	This hotel is not really a hotel. It is a former tiny apartment building with four rooms per floor of all different awkward shapes and sizes. tiny tiny tiny. For what we pa
1	neg	neg	Small bathroom with sliding door and no bath. dirty and stained carpet with rubbish from previous occupants under the bed. No housekeeping facility. Lifts always t
1	pos	pos	Loved everything about the hotel, from the super friendly employees, to the amenities like free breakfast and evening wine/cheese. I was concerned about sounds b
1	neg	neg	Room is
1	pos	pos	Carpets,
1	neg	neg	Didn't
1	neg	neg	Hotel
1	neg	neg	Small Room, No Desk or chair in the room, dirty and old carpet. Ugly forniture. Over priced for what it is. In the room you can not see difference between night and da
1	neg	neg	Shower broken so could not use it. In this heat not being able to shower was awful. Very overpriced for such a tiny room and broken shower. Breakfast room very sma
1	neg	neg	Insects in the bathroom, no conditioner, view from window was disgusting Close to the central park. Bed is ok
1	pos	pos	Nothing Impeccable service, charming and tasteful decor, super comfortable bed, evening drinks and nibbles, 24hr access to refreshments, and fantastic location just
1	neg	neg	The
1	neg	neg	This hotel does not guarantee room types and after a 9.5 hour flight from Europe, a double bed did not cut it for this 6'5" man! My ankles and feet hung over the end c
1	neg	neg	False
1	neg	neg	Staff extremely unhelpful and unfriendly. Noisy and unappealing reception area. Long queues. Extra for wifi. Will not return. Good location was the only benefit
1	neg	neg	Old
1	neg	neg	The room
1	neg	neg	Room is

Figure 5.6 :Dictionary Based Right Prediction.

5.4 SVM Result

```
> library('caret')
Loading required package: lattice
Loading required package: ggplot2
> confusionMatrix(table(as.numeric(as.factor(tweets[3401:5000,1])), results[,"SVM_LABEL"]))
Confusion Matrix and Statistics


      1   2
  1 690 121
  2 110 679

               Accuracy : 0.8556
                 95% CI : (0.8374, 0.8725)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.7112
 Mcnemar's Test P-Value : 0.5106

            Sensitivity : 0.8625
            Specificity : 0.8488
         Pos Pred Value : 0.8508
         Neg Pred Value : 0.8606
             Prevalence : 0.5000
         Detection Rate : 0.4313
   Detection Prevalence : 0.5069
      Balanced Accuracy : 0.8556
```

Figure 5.7 : SVM Result

5.5 Random Forest Result

```
> confusionMatrix(table(as.numeric(as.factor(tweets[3401:5000,1])), results[,"FORESTS_LABEL"]))
Confusion Matrix and Statistics


     1   2
 1 654 157
 2 105 684

               Accuracy : 0.8362
                 95% CI : (0.8172, 0.8541)
    No Information Rate : 0.5256
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.6727
 Mcnemar's Test P-Value : 0.001628

            Sensitivity : 0.8617
            Specificity : 0.8133
         Pos Pred Value : 0.8064
         Neg Pred Value : 0.8669
             Prevalence : 0.4744
         Detection Rate : 0.4088
   Detection Prevalence : 0.5069
      Balanced Accuracy : 0.8375

       'Positive' Class : 1
```

Figure 5.8 : Random Forest Result

5.6 Decision Tree

```
Confusion Matrix and Statistics


      1   2
  1 582 228
  2 305 485

               Accuracy : 0.6669
                 95% CI : (0.6432, 0.69)
    No Information Rate : 0.5544
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.3328
 Mcnemar's Test P-Value : 0.000995

            Sensitivity : 0.6561
            Specificity : 0.6802
         Pos Pred Value : 0.7185
         Neg Pred Value : 0.6139
             Prevalence : 0.5544
         Detection Rate : 0.3638
   Detection Prevalence : 0.5062
      Balanced Accuracy : 0.6682

       'Positive' Class : 1
```

Figure 5.9 : Result Of Decision Tree

5.7 Maximum Entropy Result

```
> library( caret )
Loading required package: lattice
Loading required package: ggplot2
> confusionMatrix(table(as.numeric(as.factor(tweets[3401:5000,1])), results[,"MAXENTROPY_LABEL"]))
Confusion Matrix and Statistics


     1   2
  1 652 159
  2 141 648

               Accuracy : 0.8125
                 95% CI : (0.7925, 0.8314)
    No Information Rate : 0.5044
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.625
 Mcnemar's Test P-Value : 0.3263

            Sensitivity : 0.8222
            Specificity : 0.8030
         Pos Pred Value : 0.8039
         Neg Pred Value : 0.8213
             Prevalence : 0.4956
         Detection Rate : 0.4075
   Detection Prevalence : 0.5069
      Balanced Accuracy : 0.8126

       'Positive' Class : 1

>
```

Figure 5.10 : Maximum Entropy Result.

5.8 Genralised Linear Model Result

```
> confusionMatrix(table(as.numeric(as.factor(tweets[3401:5000,1])), results[,"GLMNET_LABEL"]))
Confusion Matrix and Statistics


     1   2
  1 695 115
  2 149 641

               Accuracy : 0.835
                 95% CI : (0.8159, 0.8529)
    No Information Rate : 0.5275
    P-Value [Acc > NIR] : < 2e-16

                  Kappa : 0.6698
 Mcnemar's Test P-Value : 0.04225

            Sensitivity : 0.8235
            Specificity : 0.8479
         Pos Pred Value : 0.8580
         Neg Pred Value : 0.8114
             Prevalence : 0.5275
         Detection Rate : 0.4344
   Detection Prevalence : 0.5062
      Balanced Accuracy : 0.8357

       'Positive' Class : 1
```

Figure 5.11 : Result of Generalised Linear Model.

5.9 Stabilized Linear Discriminant analysis

```
> confusionMatrix(table(as.numeric(as.factor(tweets[3401:5000,1])), results[,"SLDA_LABEL"]))
Confusion Matrix and Statistics


     1   2
 1 537 273
 2 202 588

               Accuracy : 0.7031
                 95% CI : (0.6801, 0.7254)
    No Information Rate : 0.5381
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.4068
 Mcnemar's Test P-Value : 0.001319

            Sensitivity : 0.7267
            Specificity : 0.6829
         Pos Pred Value : 0.6630
         Neg Pred Value : 0.7443
             Prevalence : 0.4619
         Detection Rate : 0.3356
   Detection Prevalence : 0.5062
      Balanced Accuracy : 0.7048

       'Positive' Class : 1
```

Figure 5.12 : Result of Stabilized Linear Discriminat Analysis.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

This thesis presents an implementation of classification of sentiment analysis by aspects base ontology for semantic feature extraction and training the feature on different classifiers: CNN and others like SVM, Random Forest, Decision Tree, Maximum Entropy, Generalized Linear Model, Stabilized Discriminant Analysis.

1. In experimental observation, it is found that ontology implementation provides the highly processed data. Information collected by parsing the reviews of specific domain reduces the false positive and false negative rate and provide high accuracy.

2. In this thesis, comparison of precision, recall and accuracy of different classifier like SVM, Random Forest, Decision Tree, Maximum Entropy, Generalized Linear Model, Stabilized Discriminant Analysis and CNN is shown. In experimental configuration, CNN shows significant difference of 88.58%,94.66 and 81.6 in accuracy, precision and recall respectively.

3. Based on experiment setup using ten cross validation and convolution neural network show high accuracy for particular dataset grouped into positive and negative reviews.

6.2 Future Scope

An interested researcher may implement a few more things to this work:

- In CNN, important challenge is that how sources can be reduced? For this, enhancement can be done on the basis of effective data structure or parallel computing which speed up the process.
- For future enhancement our work will be on the semantic features optimization by meta-heuristic relative feature extraction.Ontology

automation and developing web based application to implement sentiment analysis.

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APPENDIX A

PUBLICATION

R. Kumar and H.S. Pannu. "Sentiment Analysis Algorithms for Opinion Mining" *International Conference on Information and Communication Technology for Intelligent Systems,* 2017. *(***Accepted***)*

R. Kumar and H. S. Pannu. "*Aspect Based Sentiment Analysis Using the Deep Learning Convolutional Neural Networks* " *International Journal of Computational Intelligence Studies" , Inderscience Publishers and "International Journal of Data Science and Analytics (IJDSA), Springer Publication,* 2017. (**Accepted**)

APPENDIX B

VIDEO PRESENTATION LINK

https://youtu.be/9OavIHmxNfU

APPENDIX C

PLAGIARISM REPORT

ORIGINALITY REPORT

%9	%7	%5	%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	gdeepak.com Internet Source	%2
2	www.ijcaonline.org Internet Source	%1
3	dspace.thapar.edu:8080 Internet Source	%1
4	anthology.aclweb.org	1