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Leveraging Deep Learning for Improved Sentiment Analysis in Natural Language Processing

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Abstract: **Sentiment analysis is viewed as quite possibly of the main works in mental science and normal language handling. To work on the productivity of sentiment analysis techniques, it is crucial for separate the useful words that add to the grouping choice as well as characterize the sentences as indicated by their profound names. Profound brain networks that depend on the consideration component have taken huge steps toward this path as of late. Reads up on consideration processes for message arrangement, and especially sentiment analysis, are as yet not many, in any case. This research fills this gap by presenting a Convolution Neural Network (CNN) combined with an attention layer that can extract relevant words and give them greater weights according to the context. The suggested model uses a context vector at the attention layer and attempts to gauge a word's relevance based on how similar the word vector and context vector are to one another. New vectors from the consideration layer are incorporated into sentence vectors and utilised for organization once they have been supplied. The suggested model was validated using a small number of tests on the Stanford datasets. The trial discoveries show that the recommended model works far superior to past research studies and can separate significant expressions from setting that have an incentive for analysis and application.**

Keywords—Natural language processing, Sentiment analysis, Deep Learning, Convolutional neural network, Attention mechanism.

I. INTRODUCTION

Web 2.0, online social networks, blogs, and forums have become popular places where people can talk about anything and express their thoughts. They could discuss current events, air grievances about a purchase they made, or share their political opinions. Utilizing this kind of user data is essential to the functioning of numerous apps (such as recommender systems), organization survey studies, and political campaign preparation [1]. Online web-based entertainment stages are the essential wellsprings of information for sentiment analysis (SA), since their clients give a constantly developing volume of information. Due to the additional issues that should be settled to achieve compelling information stockpiling, access, and handling as well as to ensure the precision of the discoveries procured, these sorts of information sources should accordingly be considered while utilizing the huge information technique.

Research on the issue of robotized sentiment analysis (SA) is extending. Despite the fact that SA is a critical field with countless applications, it is clear that it's anything but a simple endeavor and has a few troubles relating to normal language handling (NLH). The general exactness of late examination on sentiment analysis in extremity acknowledgment is hampered by hypothetical and mechanical issues. Hussein et al. investigated how such problems related to the sentiment structure and how they affected the precision of the findings. This research demonstrates that accuracy is impacted by certain issues, such as resolving negation or domain dependency, and affirms that exactness is a main pressing issue among the latest examination on sentiment analysis.

Social media platforms are crucial data sources for SA. Social networks are growing all the time, producing ever more intricate and connected data. Thai et al. prescribed a long lasting learning strategy to manage information show, analysis, derivation, representation, search and route, and dynamic in complex organizations in this setting rather of focusing simply on the design and connections of the information [2]. CNN and RNN models may address the weakness of brief text in deep learning models, as shown by Hassan and Mahmood. Long Short-Term Memory (LSTM) performs well when applied to various text levels of weather-and-mood tweets, as shown by Qian et al.

A. Deep Learning

Deep learning applies a multi-facet methodology to the brain organization's secret layers. Customary AI strategies incorporate the human definition and extraction of elements utilizing highlight determination procedures. Deep learning models, then again, provide higher accuracy and performance since features are automatically learnt and extracted. Generally speaking, classifier models' hyper parameters are also automatically monitored. The distinctions in sentiment polarity categorization between deep learning and conventional machine learning, which uses Bayesian networks, decision trees, and Support Vector Machines (SVM).

B. Deep Neural Networks (DNN)

A neural network having multiple layers, some of which are covered up layers, is alluded to as a deep neural network. Deep neural networks break down input in various ways by utilizing complex numerical displaying. A versatile model of results as elements of information sources, a neural network is comprised of many layers: an info layer that contains input information; stowed away layers that incorporate hubs that interaction data, known as neurons; and a result layer that contains at least neurons, the results of which are the network's results

C. Convolutional Neural Networks (CNN)

Convolutional neural networks, a kind of feed-forward neural network, were first used in computer vision, recommender systems, and natural language processing. It's a set-up for deep neural networks that uses pooling or subsampling layers to feed information into a fully connected characterization layer, alongside convolutional layers. Convolution layers use channels to separate highlights from their bits of feedbacks, and they might join the results of many channels.

D. Recurrent Neural Networks (RNN)

A family of neural networks known as recurrent neural networks (RNNs) includes feedback loops inside of them because the associations between their neurons structure a coordinated cycle. Processing sequential data using the internal memory that is collected by the directed cycles is the primary function of RNNs. RNNs are not like typical neural networks in that they are able to retain the results of past computations and apply them to the resulting component in the info succession. Long short-term memory (LSTM) is an interesting sort of RNN that can involve long memory as the secret layer's enactment capability input. Hochreiter and Schmidhuber (1997) introduced this. To modify the info information for the implanting grid, preprocessing is finished (the system is indistinguishable from the one made sense of for the CNN).

II. LITERATURE REVIEW

This research's goal is to examine several sentiment analysis techniques and methodologies that may be used as a guide for next empirical research. We have concentrated on important facets of research, including datasets, technical difficulties, suggested methodologies, and application fields for each research [3]. Deep learning models (like CNN, RNN, and DNN) have been utilized as of late to help sentiment analysis task effectiveness. Current deep learning-based strategies for sentiment analysis are analyzed in this part.

Numerous scholars have subsequently assessed this pattern, starting in 2015. Tang et al. presented deep learning-based methods for word embedding, sentiment classification, and opinion extraction, among other sentiment analyses. Zheng and Zhang spoke about sentiment analysis using machine learning [4]. Both review bunches registered the heaviness of words for the analysis utilizing TF-IDF and utilized grammatical feature (POS) as a text highlight. Sharef et al. talked about the capability of huge information sentiment analysis strategies. In articles, the latest deep learning-based strategies (to be specific, CNN, RNN, and LSTM) were analyzed and diverged from each other comparable to sentiment analysis issues.

Jeong et al. combined topic modelling with the findings of a sentiment analysis conducted on user-generated social media data to identify potential avenues for product development. In quickly changing product situations, it has been used as an ongoing checking device for investigation of moving client requests. Pham et al. broke down movement assessments utilizing many layers of information portrayal to determine perspectives for five angles: esteem, room, area, neatness, and administration [5]. An elective strategy incorporates sentiment and semantic qualities into a LSTM model that depends on feeling acknowledgment. Preethi et al. utilized the food dataset from Amazon to apply deep learning to sentiment analysis for a cloud-based recommender framework. Salas-Zárate et al. utilized a metaphysics based, viewpoint level sentiment analysis method to break down diabetes-related tweets in the wellbeing area.

Deep learning with polarity-based sentiment applied to tweets was discovered [6]. The authors explained how they improved the accuracy of their individual sentiment analyses by using deep learning models. A small number of models handle tweets in languages other than English, including as Spanish, Thai, and Persian, although the majority are utilised for information posted in English. Previous studies have used several polarity-based sentiment deep learning models to analyze tweets. These models consist of hybrid methods, CNN, and DNN [7].

III. METHODOLOGY

One major drawback of classical models is that they disregard the reality that various words carry varying amounts of significance when determining a sentence's meaning. Put another way, determining the significance of a word in a phrase usually depends on its context; the same word may have many meanings depending on the text. This research presents a solution to this problem: a convolutional neural network connected with the use of a multi-tiered system of focus that can extract the words more important to the sentences' meaning [8].

There are two key features of the suggested attention mechanism. It makes use of text data's hierarchical structure. Indeed, letters make up words, sentences make up sentences, and paragraphs make up phrases, and so on. Thus, there is an order among the parts that make up a report [9]. The recommended model utilizes this progressive construction, encoding words at the principal level and involving them to foresee yield probabilities in the last layer, which shows the sentence's extremity. It is applied on two levels: first, at the word level, and then, when combined, at the sentence level. Stated differently, word attention arranges and assigns weights to words according to their significance in creating a sentence's meaning [10]. As a result, the suggested attention mechanism categorizes the material and aids in improving understanding of its general semantic structure. The suggested model has four levels, as shown in Fig. 1's schematic.

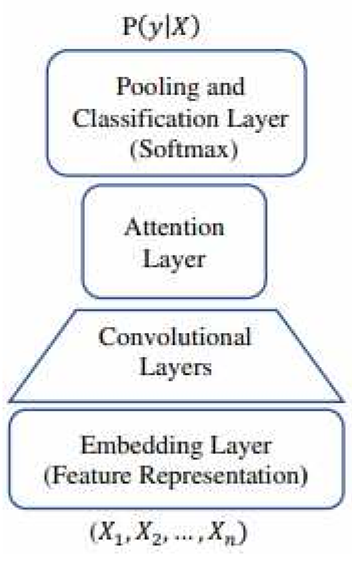

Figure 1: The suggested method's diagram.

Experiments Dataset:

The experiments in this publication made use of data collected at Stanford to allow for a thorough analysis of the suggested method's efficacy [11, 12]. These datasets, which are regarded as the most significant benchmark in this field, were provided by Stanford University's natural language processing lab.

The following is a short explanation of the used datasets, and Table 1 displays their summary statistics after tokenization.

SST1: With fine-grained labelling and train/dev/test divides, it is an expanded version of the MR Dataset [13].

SST2: Neutral labels have been removed from the improved version of SST1.

It should be mentioned that the studies were carried out using the standard train/test sets of SST1 and SST2, which are datasets for sentence-level categorization [14].

Table 1: Dataset Comparison Statistics for SST1 and SST2

Dataset	Class	Vocabulary Size	Average Length	Text Size	Test Size
SST1	6	18 K	17	2235 4	332 6
SST2	3	15 K	18	8569	231 0

Model configuration and training

Stochastic gradient descent was performed using the ADADELTA update rule batch size of 25, learning rate of 0.01, and mini-batch learning. Filter size and number were regarded as hyper parameters in a convolutional neural network [15]. Table 2 shows their qualities for preparing the recommended model.

Table 2: Arrangement of the Proposed Model Hyper Boundaries

Hyper parameter	**Value**
Scale of filtered region	4, 5, 6
Filter count	136
Exit Poll	1.6
Number of items in a batch	36
Purpose of Activation	ReLU

Better results were obtained with filter sizes of 4, 5, 6, and 136 filters, as the illustration shows. The model was likewise trained across 60 epochs.

IV. RESULTS AND DISCUSSIONS

Two parts of Table 3 describe the outcomes of the tests conducted over the introduced datasets. Probably the best in class models in sentiment analysis might be tracked down in classifications A through E, while changes of the proposed model can be tracked down in classification F. It is critical to take note of that the models' precision in classifications A through E is gotten from the first examination.

It is evident that deep learning models in this field are strong since, on average, neural network-based models outperform conventional models (Category A) that rely on machine learning approaches. Furthermore, DMN and MVCNN perform the best on SST1 and SST2, respectively, in comparison to all neural network-based models.

Table 3: Test Results on SST1 and SST2 Dataset. Classifications A-E incorporates probably the best cutting edge models, while Category F has other proposed models.

Category	**Model**	**Datasets**	
		SST1	**SST2**
A	NB BiNB SVM WordVec-AVE	41 41.9 40.7 32.7	81.8 83.1 79.4 80.1
B	CNN-1 layer CNN-non static CNN- multichannel DCNN MVCNN	37.4 48 47.4 48.5 49.6	77.1 87.2 88.1 86.8 89.4*
C	LSTM Bi-LSTM Tree-LSTM Tree-GRU DMN	46.2 49.1 51.0 50.5 52.1*	85.2 87.5 88.0 88.6 88.6
D	RecRNN RNTN MVRNN	43.2 45.7 44	82.4 85.4 82.9
E	Tree-GRU+ interest LSTM+RNN attention Tree-BiGRU attention CRAN-rand Attention CRAN-pre-train CNN+LSTM Attentive Pooling with CNN+ Attention vector + CNN	51.0 52.4 48.0 50.0 48.1 49.22 49.58 49.69	89.0 89.5 86.1 87.7 86.9 88.77 88.81 88.83
F	Attention-Rand- CNS CNN-Static- Attention Non-Static CNN-Attention CNN-Alert: Two Channels Attention, CNN- Four Channels	49.76 50.06 51.61 53.54 52.72	88.61 89.95 90.64 91.92 92.34

Furthermore, it is clear that vector representation significantly affects the suggested model's performance. Furthermore, keeping in mind that CNN Attention-Static, beside CNN-Consideration Rand, has the least grouping precision, it tends to be reasoned that refreshing word vectors during preparing can bring about better execution, whether or not the word vectors have been prepared previously or not. Lastly, CNN-Attention-4channel and CNN-Attention-2channel had the greatest classification accuracy, respectively, at 92.34% and 53.54% on the SST2 and SST1 datasets. Overall, the suggested model's improved classification performance throughout all iterations amply illustrates its superiority over other current models for the sentiment analysis job.

Actually, focusing on more pertinent terms is the goal of CNN's attention mechanism. In the absence of the attention mechanism, CNN may function effectively and give significant and unimportant words, respectively, a high and low weight without taking the context into account. Although a word's significance varies greatly depending on its context, the suggested model aims to capture this context-dependence significance.

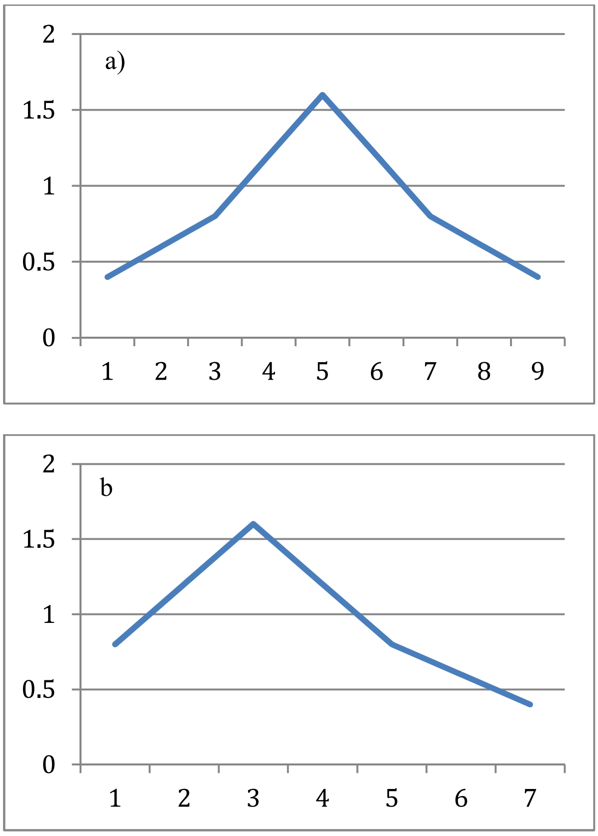

Figure 2: On SST1 dataset test split, combined focus.

The X-axis represents the subject's attention level from 0 to 1.

On the y-axis = the relative importance of the positive (a) and negative (b) terms in the test split of SST1.

V. CONCLUSION AND FUTURE DIRECTIONS

The purpose of this research is to present a novel convolution neural network that is combined with the attention mechanism for sentiment analysis. The capacity of the suggested approach to extract relevant terms while taking the context into account sets it apart from earlier research. To produce a hidden representation in this way, identically sized feature maps that were taken out of the convolutional layer are joined and taken care of into a one-layer perceptron. Accordingly, the consideration instrument works by checking the meaning of the closeness between the word and setting vectors. In the accompanying, enlightening word vectors from the consideration layer are amassed to make separated highlight maps, which are then utilized for grouping, to make the sentence vectors.

By combining an attention mechanism with a convolutional neural network (CNN), the research presents a unique method for attitude analysis. Sentiment analysis in multiple languages, fine-grained sentiment analysis, aspect-based sentiment analysis, real-time sentiment analysis, sentiment analysis of user-generated content, cross-domain sentiment analysis, transfer learning, visualization and interpretability, ensemble models, practical applications, handling of irony and sarcasm, ethical considerations, and user interface integration are some of the future research directions that will be explored. These areas seek to broaden the practical uses and interpretability of sentiment analysis while improving its accuracy, applicability to other domains, and ethical issues.

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