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PRODUCT REVIEW SENTIMENT ANALYSIS USING RECURRENT NEURAL NETWORK

V. UMA DEVI[1], Dr. VALLINAYAGI V[2]

[1]Research Scholar, Register Number: 182212621620010, [2]Associate Professor & Head, Sri Sarada College for Women, Affiliated to Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli

[2]Department of Computer Science, Sri Sarada College for Women, Affiliated to Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli.

ABSTRACT

Determining the sentiment polarity of product reviews has become a landmark work in natural language processing (NLP) and data science. This is perhaps easing the way of understanding and it is also easy to get good results with very simple methods (e.g. positive – negative words counting).In this paper deep architecture based sentiment analysis product reviews are done by Convolution Neural Network (CNN) and Long Short Term Memory (LSTM). The publically available online item reviews from Amazon reviews web portal are used for analysis. Experiments with neural network methods show promising outcomes.

Keywords—Natural Language Processing; Neural Networks; Sentiment Analysis

I.INTRODUCTION

Now a day's lots of people are purchasing products online. A common procedure for online merchants is to allow their consumer to write reviews on products that they have brought. Appropriately, the product reviews grows rapidly. Sentiment analysis has improved much more consideration in these modern years. It arranges texts based on the Sentimental Orientation (SO) of opinions they contain. Sentiment makes sense of item reviews has these days end up very popular in textual content mining and computational linguistics research. In the area of sentiment analysis, there have different existing algorithms exist to tackle Natural Language Processing (NLP) problems.WWW has become the famous communication platforms to the customer reviews, opinions, comments and sentiments [10]. These sentiments refer to opinions about products, places, books or research papers become regular text reviews. The quantity of dynamic consumer bases and the size of their reviews made regular on online websites are massive. Nearly, 2.4 billion online public reviewers read and write online comments around the world. As per to 2013, a study shows 79% of client's certainty depends on the online personal recommendation reviews [8]. Outcomes of research show that a large number of online resources year by year [11].

Currently, many websites support researchers to exchange and express their suggestions, views and suggestion related to scientific papers. Sentiment analysis provides user mindset with concerning to some topics or the overall sentiment polarity of a text, such as positive or negative. Sentiment analysis [7] frame-up on two channels, sentiment polarity and sentiment score. Sentiment polarity is a binary value this one is positive or negative. The next one is, sentiment score rank on one of three types. They are Bag-of-words (BOW), Parts Of Speech (POS) and semantic relationship. BOW method is the most popular one for representing terms. It slights the language grammar and words ordering. POS tagging is a grammatically pining process especially verbs, adjectives and adverbs. For example; (The book is not good.) declaring in (The/DT book/NN is/VBZ not/RB good/JJ. /.). In the model DT alludes to "Determiner", NN alludes to "Thing", solitary or mass, VBZ alludes to "Action word", RB alludes to "Verb modifier", and JJ alludes to "Descriptive word" anyway it dismisses legitimate importance. Semantic relationship is the most perplexing technique. It is based on the relationship between concepts or meanings. Examples are antonyms, synonyms and homonyms.

The other name of Sentiment analysis called as opinion mining [9]. Sentiment evaluation refers to the utilization of herbal language processing, text evaluation, and computational semantics to perceive and extract subjective statistics in source substances. Sentiment analysis is extensively implemented to reviews and social media for a diffusion of programs, ranging from marketing to customer support. The aim of sentiment analysis is evaluating the sentiments and opinions of a writer. It valuation the total sentiment polarity of online real reviews for one topic based on sentiment classification levels, such as positive or negative. Old techniques to sentiment reviews can be grouped into four main categories such as entity level, word level, document level and sentence level. Sentiment analysis is also called as opinion mining, opinion extraction and affects analysis in the literature. Beyond, the terms sentiment analysis and sentiment classification have frequently used interchangeably. It is useful, however, to categorize between two subtly different concepts.

I. METHODOLOGY

The overview of the methodology is shown in Fig. 1. Following steps are followed for developing and validating the prediction models. Pre-processing of data is done and the features are isolated. The word vector is developed for data model I using unigram attributes and product attributes as features. Data model II is developed using unigram and bigram and data model III using unigram, bigram and trigram features. The prediction model is constructed using training data set that has dimension reduced feature set. Using CNN the neural network model is designed. Prediction of the class (positive, negative or neutral) for each review is performed on the test data set. With actual values obtained, the prediction results are compared. The various quality parameters are evaluated and the prediction results are compared.

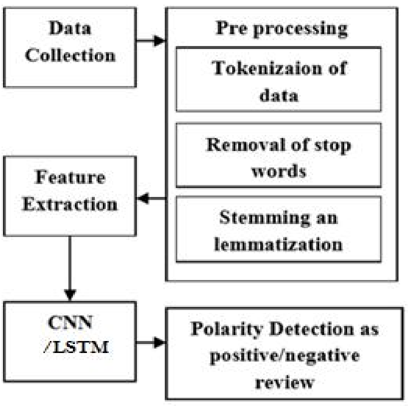

Fig 1: Overview of the proposed method

A. DATA SOURCE

For any consumer to make an effective decision on buying a product, online product reviews serve as excellent sources. The consumer can get product related information through online reviews. A star rating of a product provides excellent cues for decision making. It also provides a immediate indication of a review.

B. DATA PREPARATION

The dataset is collected from Amazon. Amazon website consists of data products obtained using digital cameras, mobile phones and laptops. The review obtained is divided as of subjective and objective sentences. Subjective sentences means influenced by emotion or opinion. Objective sentences mean no personal feelings in it. This data set consists of 5774 reviews as subjective sentences where 3750 are positive reviews and 2024 are negative reviews. This data set consist of 5980 reviews as objective sentences where 1860 are positive reviews and 4120 are negative reviews. Totally 5610 reviews are positive and 6144 reviews are negative. The sentiment data set used in this work contains a set of product review sentences which were categorized as positive and negative.

In binary classes, the words are classified as either positive class or negative class leaving no room for neutrality. This leads to over fitting and becomes vulnerable to situations that occur due to randomness. A particular neutral word occurs more time in positive or negative class. For constructing the data set, customer reviews are collected for a particular product from publicly available website www.amazonreviews.com.

In this work, Digital camera reviews have been considered. Totally 11754 reviews, sentences are crawl using Amazon reviews downloader and parser. For the customized dataset used, a sample review crawled from the star review. Since the reviews are provided by various individuals with ranging backgrounds, the meaning of a 5- star review changes from a person to person. Then the reviews are extracted and sentiment class is assigned based on the review score in the data format (sentiment class is positive if review score is >3, If overview rating is < three the class label is assigned negative).Amazon website is as given below in Fig 2. Then product ID is given as input to the downloader. The data format after downloaded is shown in Fig 3.

Fig 2: Sample review from Amazon

Fig 3: Data format of downloaded review CNN

product/productId: B003ZYF3LO
review/userId: A1RSDE90N6RSZF
review/profileName: Joseph M. Kotow
review/helpfulness: 9/9
review/score: 5.0
review/time: 1042502400
review/text:Good camera with quality pictures. Many features some of which never used. Holds battery life OK.

CNN's were neurobiological inspire by the findings of locally sensitive and orientation-selective nerve cells in the visual cortex. It consists of a network structure which essentially extracts suitable features. CNN are a unique kind of multi-layer neural networks.

CNN is a feed-forward neural network which extracts topological values in an image. Likewise related neural networks, CNN are trained with a variant of the back-propagation algorithm. CNN is considered to identify visual patterns directly from pixel images with minimal preprocessing.CNN can also identify patterns with extreme variability (such as handwritten characters). A Convolution Neural Networks have following steps

Step 1: Convolution Operation

The first building block action is convolution operation. In this step, feature detectors will basically serve as the neural network's filters. Patterns are detected using parameters of feature maps.

Step 1(b): ReLU Layer

The second part of this step consists of Rectified Linear Unit or ReLU. This ReLU layers has linearity functions in the context of CNN.

Step 2: Pooling

In this part, max pooling is applied. Mean and sum pooling is performed.

Step 3: Flattening

In CNN, flattening is an important concept. Here it is moved from pooled to flattened layers.

Step 4: Full Connection

In this section, all outputs are merged together. Finally, the produced neuron will to classify images.

C. LSTM Network

LSTM [12] is a counterfeit Recurrent Neural Network (RNN) design utilized in the field of profound learning. RNN-based model is an augmentation of the feed forward model. RNN with LSTM allows the network to make a decision at any point in the sequence of transitions. Based on time series data, there can be lags of unknown duration between important events

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in a time series.

LSTMs were created to manage the detonating and disappearing slope issues that can be experienced when preparing customary RNNs. Relative harshness toward hole length is a bit of leeway of LSTM over RNNs, shrouded Markov models and other succession learning strategies in various applications. The LSTM contains Forget Gate, Input Gate and Output Gate. In LSTM, the uninterrupted connection in internal states throughout the sequence is an important part. The definition of the LSTM is shown from Eq. (1) to Eq. (6)

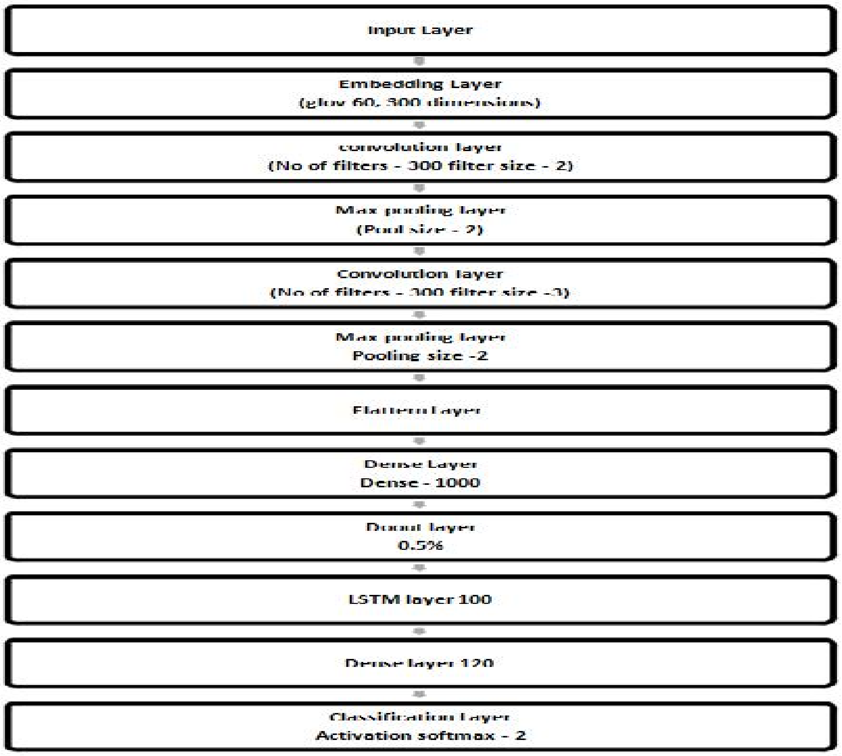

Fig 4 LSTM layer representation

$$q_t = \delta\left(V_{x_q} x_t + V_{y_q} y_{t-1} + b_q\right) \tag{1}$$

$$a_t = \tanh(V_{x_r} x_t + V_{y_r} y_{t-1} + b_i) \tag{2}$$

$$z_t = \delta(V_{x_u} x_t + V_{y_u} y_{t-1} + b_u) \tag{3}$$

$$s_t = \delta(V_{x_s} x_t + V_{y_s} y_{t-1} + b_q) \tag{4}$$

$$e_t = e_{t-1} \odot z_t + q_t \odot a_t \tag{5}$$

$$f_t = \tanh(e_t) \odot s_t \tag{6}$$

With final soft max layer to predict the data.

$$y = \mathrm{softmax}(V_y\, f_t)$$

Figure 4 represents the architecture of LSTM used in this system.

II. PERFORMANCE EVALUATION

The dataset is then subject to evaluation in the following criteria:
Here confusion matrix is considered. Confusion matrix has a table where the performance of a classification model is analyzed. A set of test data is prepared for the known true values.

TP - True Positive
TN - True Negative
FP - False Positive
FN - False Negative

Accuracy is defined as the important performance measure. It is estimated as the ratio of correctly predicted results to the total results.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FN+FP} \tag{8}$$

Precision is defined as the ratio of correctly predicted positive results to the total predicted

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positive results.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{9}$$

Recall is defined as the ratio of correctly predicted positive results to the all result in actual class.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{10}$$

F1Score is the important metric while calculating accuracy in uneven distribution. It is defined as the weighted average of Precision and Recall.

$$\text{F1Score} = \frac{2*\text{Recall}*\text{Precision}}{\text{Recall}+\text{Precision}} \tag{11}$$

Table 1 shows the accuracy comparison of CNN and LSTM. The results of LSTM are 85% accuracy, 81% precision, 82% recall. While comparing CNN with LSTM, LSTM gives better performance of 5% more accuracy than CNN and 2% improvement in F1-Score.

Table 1

Comparative analysis between CNN and LSTM

Performance metrics	**CNN**	**LSTM**
Accuracy	80.98	85.51
Precision	80.325	81.116
Recall	79.312	82.496
F1Score	79.815	81.800

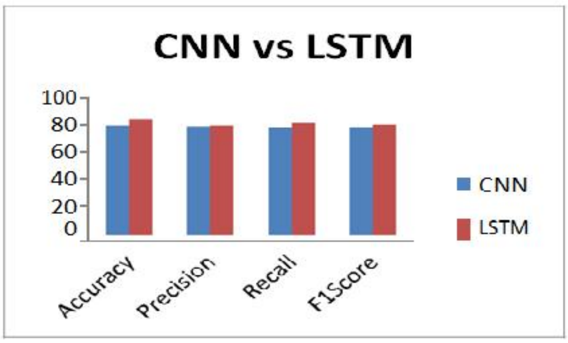

Fig 5 Comparison representation between CNN and LSTM

In figure 5, CNN is compared with LSTM in terms of Accuracy, precision, recall and F1 score. Figure 5 clearly depicts the performance of LSTM is better when compared to CNN, LSTM improves the results in terms of Accuracy, precision, recall and F1 score.

IV. CONCLUSION

In this work, Amazon electronic products are considered using sentiment analysis in a real review stream. Reviews are evaluated by following uniform sentiment distribution. Totally, 5774 reviews are considered as subjective sentences and 5980 reviews are considered as objective sentences in this work. Here, CNN is compared with LSTM in terms of Accuracy, precision, recall and F1 score. The results show that LSTM shows an improvement of 5% more accuracy than CNN.

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