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Keywords: *sentiment polarity, social media analytics, electronic word of mouth.*

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Sentiment Polarity Identification of Social Media Content using Artificial Neural Networks

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Abstract- Sentiment of people about consumer goods and government policies for decision making is normally collected through feedback forms, surveys etc. The social network sites and micro blogging sites are considered a very good source of information nowadays because people share and discuss their opinions about a certain topic freely. With the increased use of technology and social media, people proactively express their opinion through social media sites like Twitter, Facebook, Instagram etc. A social media sentiment analysis can help companies to understand how people feel about their products. On the other hand, extracting the sentiment from social media text is a challenging task due to the complexity of natural language processing of social media language. Often these messages reflect the emotion, opinion and sentiment of the public through a mix of text, image, emoticons etc. These statements are often called electronic Word of Mouth (eWOM) and are much prevalent in business and service industry to enable customers to share their point of view. We cannot use standard natural language processing tools to analyze the sentiment. Labeling the sentiment as positive, negative or neutral is a classification problem. We propose to use Artificial Neural Networks to identify the sentiment polarity of social media content. Without getting into the complexity of understanding the eWOM, we use machine learning algorithm to solve this classification problem.

Keywords: sentiment polarity, social media analytics, electronic word of mouth.

1. INTRODUCTION

Social media analytics provides useful insights about public opinion to various decision makers like commercial organizations and government authorities. People openly discuss their opinion using short messages in social media sites. A simple tally of social mentions tells you how much people are talking about a product online. But, what are they saying? Social media sentiment analysis helps you answer this question. Rather than a simple count of mentions or comments, sentiment analysis considers emotions and opinions. It involves collecting and analyzing information people share in social media. Ongoing social media sentiment analysis can quickly alert someone when customer preferences and desires change. Social sentiment analysis tools can help to ensure that you are on top of changes in what your audience expects from your brand. First, it can alert service and support teams about any new issues they should be aware of. Then,

the company can prepare a proper response, strategy or script. Organizations may even learn about issues with their product or service. Second, monitoring for social mentions with negative sentiment allows owners to reach out to people who may be having a challenging experience with their product. A simple response or follow-up can often go a long way to resolve a customer complaint. A traditional opinion poll would involve surveys with many people traveling, making phone calls etc., resulting in thousands of dollars to run. If we develop a method to identify sentiment of social media content, then this can be used to identify events of potential impact to decision makers like government agencies, commercial organizations etc. For example, online advertisers could use this analysis for efficiently targeted marketing campaigns. Government organizations can know how the society is influenced by a decision or policy and then determine how to respond to the public opinion. In addition to large volume, social media also gives the facility to collect messages pertaining to a specific region, language, a historical period etc. With the dramatic increase of social media usage nowadays, we can use the opportunity to analyze the text rich blogs and messages in a faster and cost-effective way than traditional polls. The research on social media analysis is still evolving. It might be just impossible to write natural language parsers to understand the context of these messages. We try to classify the sentiment polarity of the message as positive or negative or neutral. Hence identifying the sentiment polarity is a classification problem. Understanding the language of eWOM becomes complicated due to the non-standard structure of messages. Our objective is to develop a system which will find out sentiment polarity of people over a topic. First, we try to extract the text content after removing non-textual content like emoticons and images. Then the message is sent to a well-trained Convolutional Neural Network (CNN) for classification. The neural network classifies the sentiment as Positive or Negative or Neutral.

The remainder of this paper is organized as follows. In section 2, we discuss related work. We formally formulate the problem and we propose our methodology in Section 3. Section 4 describes how CNN is used to predict sentiment polarity and the results of our experiment are described. Finally, the paper is concluded in Section 5.

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II. RELATED WORK

Prediction of popular events from news and social media has been done by many people in the past. Twitter is significantly different from most text streams (e.g., news stream and blog stream) that have been extensively studied in the literature for bursty feature/event detection because of its informal writing style and topic diversity. A simple statistic in our study shows that the number of distinct bursty segments is about 75% of the number of distinct tweets in a randomly chosen time window. Among the bursty segments detected, many contain misspelled words, informal abbreviations and emojis. These noisy bursty segments would not only incur unnecessary computational cost but also hurt the event detection accuracy in further processing. We therefore source for the wisdom of the crowds to filter out the non-textual content. In this section, we present an overview of the previous works done in the field of event detection and extraction. Sentiment analysis algorithms fall into one of three buckets:

- i) *Rule-based*: These systems automatically perform sentiment analysis based on set of manually crafted rules.
- ii) *Automatic*: These systems rely on machine learning techniques to learn from data.
- iii) *Hybrid*: These systems combine both rule-based and automatic approaches.

Usually, a rule-based system uses a set of human-crafted rules to help identify subjectivity, polarity or the subject of an opinion. These rules may include various NLP techniques developed in computational linguistics such as stemming, tokenization, part-of-speech tagging and parsing.

Automatic methods, contrary to rule-based systems, don't rely on manually crafted rules, but on machine learning techniques. A sentiment analysis task is usually modeled as a classification problem, whereby a classifier is fed a text and returns a category, e.g. positive, negative, or neutral.

Hybrid systems combine the desirable elements of rule-based and automatic techniques into one system. One huge benefit of these systems is that results are often more accurate. We analyzed machine learning approaches used by researchers in the past. The text classification using ML approach can be roughly divided into supervised and unsupervised learning methods. The supervised methods make use of large number of labelled documents. The unsupervised methods are used when it is difficult to find these labelled training documents. Chi-square method is used in many applications; one of them is contextual advertising as presented by Fan and Change [3]. They discovered bloggers' immediate personal interests in order to improve advertising. They used Support Vector

Machines (SVM) for classification and Chi-square for Feature Selection (FS). Hagenau and Liebmann [4] used feedback features by employing market feedback as part of their feature selection process regarding stock market data. They used SVM as classifier. The feature selection scheme proposed by Duric and Song [5] achieved competitive results for document polarity classification specifically when using the syntactic classes and reducing overlaps with semantic words. Maximum Entropy (ME) classifier was used by Kaufmann [6] to detect parallel sentences between any two language pairs with small amount of training data. Their results showed that ME classifier can be produce useful results for almost any language pair.

SVMs are used in many applications for classification problems. Sentiment polarity identification is a classification problem. Chen and Tseng [7] have used multi class SVM based approaches. SVM have been extensively and successfully used as a sentiment learning approach while Artificial Neural Networks (ANN) have rarely been considered in comparative studies in the sentiment analysis literature. Moraes and Valiati [9] presented an empirical comparison between SVN and ANN for document level sentiment analysis. Van de Camp and Van den Bosch [10] showed that SVM and ANN can be used to mark the relationship between two persons (positive, negative or unknown). They also proved that SVM and one layer NN achieve the highest scores. The supervised learning algorithms when combined with ANN achieve good results for classification problems. However, we need sufficiently large data set with labelled classifiers for training. Though the social media sites emit huge number of messages every day, attaching labels and creating training data set is still a challenging task due to the noisy and unstructured content. Automated NLP tools also cannot be used to attach labels to them. Creating a sufficiently large training data set by manually labelling social media messages is cumbersome. So, we propose a novel approach of using semi-supervised artificial neural networks to process the social media content.

III. METHODOLOGY

In sentiment analysis, 'sentiment polarity' takes a context sensitive meaning. Rule based systems calculate the sentiment polarity based on the net of positive and negative opinion expressed about an event but fail to include the context of the event. In general, we derive day-to-day sentiment scores by counting positive and negative messages. A message with more negative words (reflecting anger, sad, violence) than positive (reflecting happy, joy, celebration) is considered as negative polarity. Application of a lexicon involves calculating the sentiment from the semantic orientation of word or phrases that occur in a sentence. With this

approach a dictionary of positive and negative words is required and a positive or negative sentiment value assigned to each of the words. Different approaches to create dictionaries have been proposed, including manual counting and automatic approaches. In lexicon-based approaches a piece of text message is represented as a bag of words. Following this representation of the message, sentiment values from the dictionary are assigned to all positive and negative words or phrases within the message. A combining function, such as sum or average, is applied in order to make the final prediction regarding the overall sentiment for the message. For example, sentence 'Enjoying my lazy Sunday!!' represents a positive message that contains one positive (enjoying) and one negative (lazy) word. It will be difficult for rule-based classifier to decide between positive and negative in such a case. A tweet message may be even worse for parsing because it might contain emoticons and special symbols. To alleviate this issue, we use machine learning to predict polarity and the decision making is similar to human behavior. Sentiment analysis of social media content is a classification problem. KNN is widely used for classification problems. But it requires sufficiently large amount of labeled data set for training. Labelling the social media content and generating few millions of training data is cumbersome due to the varying style of micro bloggers. In this paper, we propose a semi-supervised method using Neural Networks. Deep learning is very influential in both unsupervised and supervised learning.

a) Feature extraction from eWOM

The social media messages are not plain text messages. The eWOMs often contain emoticons, abbreviations etc. Sentiment analysis will not be accurate unless we translate these messages into plain text without losing the context and emotions attached. For example, the context of the sentence 'Enjoying my lazy Sunday 😊' cannot be understood unless we know the meaning of 😊. It has two positive (enjoy, 😊) and one negative (lazy) word. The local context of the message will be lost unless we take the emoticons also into consideration. So, our first step is to develop a feature extractor which will produce plain sentence from eWOM. The feature extractor works as follows.

- We pick up only English text message. Other language sentences are removed.
- Emojis are replaced with CLDR meaning, if mapping is available (Table 1). Removed otherwise.
- All words are converted to lowercase.
- Stop words and punctuation like periods, commas and brackets are removed.
- Remove all words that are not purely comprised of alphabetical characters (words having special characters and numbers).

The cleaned-up sentence is now used for identifying the sentiment polarity.

Following table shows example of few emojis translated using Unicode Common Locale Data Repository (CLDR).

Table 1: CLDR translation of emotions

UNICODE	EMOJI	CLDR MEANING
U+1F600	😄	Grinning face
U+1F642	😊	Smiling face
U+1F609	😉	Winking face
U+1F615	😕	Confused face
U+1F622	😭	Crying face
U+1F602	😂	Tears of joy
U+270C	✌️	Victory hand

For example, the tweet message 'Salute to our warriors 🙏 who taught us to raise voice against evil!' is converted into the plain text 'Salute to our warriors with tears of joy who taught us to raise voice against evil' using our feature extractor.

We created a limited data set from social media for supervised learning. Using movie review or customer review data set for social media sentiment analysis does not provide high accuracy prediction. A hand-crafted training data set consisting of 2000 positive, 2000 negative and 2000 neutral messages which were classified manually by experts was used to train the neural network. Our model learns to associate a given

input (sentence) to the corresponding output (polarity) based on the test samples used for training. Pairs of feature vectors and tags (e.g. positive, negative, or neutral) are fed into the machine learning algorithm to generate a model. The well-trained model generates predicted tags (positive, negative, or neutral) for a given input.

b) Polarity Sensitive Convolutional Neural Network (PSCNN)

Deep learning is prosperous because of three main and important reasons, i.e., improved abilities of chip processing (GPU units), extensively lower

expenditure of hardware and significant enhancements in machine learning algorithms. It is a promising approach and has been extensively applied in artificial intelligence fields like computer vision, transfer learning, semantic parsing, natural language processing and many more. People use deep neural network architecture to evaluate the similarity of documents. We present a new architecture for sentiment analysis which operates directly at the sentence level and uses only small convolutions and pooling operations. We will use a pre-trained word embedding prepared on a very large text corpus. We propose a Polarity Sensitive CNN (PSCNN) for eWOM sentiment modeling. The PSCNN is a hierarchical model, where feature extractor formats sentence vectors which are fed to the convolution and max-pooling layers to generate the document representation. Skip - gram models is best suited for context-based prediction. The model learns each term within a

given context window in the order of a word sequence to capture the skip-gram based contextual features. Then, based on the significance learned from the skip-gram features, the PSCNN structures the feature vectors up onto the sentence level. As a result, the model applies a nonlinear transformation to generate a continuous vector representation for the entire text corpus by extracting the high-level semantic information. Convolution in the proposed model is followed by global max-pooling. use sequence of word embeddings trained on large data collections as inputs to train a CNN-based representation learning model where each sequence of k words is compacted in the convolutional networks. Following diagram shows our two-step methodology which overcomes the natural language processing challenge through feature extractor and CNN.

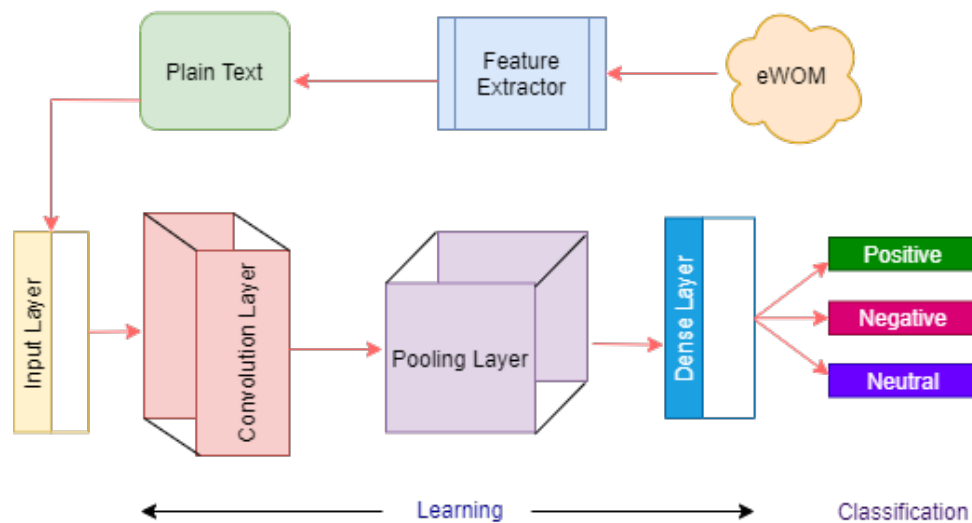


Figure 1: Hierarchical model for PSCNN

The purpose of the model was to match two sentences and to serve the paraphrasing tasks originally. PSCNN first learns and extracts representations from the two sentences separately, and then it compares the extracted features with max layer pooling to generate a matching degree. Following are the major steps involved in the convolution layer.

- The first step is to load the word embedding as a directory of words to vectors.
- The model performs a 1-D convolutional operation to learn text representations.
- This representation makes it possible for words with similar meaning to have a similar representation.

The trained model produces an output -1 (negative) or 0 (neutral) or 1 (positive).

IV. EXPERIMENTS AND RESULTS

Sentiment Analysis using Artificial Intelligence makes the life of commercial product organizations

easier. A company which sells hundreds of products cannot afford to employ many reviewers to read all the customer reviews manually and classify them. Sentiment analysis can identify critical issues in real-time, for example:

- Is a public crisis on social media escalating?
- Is an angry customer about to churn? etc.

Artificial Intelligence based Sentiment Analysis is really an efficient and cost-effective tool for many commercial organizations and government agencies. We used twitter data related to product reviews for our experiments and analysis.

In this section, we describe the evaluation tasks, the data sets used and the experimental results of the proposed approach.

Evaluation Tasks:

- We evaluate our approach on twitter data set.
- We evaluate our approach on popular benchmarks.

Our goal is to prove the real-life application of our approach. We aim to evaluate the quality of sentiment classification. The empirical probability is compared with real time data to harness the accuracy. The results show promising output.

a) Data Set

Twitter is a micro blogging site used by public nowadays to openly express their opinions and sentiment. Every day more than 500 million tweets are

generated by people around the world and this text rich social media platform serves as a desirable platform to analyze the information from many perspectives like politics, elections, consumer products and many more. Twitter API provides facility to search for messages using filters like place, language etc. Our data set for evaluation was set of tweets from May 2021 to July 2021 in English language related to India region.

Table 2: Sentiment in twitter stream

DESCRIPTION	MAY 2021	JUNE 2021	JULY 2021
Total number of tweets	5,423,667	5,212,765	5,314,443
Tweets with sentiment	1,789,810 (33%)	1,563,830 (30%)	1,647,477 (31%)
Tweets with sentiment and hashtag	759,313 (14%)	781,915 (15%)	690,888 (13%)

From the above table, we observe that appreciable number of tweets with sentiment are available for analysis. The below figure shows that tweet messages always reflect sentiment at any point in time.

We observed that the volume of positive and negative sentiments might vary over the time, but people always express their sentiment through tweets.

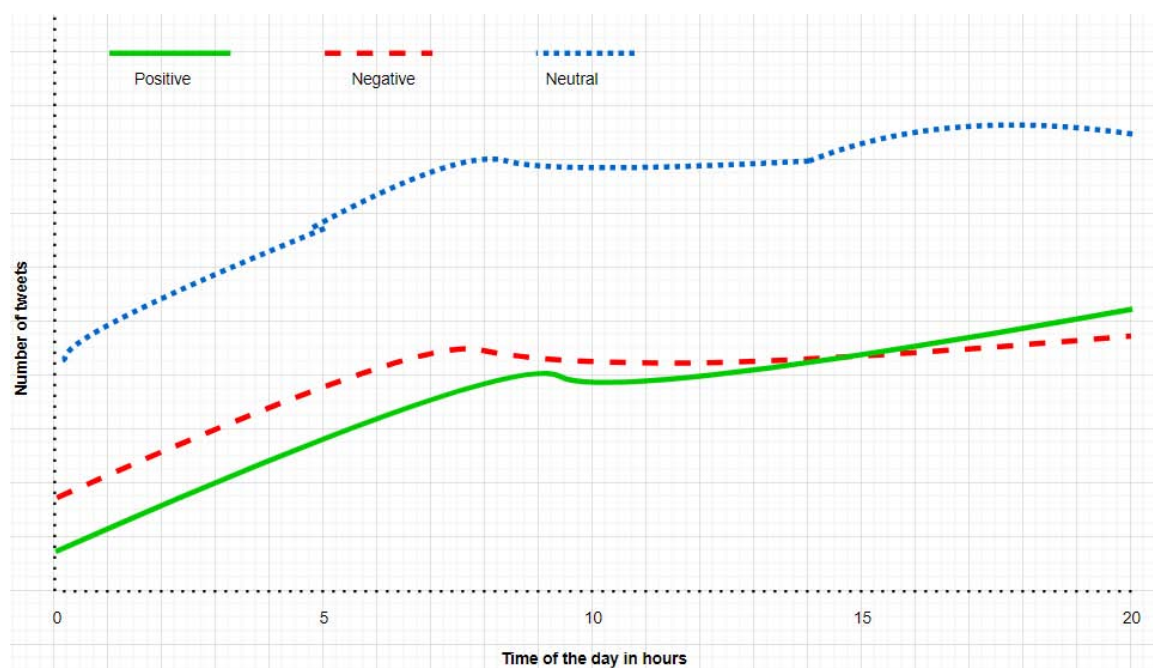


Figure 2: Distribution of sentiment in tweets

b) Popular Metrics

In this section, we first describe a set of metrics commonly used for evaluating performance of our model and then present a quantitative analysis of the performance evaluated using popular benchmarks.

Accuracy and Error Rate: These are primary metrics to evaluate the quality of a classification model. Let TP, FP, TN, FN denote true positive, false positive, true negative, and false negative respectively. The classification Accuracy and Error Rate are defined in Eq. 1

$$\text{Accuracy} = \frac{(TP + TN)}{N}, \quad \text{Error rate} = \frac{(FP + FN)}{N} \quad (1)$$

Where N is the total number of samples. Obviously, we have **Error Rate = 1 – Accuracy**.

Precision, Recall and F1 Score: These are also primary metrics and are more often used than accuracy or error rate for imbalanced test sets. Precision and recall for binary classification are defined in Eq. 2. The F1 score is the harmonic mean of the precision and recall, as in Eq. 2. An F1 score reaches its best value at 1 (perfect precision and recall) and worst at 0.

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}, \quad \text{F1-score} = \frac{2 * \text{Prec} * \text{Rec}}{\text{Prec} + \text{Rec}} \quad (2)$$

For multi-class classification problems, we can always compute precision and recall for each class label and analyze the individual performance on class labels or average the values to get the overall precision and recall.

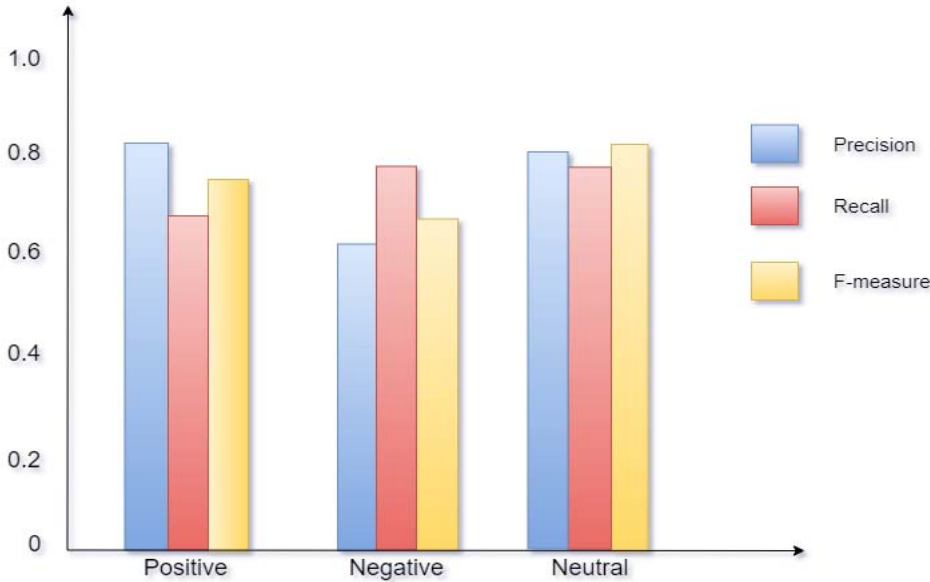


Figure 3: Quantitative metrics analysis

From the above results it can be noticed that for twitter eWOMs better accuracy is achieved at message level sentiment.

c) Empirical Results

Our aim is to make use of our PSCNN to analyze social media and identify impactful events trending in the twitter. Following are examples of sentiment-full events identified using our PSCNN.

Table 3: Events identified from twitter stream

No.	TWITTER eWOM	SENTIMENT	HASHTAG
1	Samsung Galaxy M12 is out👏. This Phone is totally Outstanding 😊!	Positive	#SamsungGalaxyM12
2	Salute to our warriors who taught us to raise voice against evil 🙏!	Positive	#MartyrsDay
3	Their sacrifice for our motherland will continue to inspire the coming generations 🙏 We respect, value your sacrifices, we are forever indebted to your sacrifices 🙏	Positive	#MartyrsDay
4	She is the hope of Uttar Pradesh 🙏, the only leader who is consistently raising the issues and fighting for the people everyday 😊. Young charismatic, with	Positive	#UPKiUmeedPriyanka

	impeccable credentials and history 🙏!		
5	The people of UP are urging for relief from gundarj, terror & hypocrisy of Saffron reign 😞	Negative	
6	Paranoid, vindictive government will not let farmers survive 😞. Through attacks on farmers the government has finally declared that there is emergency in India now 🙏	Negative	#FarmersParliament
7	Farmers will discuss about APMC mandis in today's Parliament of farmers 😊. Groups of 200 farmers will protest outside the Parliament every day 🙏, during the monsoon session, to strengthen the voice in the temple of Democracy 😞	Negative	#FarmersParliament

From the above table, we observe that people talk about various events and express their sentiment in social media. This is really an alternate to traditional polling and cost effective solution for decision makers to understand the situation and respond to any emerging crisis.

V. CONCLUSION AND FUTURE WORK

The proposed method accomplished superior performance in terms of sentiment classification of eWOMs according to polarity. The major challenge in using the NLP tools for understanding the social media messages is eliminated by our two-step methodology namely feature extractor and CNN. By using a centralized sentiment analysis system, commercial organizations can improve accuracy and gain better insights while analyzing customer feedback and complaints. The overall benefits of AI based sentiment analysis include:

Sorting Data at Scale: Manually sorting through thousands of tweets, customer support conversations, or surveys is complex and time consuming. AI based Sentiment analysis helps businesses process huge amounts of data in an efficient and cost-effective way.

Real-Time Analysis: The social media analysis can help organizations immediately identify alarming situations and they can act right away before customer churn out.

Tagging text by sentiment is highly subjective, influenced by personal experiences, thoughts and beliefs. Intensifiers refer to words such as very, quite, most etc. These are the words that change sentiment of the neighboring non-neutral terms. They can be divided into two categories namely amplifiers (very, most) and down toners (slightly) that increase and decrease the intensity of sentiment, respectively. Identifying intensity of emotion may not be simple through rule based approached. Our AI based model can be enhanced further to identify intensity of emotion.

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