Different Techniques of Sentimental Analysis using Deep Learning

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DOI: 10.29322/IJSRP.12.02.2022.p12268
http://dx.doi.org/10.29322/IJSRP.12.02.2022.p12268

Paper Received Date: 30th January 2022
Paper Acceptance Date: 08th February 2022
Paper Publication Date: 20th February 2022

Abstract- World Wide Web like social media forums, review sites and blogs that generate a lot of data the type of users views, feelings, ideas and arguments about various social events, products, products, and politics. Emotions of users exposed to the web has a huge influence on it students, product retailers and politicians. Unstructured the type of data from social media is required for analysis and is well organized and for this purpose, emotional analysis has been required the saw important attention. Emotional analysis is called the textual structure used to distinguish the expressed attitude or emotions in different ways such as negative, positive, favoble, wrong, thumbs up, thumbs down, etc. This is a challenge emotion analysis lacks sufficient label data in the field Indigenous Languages (NLP) Processing. And to solve this problem,Emotional analysis and in-depthlearning strategies have been are integrated because in-depth learning models work for them the ability to read automatically. This Review Paper highlights the latest lessons on the implementation of in-depth learning models such as deep neural networks, convolutional neural networks as well many more to solve various emotional analysis problems such as emotional isolation, problems of different languages, text as well as visual analysis and product review analysis, etc.

Index Terms- Emotional analysis; recurrent neural network; deep neural network; convolutional neural network; recursive neural network deep belief network.

I. Introduction

A. Sentiment Analysis

Emotional analysis refers to emotional management, ideas, as well as direct text [1].

Tweets and reviews. It is a proven tool by predicting many important events as a box office performance of movies and national elections [2]. Public reviews are used to evaluate a particular business, i.e., a person, product or location and can be found on various websites like Amazon and Yelp. Ideas can be categorized negative, positive or neutral. The purpose of emotional analysis automatically specify user guide updates [3]. The need for emotional analysis is raised due to increasing the need for analysis and hidden structure information from social media on the way of random data [4].

1) Features Analyzing Sentiment: Emotions contain
a variety of included values such as trigrams and bi-grams per polarity methods and combinations. So emotions become tested both as negative and positive features through many support systems, using training algorithms. Neural networks are used emotionally analysis to calculate label participation. To help data release at context level is conditional dependence between several edges and active acyclic graph notes used by Bayesian networks. By arranging the words once sentences, readings and data accuracy can be found on social media media court. At the root word level, a data token is used generating negative and positive aspects of the data. Strategies are used to reduce errors in emotional analysis to him get the highest level of accuracy in social media data. [5]

2) Emotional Analysis as a Different Field:
Emotions: analysis is a different field, because it includes many fields such as computational linguistics, information retelling, semantics, natural language processing, practicality ingenuity and machine learning [6]. Separation of emotional analysis methods can be performed three times output levels a) feature or feature level; b) text quality; and c) sentence level [5].

3) Methods of Emotional Analysis: Emotional analysis: it relies on two types of strategies, namely, a once-based dictionary machine learning strategies [5].

a) Machine learning strategies: This type of techniques used for sentence extraction as well Feature levels. Features include Speech Parts (POS) tags, n-grams, bi-grams, uni-grams and word bag. The machine reading consists of three types of taste in the sentence and the element, namely, Nave Bayes, Support Vector Machine (SVM) and Maximum Entropy.b) Lexicon-based or corpus-based strategies: These strategies based on decision trees such as k-Near Neighbors (k-NN), Informal Forum (CRF), Hidden Markov Model (HMM), Single Dimensional Editing (SDC) and Sequential Minimal Optimization (SMO), related in ways of separating emotions. Machine learning approach has three categories: i) supervised ii) semi supervised; and iii) unsupervised. This approach is capable of automation and can handle huge amount of data therefore these are very suitable for sentiment analysis.[6].

B. *In-depth reading*

In-depth study was first proposed by G.E. Hinton in the middle 2006 and is part of a targeted machine learning process in the Deep Neural Network [7]. Neural network is affected with the human brain and contains several neurons impressive network. In-depth learning networks are capable to provide training to both supervised and unsupervised stages [8].In-depth study includes many networks such as CNN.(Convolutional Neural Networks), RNN (Recurrent Neural Networks), Repetitive Nervous Networks, DBN (Deep Belief Networks) and much more. Neural networks are very beneficial in text production, vector representation, word representation scale, sentence classification, sentence model and feature presentation. [9].

1) In-depth Learning Requests: In-depth structures contain of many indirect levels of activity. Ability modeling works of intellectual craft raises hopes that deep structures will work well in less supervised learning as a deep belief network (DBN) will also find significant success in natural language critical society [10]. Deep Learning contains advanced software engineering, advanced learning processes and access to computer power and training data [11]. Inspired by neuro science and has a positive impact on a breadth of applications such as speech recognition, NLP (Natural Language Processing) and computer perspective. One of the basics the challenge of in-depth learning research is the learning process model structure and number of layers and value of this hidden variables of each layer [12]. While dealing with various tasks, the formation of in-depth reading demonstrates full potential and requires labeled samples with a high amount of data capture for deep structures. Deep learning networks and strategies have been developed widely in various fields such as in visual separation, pedestrians discovery, off-road robot navigation, object categories, acoustic signals and predictive timing functions [13]. A The most inspiring approach to natural language processing has explored that performs many complex tasks such as semantic labeling can be largely done using deep structures [13]. In terms of data, in-depth learning efforts to learn high quality abstractions through hierarchical structures. it is a promising and widely used method in the field of artificial intelligence, such as computer vision, transmission reading, semantic grammar, natural language processing and many more. Nowadays, in-depth learning thrives because of the three most important and important factors, namely, developed skills chip processing (GPU units), very low cost hardware and advanced enhancements to machine learning algorithms [14].

C. *Integrating Emotional Analysis and In-depth Reading*

Deep learning has a profound effect on both unattended and supervised learning, many researchers treat emotions analysis through in-depth reading. It contains many functional and popular models and these models are used to solve various problems effectively [15]. Very popular for example Socher used the Recursive Neural Network (RNN) to produce reviews of movies from website rottentomatoes.com [16]. Following the effort of [17], many researchers have done so emotional separation through neural networks. Because for example, Kalchbrenner [18] was expecting DyCNN (Dynamic Convolutional Neural Network) using the integration function, i.e., incorporating a variable k-max in line sequence. Kim [19] use CNN has learned emotional vectors.In addition, the Paragraph vector proposed by Mikolov, etal. [20] which makes emotional analysis better than bagof- word model and ConvNets learning SSWE (emotions embedding certain words). Recently [21] you applied ConvNets is in characters instead of directly using the name embedding. Another model of differentiation of LSTM emotions that do not just go away on their own input method [22].

In this paper, Section II covers a detailed review of the literature and Phase III presents the conclusion while, Phase IV indicates a critical analysis phase in the literature review.

In the Literature Review section, various studies of sentiment analysis using Deep Learning techniques are discussed. This review is conducted on the basis of numerous latest studies in the field of sentiment analysis.

II. LITERATURE REVIEW

In order to accurately classify emotions, many researchers have made efforts to integrate in-depth learning with the machine learning concepts in recent years. This section is brief describes many studies, related to emotional analysis web content about users' opinions, feelings, individual reviews a variety of stories and products using in-depth reading strategies. Emotional analysis activities can be done effectively by use different models as in-depth learning models, recently expanded. These examples include CNN (convolutional neural networks), RNN (recursive neural network), DNN (deep neural networks), RNN (continuous neural networks) and DBN (deep belief networks). This section explains the efforts of various researchers regarding use in-depth learning models that perform emotional analysis [23].Several researchers have used more than one model in their research, and these are mentioned under the neural hybrid part of the network.

A. CNN (convolutional neural network)

Combining layers with sophistication as it provides a common architecture to make a sentence of variable length sentences into standard size sentences of scattered vectors. This study [25] proposed a convolutional neural novel network (CNN) framework for analyzing visual emotions in predict the feelings of visual content. CNN has already been launched using Caffe and Python on a Linux machine. Pass. The learning method and hyper parameter were used for bias and weights are applied to the pre-trained Google Net. As CNN improve its performance by increasing its size and depth, therefore the deepest CNN model, inspired by Google Net is suggested with 22 layers of emotional analysis. Improved by use SGD algorithm (Stochastic gradient descent). Isue 60 epoch made network training as GoogLeNet made 250 epoch. Experimental function, a twitter data collection containing 1269 images is selected and used for back distribution. Amazon Mechanical Turk (MTurk) and popular crowd intelligence used to label pictures. Five employees are involved in making an emotional label in favor of all images. The proposed model was tested on this database and I have found better performance than there is programs. The results show that the proposed system reaches the top working without fine adjustment to the Flickr database. However AlexNet has been used in previous applications and GoogleNet has been provided about 9% of performance progress than AlexNet. By conversion GoogLeNet enters the framework of visual analysis, Better feature release has been achieved. Stable and reliable condition is obtained using hyper parameters.

The authors [26] proposed a comprehensive reading program analyzing twitter sentiments. The main focus of this work was to initiate the weight of the convolutional parameters neural network and it is important to train the model accurately while avoiding the requirement to add a new feature. Neural Language is used to initiate embedding word and is trained with a large unsupervised group of tweets. Further refinement embedding in a large, normal supervised corpus neural network is used. To start a network, previously embedded words and the same parameters are used buildings and training in corporate supervised from Semeval-2015. The components used in the proposed project are opening, combining sentence matrix, softmax and convolutional layers. Network training, reduction of stochastic gradient (SGD) and Algorithms for improving non-convex function are also used calculating gradients back propagation algorithm was used. The cessation process is used to develop neural network configuration. An in-depth learning model is used in two functions: message level function and phrase level function from Semeval-2015 to predict polarity and achieve high results. Using a six-set test set, the proposed model lies in the first level about accuracy.

B. Recursive Neural Network (RNN)

One of the authors proposed a comprehensive reading program analyzing twitter sentiments. The main focus of this work was the beginning of the weight of convolutional boundaries neural network and it is important to train the model accurately While avoiding the requirement to add a new feature. Neural Language is used to initiate word embedding and is trained and a large unsupervised group of tweets. Further refinement embedding in a large, normal controlled corpus neural network is used. To start the network, pre-embedded names and similar parameters apply to buildings and training in supervised companies from Semeval-2015. The components used in the proposed project are open-ended, which includes sentence matrix, softmax and convolutional layers. Algorithm was used. The cessation process is used to develop neural network configuration. An in-depth learning model is used in two tasks: message-level work and sentence-level work from Semeval-2015 to predict polarity and achieve high results. Using a six-set test set, the proposed model is the first level in terms of accuracy.

For existing models, the meaning of long sentences cannot be is effectively expressed through semantic word spaces, as well as emotions detection, rich testing and surveillance and training resources are needed as they require a lot of influence design models. RNTN achieved 80.7% accuracy. emotional prediction by performing more finely labeled all the phrases and previous models work very well.

C. Deep Neural Networks (DNN)

In this study [32], the author proposed a model of emotions analysis is considered for both visual and textual content social networks. This new system utilized a deep neural network models such as Denoising auto encoders and skip gram. The origin of the program was CBOW (Continuous Names Fund) model. The proposed model consisted of two CBOW-LR components (retranslation) of text content and expanded as CBOW-DA-LR.

Separation is done according to polarity of visual and textual information. Four data sets tested, namely, Sanders Corpus, Sentiment140, SemEval- 2013 and SentiBank Twitter data set. Proposed model performed much better than CBOWS + SVM and FSLM (fully monitored possible language model). Probably ESLAM (extended a language model that can be fully monitored) in terms of a small word training data was more effective than the current model. Feature learning and skipping grams both require large data sets to improve performance. In this study [33], deep neural network architecture has it is proposed to examine the similarity of the texts. The properties were trained through several market news to produce vectors foe articles. The T&C news have been used as dataset. The cosine similarity was calculated among labeled articles and the polarity of documents was considered but contents were not considered. The proposed method accomplished superior performance in terms of similarity estimation of articles according to polarity.

D. Recurrent Neural Networks (Recurrent NN)

Recurrent neural network (RNN) [24] has an impact model in language simulation because it is not representative a context of fixed length that defiles all historical names.In this study [34], HBRNN (hierarchical bidirectional recurrent neural network) built to exclude customer reviews about completely different hotels and the shortest route. To model consecutive long-term information, HBRNN used the names RNN and the forecast process is done at the review level by HBRNN. Test data were taken from the DBS text mining Challenge 2015. HBRNN performance improved with networks parameters and fine-tuning and model was compared to LSTM (long-term memory) and BLSTM (Bidirectional LSTM). After conducting research,memory recall, F1 points and accuracy are greatly enhanced biased data. The development, the test set and the subdivision of the train were used to compare results with standing systems, ten times higher the opposite validation used to present HBRNNperformance. The biggest challenges solved are the internet shortage high quality reviews and lack of high inclination to updated data. Database test results have proven that HBRNN has done better .

TABLE 1 ANALYSIS OF CONVOLUTIONAL NEURAL NETWORKS

Researcher Name and Year	Model Used	Purpose	Data Set	Results
J.Islam and Y. Zhang 2016 [25]	Convolutional Neural Networks (CNN)	Visual SA	1269 images from twitter	GoogleNet gave almost 9 % performance progress than AlexNet.
A. Severyn and A. Moschitti, 2015 [26]	Convolutional Neural Networks (CNN)	Phrase level and message level task SA	Semeval-2015	Compared with official system ranked 1st in terms of pharse level subtask and ranked 2nd in terms of message level.
L. Yanmei and C. Yuda, 2015 [27]	Convolutional Neural Networks (CNN)	Micro-Blog SA	1000 microblog comments (HuaQiangu)	Proposed model can effectively improve the accuracy of emotional orientation, validation
Q. You, J. Luo, H. Jin, and J. Yang, 2015 [28]	Convolutional Neural Networks (CNN)	Textual-visual SA	Getty Images, 101 keywords	Joint visual and textual model outperforms the early single fusions.
X. Ouyang, P. Zhou, C. H. Li, and L. Liu, 2015 [15]	Convolutional Neural Networks (CNN)	Sentiments of sentences	rottentomatoes.com (contains movie review excerpts)	The proposed model outperformed the previous models with the 45.5% accuracy.

Romanized Bangla Text). Deep Recurrent model especially LSTM (Long Short-term Memory) was used to test the database using two loss functions, namely, binary and cross-entropy phase.

Data was collected on various sites such as YouTube, Face book, Twitter and others. Tests were performed to adjust the data set for one character to another (just the other way around)way to investigate the fact that it offers better results. This author [36] proposed a sequence model to focus on in embedding updates with temporary nature products as these reviews had little focus on existing studies. A combination of recurring gate gates with continuous neural the network is used to read the scattered product presentations and users. To separate the emotions these presentations are fed in the machine learning separator. The method was tested on three databases collected on Yelp and IMDB. Each update labeled according to the result scale. Network training back distribution algorithm with Adam stochastic optimization method used. The results show the sequence of the model dispersed product and user representation learning is improved separation of emotional performance of document level and the proposed approach achieves the results of high technology in benchmark data sets. The result of the proposed model in comparison with many bases including duplicate neural networks, neural network of user product, word2vec, role vector and JMARS algorithm.

TABLE II. ANALYSIS OF DEEP NEURAL NETWORKS

Researcher Name and Year	Model Used	Purpose	Data Set	Results
C. Baecchi, T. Uricchio, M. Bertini, and A. Del Bimbo, 2016 [32]	deep neural networks (CBOWDA- LR)	Visual and Textual SA	4 datasets: Sanders Corpus, Sentiment140, SemEval-2013 and SentiBank Twitter Dataset	CBOW-DA-LR model obtained superior classification accuracy than previous models.
H. Yanagimoto, M. Shimada, and A. Yoshimura, 2013 [33]	Deep Neural Network (DNN)	Document Similarity Estimation	T & C News	The proposed method accomplished superior performance in terms of similarity estimation of articles according to polarity

A. Deep Belief Networks (DBN)

Deep belief networks (DBNs) [17] include a few hidden ones layers, built by RBM (Boltzmann limited equipment).DBN has been shown to be effective in representing the feature. It uses non-labeled data and complements the shortcomings of written analysis problems.

In this paper [38], the new structure of the deep neural network introduced called WSDNNs (Weakly Shared Deep Neural Networks). The purpose of WSDNN is to simplify two languages sharing emotional labels. Features of A specific language and another language are introduced by building layers of many weakly shared features. The data from Prettenhofer and Stein used contains four languages French, German, English and Japanese. Ku compared with existing studies. the address of the proposed activity the challenge of minimizing the overlap between feature spaces both source and target language data using multilingualism the process oftransmitting information using backpropagation. DNNs used for the conversion of information from source to target language. Tests are made for emotions multidisciplinary product product review functions Amazon. the results concluded that the proposed method is superior is active and emotionally strong in different languages segregation than previous studies. Other studies [17] have used a deeper belief network with a vector of words for political adoption in Korean articles. The proposed model uses SVM in bias calculations, five stages pipeline to detect political bias, python web crawler to compile newsletters, KKMA morpheme analysis, word2Vec and a scikit-lear package. The data set contains 50,000 political articles from 01 Jan, 2014 to 28 Feb, 2015. Results are displayed 81.8% accuracy by accurately predicting labels and results contained a 0.120 square measure error.This study [37] raised a profound belief network by selecting a feature (DBNFS) to win the vocabulary problems, the network used the input corpus as well many hidden layers. Chi-squared feature method the selection was used to develop the Deep Belief Network (DBN) for the purpose of reducing vocabulary complexity input and delete non-essential features. Through Chi-Square way, the DBN reading phase has been improved on DBNFS. In this work, two aspects of new tasks, one selection and one reduction was used along with many other activities available classification methods, such as data classification, feature issuance, model training and model testing. Performance of DBNFS was shown along with the training time and accuracy of The proposed DBNFS was also compared with other algorithms. A five-set set of emotional classification was used for estimation, datasets are books (BOO), electronics (ELE), DVDs (DVD), Kitchen Appliances (KIT) and Movie Review (MOV). For good comparison, the study parameters were the same as existing jobs. Accuracy was measured by comparison number of features before and after feature selection and reduction. The accuracy results were compared with previous operations also proved to be much better for DBNFS than DBN. Training time was lower in DBNFS than DBN. Training time has improved due to the deep simple structure and proposed how to select features. The only drawback of DBN was that it is expensive and time consuming. Summary analysis of available emotional analysis methods using DBN

III. CONCLUSION

Emotional analysis refers to emotional management, ideas, and direct text. The need for emotional analysis is suggested due to the need for analysis and editing confidential information, released on social media in an informal manner data. Emotional analysis is performed through in-depth reading strategies. In-depth learning includes many functional and popular models, these models are used to solve various problems effectively. Different subjects discussed in this review to provide in-depth information for the successful growth of in-depth study applications in field of emotional analysis. Many problems have arisen resolved with the highest accuracy of both emotional states in-depth analysis and reading.

IV. ANALYSIS

This review has described many studies related to emotion analysis using in-depth learning models After analyzing all these studies, it is established that by using in-depth learning methods, emotional analysis can be done in a more efficient and accurate way. As a concept analysis is used to predict user opinions and depth learning models about human speculation or imitation mind, so in-depth learning models provide more precision shallow models. In-depth learning networks are better than SVMs and normal neural networks because they are very secretive Layers compared to normal neural networks they have or two hidden layers. In-depth learning networks are capable of doing provide training in both supervised / unsupervised methods. Depth networks have created the default feature background as well it does not involve human intervention and therefore can save time because feature engineering is not required. Emotional Analysis contains different types of problem statements. Ability to resolve job differences by making minor changes the program itself includes a feather in the power of In-Depth Reading standard. This method also has some limitations as well, as compared to previous models such as SVM. It needs a lot data sets and more expensive training. These are complex models can receive weeks of training using equipped equipment are expensive GPUs.

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