Volume 8, Issue 3
June 2019

ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

Ensemble Application of Devoted Convolutional Neural Network Based Sentence-Level Sentiment Analysis for Big Data

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ABSTRACT

With the rapid development of the World Wide Web, electronic word-of-mouth interaction has made consumers active participants. Different types of sentences express sentiment in very different ways. Traditional sentence-level sentiment classification research focuses on one-technique-fits-all solution or only centers on one special type of sentences. Sentiment Analysis is one of the trending topics in the Information and Technology field. In this paper, we tried to increase the efficiency of sentiment analysis. To achieve maximum accuracy, a sentence level analysis was performed by considering devoted convolutional neural network-based sentence level sentiment analysis of big data (DCNNSLAB). The experimental results validated the effectiveness of DCNNSLAB and showed the decisions could further improve the accuracy of sentence level sentiment analysis of big data.

Keywords: CNN, POS, WTFA (Weighted Term Frequency Analyzer), Lexicon table, sentence level classification.

1. INTRODUCTION

Recent development of the Web has influenced every aspect of our lives and hence need of user view analysis is increasing exponentially. The flow of immense amount of information is affecting decision making processes in organizations. Analysis of people 's aspects, reactions, emotions, etc. regarding entities such as services, products, issues, events and their attributes based on feedback from Web pages is called opinion mining. Opinion mining is also called as sentiment analysis, opinion extraction, sentiment mining, and subjectivity analysis, affect analysis, emotion analysis, review mining, etc. [1]. Opinion mining becomes important for impact analysis and helps in making decisions on constructive developmental directions. It is a research area dealing with usual methods of opinion detection and extraction of sentiments presented in a text. Outcome of implementation of opinion mining methods are formation of efficient recommendation systems, financial study, market research and product growth. There is an enormous amount of opinionated data available in digital forms e.g., reviews, forum discussions, blogs, microblogs, Twitter and social networks [2]. Hence, research in sentiment analysis has an overwhelming impact on NLP, management sciences, political science, economics and social sciences as they are all affected by opinions of people.

A sentiment is a positive or negative opinion, feeling, emotion or assessment about a term, attribute or a feature from a sentiment holder. Positive, negative and neutral views are called as sentiment orientations (also called opinion orientations, semantic polarities or orientations). In general; opinion mining has been classified into three levels:

1. Document level: *Document*-level sentiment classification classifies a whole document as a positive or negative sentiment for a product or service. It is not relevant to documents which measures or compare several attributes at this level of analysis because it believes that each document conveys sentiments on a single attribute (e.g., a single product) [2].

2. ***Sentence level***:Sentence-level sentiment classification determines whether each sentence expresses a positive, negative or neutral opinion for a product or service. Sentence level analysis is associated with subjectivity classification which makes distinction between objective sentences and subjective sentences. The objective sentences are those sentences that express true information the subjective sentences are those sentences that express subjective views and opinions. The objective sentences can imply more opinions than the subjective sentences. e.g., "Few buttons of the remote control of a Smart TV which we purchased a couple of days back are malfunctioning" [2].

3. ***Entity and Aspect level***: Feature based opinion mining and summarization is also called as Aspect level analysis. It performs finer-grained analysis. Aspect level analysis is based on the concept that an opinion contains a sentiment (either positive or negative) and a target of opinion [7], thus directly identifies the target of opinion itself.

In many reviews, target opinions are based on aspects and/or their different entities. For example,"Although the battery backup is not that high, I still like Samsung mobile phone " has a positive sentiment but this sentence is not completely positive. In fact, the positive sentiment is about the entity Samsung mobile (emphasized), but negative sentiment is about its battery backup (not emphasized). Thus, the objective of this level of analysis is to determine opinions on aspects and/or their entities. A structured summary of opinions about entities can be used for all types of quantitative and qualitative analysis. The aspect level analysis is more challenging and difficult than the document level and sentence level classifications.

A part from these three levels of classification, regular opinions and comparative opinions are two categories of opinions. A sentiment expressed only on a particular entity or an aspect of the entity is a regular opinion, e.g., "Aamir

Khan acts very well" expresses positive sentiment on the aspect of acting of Aamir Khan. A sentiment expressed by comparing multiple aspects based on some of their shared attributes is a comparative opinion [8]. For e.g., "Vanilla pastries taste better than vanilla cake", compares pastries and cake based on their tastes (an aspect) and expresses feeling and preference for pastries.

Sentiment classification is extremely responsive to the area from which the training data are extracted. This makes it an interesting research topic which transfers learning or domain adaptation. Words and even language formats used in different areas for expressing sentiments can be somewhat different hence a classifier trained using opinionated documents from one area often performs differently from another area when it is tested or applied on opinionated documents. The same word in one area may mean positive, but in another contextual area may mean negative, making matters difficult. Thus, domain modification is needed. It is found that existing research has used labeled data class from one area, unlabeled data class from the target area and general opinion words as features for adaptation [1,3,7,8]

Most recent studies on opinion mining found that sentiment analysis has become an area of active study due to many demanding and interesting research problems. Due to its multiple practical applications, the enormous amount of start-up companies offering sentiment analysis or opinion mining services. Every company wants to know how consumers consider their products and services and those of their competitors. Thus, there is a actual and indeed requirement in the industry for such services. These technical challenges and practical requirement will keep the area active and dynamic for years to come. There are many applications for Sentiment Analysis. Some of them are:

1. Financial markets:

(a) To predict society movement based on news, blogs, reviews and social sentiment channel.

(b) To recognize clients expressing negative emotions in social media or newscast and to raise the business transactions with them for default security.

(c) To identify sentiments of the analyst and investors' emotions about the stocks of a company and price trends. It is crucial information for investors.

2. Computing customer satisfaction metrics:

To get an idea of how happy customers are with the products, from the ratio of positive to negative reviews.

3. Identifying attackers and advertisers:

It can be used for providing better consumer service to spot displeasure or problems with goods from customers' end. It can also be used by analysts to find people who are happy with their products or services and the customers' experiences can be used to promote their products.

4. Planning for a tourist spot:

Tourists would like to know the best locations to visit or good restaurants to dine in. Applying opinion mining can assist in retrieving related information for planning a tour.

5. Opinion analysis on elections:

Opinion analysis can be used to find out voters' sentiments about a particular contender.

6. Sentiment analysis on softwares or film reviews:

To identify users 'opinions from reviews published in specific websites.

The applications for sentiment analysis are endless. Sentiment analysis is in demand because of its efficiency. Thousands of text documents can be processed for sentiment (and other features including named entities, topics, themes, etc.) in seconds, compared to the hours it would take a team of people to process the same manually. Many businesses are adopting text and sentiment analysis and incorporating it into their processes because of its efficiency and accuracy.

ADVANTAGES

- Adjust marketing strategy
- Measure ROI of your Marketing campaign
- Develop product quality
- Improve Customer service
- Crisis management through constant monitoring
- Sales Revenue

2. MOTIVATION

The research in this field is rapidly picking up and has attracted the attention of academia and industry alike. Combined with ad- vances in signal processing and AI, this research has led to the development of advanced intelligent systems that intend to detect and process affective information contained in multimodal sources [16]. However, the majority of such state-of-the-art frameworks rely on processing a single modality, i.e., text, audio, or video. Ad-ditionally, all of these systems are known to exhibit limitations in terms of meeting robustness, accuracy, and overall performance re-quirements, which, in turn, greatly restricts the usefulness of such systems in real-world applications.

3. RELATED WORKS

Sentiment classification is a fundamental and important study area in sentiment analysis. It hammers at detecting the sentiment polarity of a sentence or a document [10] based on its textual content. Sentiment classification has wide applications, such as product ranking [11] and product sales forecasting [12]. Taking a panoramic view of this area, there are two main directions for sentiment classification: lexicon-based approaches and corpus-based approaches. Lexicon-based approaches typically use sentiment dictionary, intensification and negation to compute a sentiment score for each text. Sentiment words and phrases are marked with sentiment polar and sentiment strength in sentiment dictionary. There are two kinds of sentiment dictionaries according to universality. One is a universal sentiment dictionary which is applicable to almost all fields; the other is a domain sentiment dictionary which is applicable to specific fields.

Turney [13] proposed a simple but representative lexicon-based method to classify reviews into recommended or not recommended. The classification of a review is predicted by the average semantic orientation of its phrases, and the semantic orientation of a phrase is calculated by the mutual information between the given phrase and the word "excellent" minus the mutual information between the given phrase and the word "poor".

Subjectivity classification distinguishes sentences that express opinions (called subjective sentences) from sentences that express factual information (called objective sentences) [14]. Al- though some objective sentences can imply sentiments or opin-ions and some subjective sentences may not express any opinion or sentiment, many researchers regard subjectivity and sentiment as the same concept [15,16], i.e., subjective sentences express opinions and objective sen- tences express fact[17] presented a boot- strapping process to learn linguistically rich extraction patterns for subjective expressions from a large unannotated data. [18] presented a system to detect emerging political topics on twitter and the impact on concept-level senti- ment analysis.

4. PROPOSED METHOD (DCNNSLAB]

Proposed method comprises of two interrelated functional modules. They are Weighted Term Frequency Analyzer and Threshold based Variable size Window Devoted Convolutional Neural Network. The functions of these modules are explained below in detail.4.1. Weighted Term Frequency Analyzer (WTFA)

This module has access to the pre-created Lexical Table (LT). Based on the LT context, WTFA distinguishes different word features (ω), Modification Features (μ), Sentence Features (δ), Structure Features (Δ) and Document Classification Feature (Γ).

The word feature has the sub-classification members such as token, part-of-speech, context, bias and reliability. The bias is stated by the positive, negative, positive & negative and neutral. The reliability is stated as either strong or weak. The word features are treated as sets in WTFA represented as $\omega = \{\omega_0, \omega_1 \cdots \omega_{n_\omega}\}$ where ω refers the complete set of word features$\omega_0, \omega_1 \cdots \omega_{n_\omega}$ and n_ω is the maximum permitted word feature count.

The modification features are adjectives (μ_1), adverb (excluding not) (μ_2), preceded by intensifier (μ_3), intensifier (μ_4), Modifies Strong Subject (MSSS: μ_5), Modifies Weak Subject (MSWS: μ_6), Modified by Strong Subject (MDSS: μ_7) and Modified by Weak Subject (MDWS: μ_8). All these features are represented by a 0 or 1 which is stored as a single byte in memory for processing.

The memory mapping bit positions of these features are given in Figure 1.

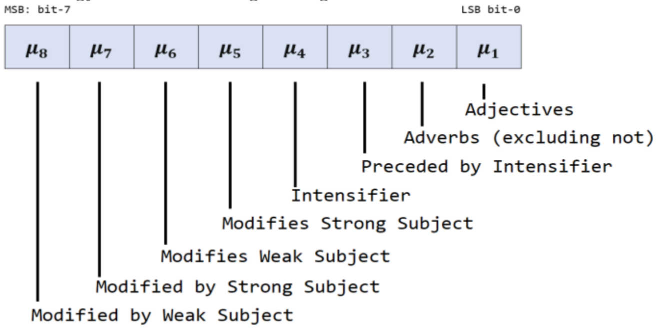

Figure 1: Bit positions of Modification Features

The special adverb 'not' is treated as the negative (-) sign which is rarely represented as μ_0. The frequent notation for not is a -VE sign. The meanings of the word with preceding adverb not are treated similar to the opposite meaning but there is a delicate difference is maintained for biasing. For example, the meaning of 'not good' is equalized nearly to the meaning of 'bad', similarly, the meaning of 'not bad' is equalized to the nearest value of 'bad'. This complication is well defined in WTFAas, [$not\ good \approx bad\ \&\ not\ good \neq bad \mid not\ bad \approx good\ \&\ not\ bad \neq good$].The modification feature set will be represented as $\mu = \{\mu_0 \to \mu_8\}$

Sentence feature δ_x of a particular sentence $x$is calculated using the following equation

$$\delta_x = \sum_{i=0}^{n} \Omega(\omega_i) + \sum_{i=1}^{8} \Omega(\mu_i)$$

Where $\Omega(\omega_i)$ is the preassigned weight factor of word feature $\omega_i$fetched from the Lexical Table. Similarly, $\Omega(\mu_i)$ is the weight factor of modification features fetched from the LT. The structural feature Δ is calculated using the following equation,

$$\Delta = \begin{cases} -VE\ iff\ \delta_x < 0 \\ 0\ iff\ \delta_x \equiv 0 \\ 1\ iff\ \delta_x > 0\ and\ \delta_x \leq \frac{1}{5} \\ 2\ iff\ \delta_x > \frac{1}{5} and\ \delta_x \leq \frac{2}{5} \\ 3\ iff\ \delta_x > \frac{2}{5} and\ \delta_x \leq \frac{3}{5} \\ 4\ iff\ \delta_x > \frac{3}{5} and\ \delta_x \leq \frac{4}{5} \\ 5\ iff\ \delta_x > \frac{4}{5} and\ \delta_x \leq 1 \end{cases}$$

The document classification feature is calculated as follows,

$$\Gamma = \begin{cases} Negative\ if\ \Delta < 0 \\ Neutral\ if\ \Delta = 0 \\ Positive\ if\ \Delta > 0 \end{cases}$$

Volume 8, Issue 3
June 2019

ITEE Journal
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ISSN: - 2306-708X

By this way WTFA finds recognize the feedback of a customer and classifies in to different star grades.

4.2. Threshold based variable size window Devoted Convolutional Neural Network

A new CNN model is proposed here to increase the accuracy of sentiment analysis. The output of word features, sentence features and structure features are given to the input of the convolutional neural network. The Artificial Neural Network concept is not used here due to the hyper connectivity count between the neurons which will increase the computational complexity drastically. In this sentence level sentiment analysis, there will be $n+8$ neurons in the input layer. There will be three hidden layers required before the output layer to provide required level of accuracy.

Therefore, the number of neuron interconnections will be $4(n+8)^2$ which is hard to process and the complication will be increased by multifold while handling big data. To reduce the computational complexity, a threshold based variable size window devoted CNN is introduced here. The threshold value is permitted to float between 2 to $\frac{n}{2}+4$, therefore, $O\left(\frac{n}{2}\right)$ computational complexity reduction is guaranteed whereas the maximum possible computational complexity reduction is $O(n-6)$.The architecture of DCNNSLAB is illustrated in Figure 2.

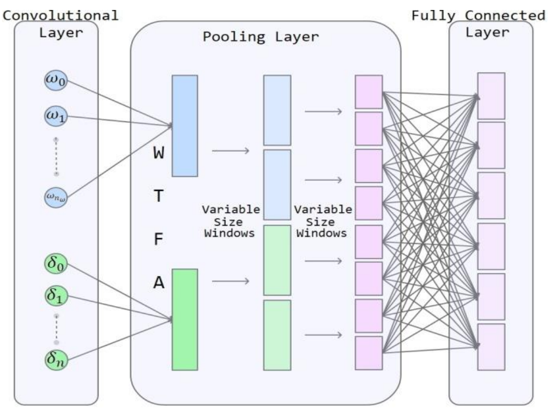

Figure 2: DCNNSLAB Architecture

There are three layers λ_0, λ_1 *and* λ_2 in the pooling section. The window sizes $\xi_{\lambda_0}, \xi_{\lambda_1}$ *and* ξ_{λ_2} are calculated using the following equation.

$$\forall i = 0 \to 2: \xi_{\lambda_i} = min\left(\frac{n}{2}+4, \left(\frac{(n+8)}{(i+1)}\right)\right)$$

5. EXPERIMENTAL SETUP

The Proposed method DCNNSLAB is designed to handle bigdata.Therefore, a large dataset [https: //s3.amazonaws .com/ amazon-reviews-tsv/index.txt] of size 4198056580 from amazon customer feedback about wireless routers is selected to test the existing and proposed methods. The first 1275417 records of size 524288000 (500MB) are taken for the evaluation process. The accuracy, precision, sensitivity, specificity and F1-Score are measured in a computer with Processor 2.4 GHz i5-4210U Quad-core processor and 4GB RAM. Visual Studio IDE is used to develop a user interface and VC++ programming language is used to code the proposed method. Standard data mining libraries are used to evaluate existing methods. The number of records taken for evaluation is treated as 100% data and standard data mining parameters are measured for every 10% of execution. Each data chunk comprises about 127542 number of records.

6. RESULTS AND DISCUSSIONS

6.1. Accuracy: It is one of the most common performance evaluation parameter and it is calculated as the ratio of the number of correctly predicted reviews to the number of total number of reviews present in the corpus. The formula for calculating accuracy is given as:

$$\textbf{Accuracy} = \frac{(TP+TN)}{(TP+TN+FN+FP)}$$

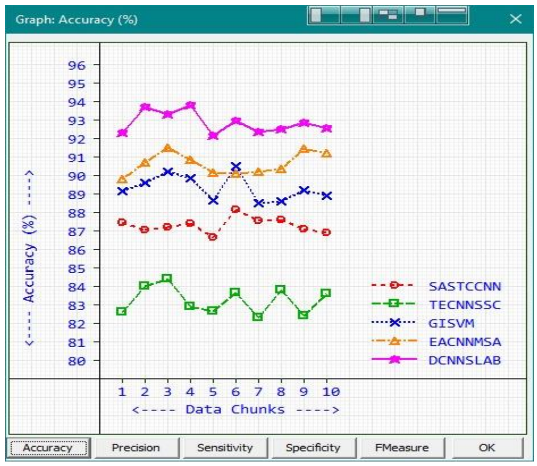

Figure 3: Accuracy

6.2. Precision*:* Precision is the fraction of the documents retrieved that are relevant to the user's information need. It is the number of correct results divided by the number of all returned results.

$$\textbf{Precision} = \frac{TP}{(TP+FP)}$$

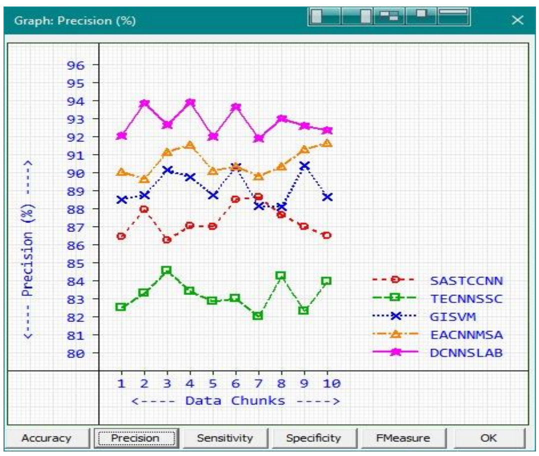

Figure 4: Precision

ITEE Journal
Information Technology & Electrical Engineering
ISSN: - 2306-708X

6.3. Recall: Recall is the fraction of the documents that are relevant to the query, which are successfully retrieved.

$$\textbf{Recall}=\frac{TP}{(TP+FN)}$$

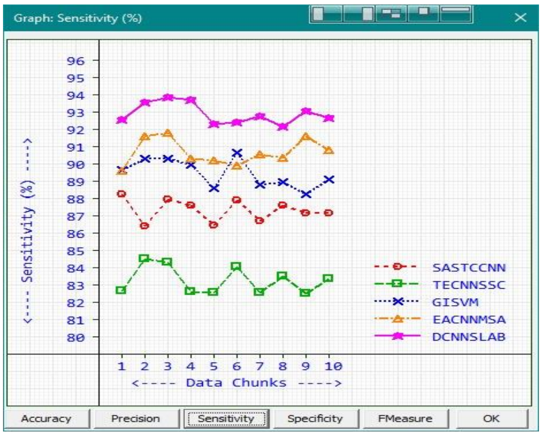

Figure 5: Recall

6.4. Specificity: Specificity is the fraction of the document retrieved to the user's information need.

$$\textbf{Specificity}=\frac{TN}{(TN+FP)}$$

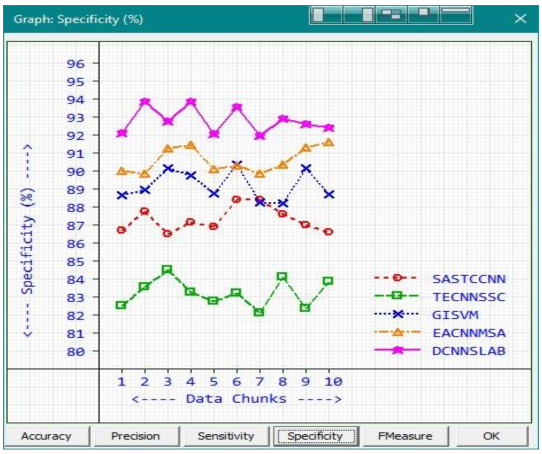

Figure 6: Specificity

6.5. F-Score: Frequency of score is the harmonic mean of precision and recall.

$$\textbf{F=2}*\frac{precision*Recall}{Precision+Recall}$$

The table 1. shows the results obtained from the,

- SASTCNN: Improving sentiment analysis via sentence type classification using BiLSTM-CRF and CNN
- TECNNSSC: Three-way Enhanced Convolutional Neural Networks for Sentence-level Sentiment Classification
- GISVM: Aspect term extraction for sentiment analysis in large movie reviews using Gini Index feature selection method and SVM classifier.
- EACNNMSA: Ensemble application of convolutional neural networks and multiple kernel learning for multimodal sentiment analysis.

These results are analyzed proposed work by follows DCNNSLAB,

Data chunk	SASTCNN	TECNNSSC	GISVM	EACNNMSA	DCNNSLAB
1.	87.36	82.60	89.10	89.85	92.33
2.	87.20	83.93	89.55	90.63	93.74
3.	87.10	84.46	90.24	91.51	93.27
4.	87.37	83.02	89.85	90.95	93.82
5.	86.74	82.71	88.70	90.16	93.18
6.	88.21	83.55	90.52	90.14	93.04
7.	87.70	82.29	88.50	90.18	92.33
8.	87.64	83.92	88.56	90.37	92.57
9.	87.10	82.42	88.34	91.47	92.85
10.	84.85	83.66	88.91	91.26	92.54

Table 1: Accuracy of F-Score (%) Measure Report

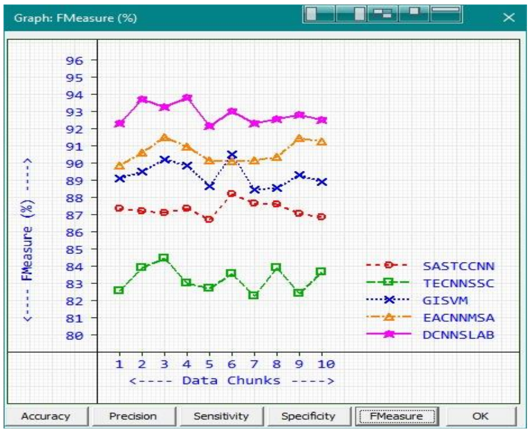

Figure 7: Accuracy of F-Score (%) Measure Report

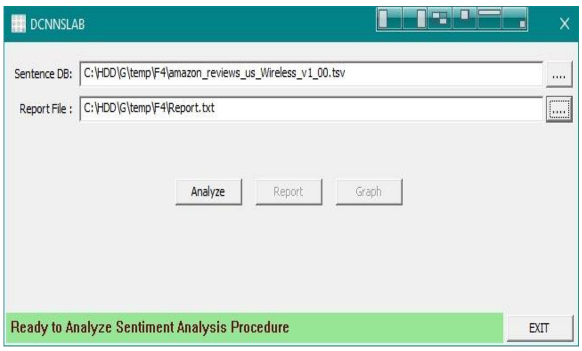

Figure 8: Reviews of Report

7. CONCLUSION

This paper has presented an ensemble application of Devoted Convolutional Neural Network based Sentence-Level Sentiment Analysis for Big data. The approach employs DCNNSLAB to extract target expression in opinionated sentences, and classifies these sentences into three types according to the number of targets extracted from them. These three types of sentences are then used to train separate WTFA for sentiment classification. We have conducted extensive experiments on four sentence-level sentiment analysis datasets in comparison with 11 other approaches. Empirical results show that our approach achieves state-of-the-art performance on three of the four datasets. We have found that separating sentences containing different opinion targets boosts the performance of sentence-level sentiment analysis. In future work, we plan to explore other sequence learning models for target expression detection and further evaluate our approach on other languages and other domains.

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ITEE Journal
Information Technology & Electrical Engineering

ISSN: - 2306-708X

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