Review of neural networks for sentimental analysis.

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Abstract

Sentiment analysis is the process of analyzing the overall sentiment of the sentence using neural networks available in deep learning. We did research based on the papers mentioned in the references in which various methods were employed by researchers to perform sentimental analysis on textual formatted documents and the accuracy they achieved was also promising. Many of the researchers used a combination of neural networks methods which helped them achieve better accuracy for the same number of datasets. In short, it is basically a comparison between the plethora methods available, the better alternative and the accuracy obtained by each one of them.

Keywords: *Sentiment Analysis, movie reviews.*

1. Introduction

Humans are social animals and the thing that all humans have in common is the presence of emotion in everything we do. The sentiment is a personal view or an emotional opinion whereas sentiment analysis is opinion mining which involves collecting and examining opinions about the product made in social media in the form of comments, reviews or tweets. Sentiment analysis can be useful in several ways, for example in marketing it helps in judging the successful new product launch, analyzing upcoming trends, determine which versions of a product or service are popular and even recommending similar products and services. We took the lexicon-based approach where we split the sentence into tokens (tags having some vector value) by the process of tokenization. Tokenization is the process of splitting text into relevant units, i.e, characters, words which are needed for determination. The tokenizer consults a predefined mapping table which allows sequences of characters to be mapped to multiple tokens and assigns a token to each vector which is a part of speech. The input to the tokenizer is a Unicode text which gives us an object vector as an output. To construct a vector object, you need a particular tagged word instance which is a sequence of word strings and optionally a sequence of spaces booleans. After the sentence is tokenized the vector objects are given to the neural network where the sentiment is computed based on the vectors and accordingly the sentiment is determined.

Text classification aims to assign documents into one or many classes and this is used in many applications like spam filtering, topic prediction, and related advertising recommendations. Another application of sentiment analysis is to determine the writer's point of view about a particular topic, product, service, etc. in his comments and feedback reviews.

Reviews are what help us grow and work on our mistakes to perfect our design. However, time is a matter of uttermost concern as it limited we need to use as efficiently as possible. Thus, using deep learning we can automatically analyze the sentiments of the sentence which will give us linguist output variables. This can then later be used for automatic replies, spam detection, etc.

2. Literature review

In this paper [5], the idea of sentiment analysis with the help of different architectures of Recursive – Recurrent neural networks has been proposed. Their technical approaches include the following techniques:-

1. Using Semantic Word Vectors and Recurrent Architecture.
2. Recursive Neural Network with mean likelihood.
3. Recursive Neural Network with Affine NN.
4. Averaged Semantic Word Vectors.
5. Semantic Word Vectors and Bag-of-Words Features.
6. Recursive-Recurrent Neural Network Architecture.

The dataset used for analysis purpose is IMDB movie review dataset. They have used word2vec to generate 100-dimensional vectors for each word in the corpus.

They separated each sentence from one another in the review and gave it to a Recursive neural network (RNN). From this, the class is decided and the average semantic vector is then analyzed by the neural network to find the sentiment of the statement. The workings of above-mentioned techniques have been compared on accuracy basis and the following results have been tabulated:-

Table 1. ***Accuracy comparison for different models.***

Sr No	Approach Test	Accuracy Method
1	Mean Word – RecNN	82.35%
2	Mean Prob – RNN	81.8%
3	RNN-Affine	81.42%
4	SVM-RBF	76.69%
5	SVM-Linear	**86.496%**
6	RecNN-RNN	83.88%

So the conclusion drawn was Support Vector Machine classifier (SVM) – Linear is more accurate than RecNN -RNN ie. Recursive and Recurrent Neural Network Architecture.

The authors [6] proposed a Compositional Vector Grammar (CVG), which combines PCFGs that is Probabilistic Context-Free Grammar which is syntactically untied recursive neural network that learns from its compositional vector representations. The CVG model proposed certainly improved the PCFG using the Stanford Parser to obtain an accuracy of 90.4%. In addition to being fast, the model is also more efficient and also about 20% faster than the current Stanford factored parser. The proposed network model learned and trained itself from the input and to improve its performance based on the types of ambiguities present in the semantic information provided.

In the paper [4], the evaluation of CVG has been done in two ways: First, by a standard parsing evaluation on Penn Treebank WSJ and then by analyzing the model errors in detail. The conclusion drawn was that Compositional Vector Grammars (CVGs) is a parsing model that combines the speed of small-state PCFGs with the semantic richness of neural word representations and compositional phrase vectors. The compositional vectors had been learned with a new syntactically untied recursive neural network. The given model is linguistically more plausible since it chooses different composition functions for a parent node based on the syntactic categories of its children. Based on the WSJ test set, the CVG was able to outperform the previous Standford parser by 20%.

In this paper [3] Sentiment Treebank has been introduced. It includes fine-grained sentiment labels for phrases, sentences and presents new sentiment compositionality. To address them, the Recursive Neural Tensor Network is been introduced. It is able to classify the sentence based on the polarity with an accuracy of 80% and can go up to 85.4%. For fine-grained sentiment labels, an accuracy of 80.7% can be reached using a bag of features baselines. So overall, this model is good for parse tree and can be used to classify sentiments polarity whether the mentioned statement is positive or negative.

The three types of neural networks have been compared briefly based on classification on simple fine-grained sentences and positive – negative sentences. Those three neural networks are:-

1. RNN: Recursive Neural Network
2. MV-RNN: Matrix-Vector RNN
3. RNTN: Recursive Neural Tensor Network

Their experimental results are displayed below:-

Table 2. Comparison between models of RNN

Sr No	Model	Fine-grained		Positive/Negative	
		All	Root	All	Root
1	RNN	79.0	43.2	86.1	82.4
2	MV-RNN	78.7	44.4	86.8	82.9
3	RNTN	**80.7**	**45.7**	**87.6**	**85.4**

Further experiments have been done based on the type of sentences:-

1. Fine-grained Sentiment For All Phrases
2. Full Sentence Binary Sentiment

3. Model Analysis: Contrastive Conjunction
4. Model Analysis: High-Level Negation
   a) Negating Positive Sentences.
   b) Negating Negative Sentences.

Table 3. Comparison of models based on accuracy of polarity obtained.

Sr No	Model	Accuracy	
		Negated Positive	Negated Negative
1	biNB	19.0	27.3
2	RNN	33.3	45.5
3	MV-RNN	52.4	54.6
4	**RNTN**	**71.4**	**81.8**

The authors [6], thus concluded that the combination of new model and data results in a system for single sentence sentiment detection that pushes state of the art by 5.4% for positive/negative sentence classification. The RNTN, as shown above, gives us an accuracy of 81.8% on fine-grained sentiment prediction.

The authors of this paper [7] introduced a neural network model to learn vector-based document representation in a unified, bottom-up fashion. The model used here is CNN-LSTM which is a convolutional neural network using long-short-term memory. The semantics of sentences and their relations are then analyzed by the neural network. The research conducted was using a document for sentimental level classification of four large-scale review datasets.

Further, they have compared methods (Conv-GRNN and LSTM-GRNN) with the following baseline methods for document-level sentiment classification.

1. The majority is a heuristic baseline, which assigns the majority sentiment label in training set to each document in the test set.
2. In SVM+Ngrams, we use bag-of-unigrams and bag-of-bigrams as features and train SVM classifier with LibLinear.
3. In Text Features, we implement sophisticated features including word n-grams, character n-grams, sentiment lexicon features, cluster features.
4. In AverageSG, we learn 200-dimensional word vectors with word2vec6 average word embeddings to get document representation and train an SVM classifier.
5. Also implemented a state-of-the-art neural network baseline Paragraph Vector because its codes are not officially provided. The window size is tuned on the development set.

The conclusions of this paper [7] are -

(1) The traditional recurrent neural network is not as efficient in modeling document composition while adding more layers does significantly boosts the performance.

(2) LSTM performs better than a multi-filtered CNN in modeling sentence representation.

In this paper [8], the sentences are analyzed & classified as ‘Thumbs up’ or ‘Thumbs down’. To determine this sentiment polarity, they used a machine learning method that applies Text categorization to just subjective portions. In this research, they focused on compressing the reviews in small extracts which contain the information necessary for the neural network to determine the relation between subjectivity detection and polarity classification. Here they focused on the development of efficient algorithms using the minimum-cut framework for sentiment analysis. This model then uses contextual information through this framework to statistically improve polarity-classification accuracy. Future research includes developing parameter selection techniques, including sources for contextual cues, and developing new means for modeling such information.

In this paper [1], a model that uses a mix of Unsupervised & Supervised techniques to learn word vector is used. Accuracy is approximately 82.5% for sentiment classification. In order to efficiently use the abundant sentiment labeled dataset, an unsupervised model was employed. This model is then used to capture both sentiment and semantic relations. They demonstrated the utility of such representations on two tasks of sentiment classification, using existing datasets as well as a larger one that we release for future research. Even though this model is used for simple sentiment analyzes, it can be employed for a wide variety of annotations and in growing areas of sentiment retrieval as it is highly flexible.

The research paper [9], discusses the sentiment analysis of short texts in single sentences and Twitter messages. It uses the concept of a deep convolutional neural network which extracts the character- to sentence-level information with the help of two corpora of two different domains:

(a) The Stanford Sentiment Treebank (SSTb), for sentences with regard to movie reviews.

(b) The Stanford Twitter Sentiment corpus (STS), for sentences which contains Twitter messages.

From the paper [9], we have concluded that the idea of using convolutional neural networks to extract from the character- to sentence level features. It even demonstrates a feed-forward neural network architecture can be as effective as RNTN for sentiment analysis of sentences. A success rate of 85.7% accuracy has been achieved for SSTb corpus whereas for STS corpus, 86.4% is achieved.

The paper [10], deals with traditional text classifiers often rely on many human-designed features, such as dictionaries, knowledge bases and special tree kernels. In this model, a recurrent structure was used to capture contextual information through word representations which introduced considerably less noise as compared to other neural networks used which in turn helped boost the efficiency. It also employs a max-pooling layer that automatically judges which words play a key role in text classification to capture the key components in a sentence. Experiments have been conducted on four commonly used datasets. In the comparison of the basic neural network approaches with the other traditional methods, the experimental results show that the neural network approaches outperform the traditional methods for all the provided datasets. In the comparison of CNN and RNN when it comes to dealing with the SST dataset we observe that CNN proves that it achieves better results. As results and accuracy are things we look up to in a neural network, CNN seems to be suitable for constructing the semantic representation of texts. This model introduces a combination of recurrent and convolutional neural networks to text classification. This model considers the best of both neural networks as it analyzes contextual information with the help of RNN and constructs the representation of text using a CNN. This hybrid model certainly is the best of both networks and out-delivers the results delivered by the independent networks.Overall Literature review in tabular form is given below:-

Table 4. Comparison of all review papers with work done is shown as:

Sr No	Authors	Paper name	Year	Work Done
1	Aditya Timmaraju, Vikesh Khana	Sentiment analysis on movie review using recursive and recurrent network architecture. [5]	2015	They separated each sentence from one another in the review and gave it to a Recursive neural network (RNN). From this, the class is decided and the average semantic vector is then analyzed by the neural network to find the sentiment of the statement.
2	Richard Socher, John Bauer.	Parsing with Compositional Vector Grammars.[5]	2013	Using weights and computational vectors group, the neural network is trained and the semantic vector of the sentence is determined
3	Richard Socher, et al	Using Recursive deep models for analyzes of semantic compositionality over a treebank.[2]	2013	Introduced Recursive Neural Tensor Network (RNTN) and sentiment bank. They concluded RNTN results in 80.7% accuracy on sentiment prediction.
4	D. Tang, et al	Document modeling with Gated RNN for sentiment classification. [7]	2015	Concluded that LSTM-GRNN, ie, Long Short Term Memory Gated Recursive Neural Network performs better than multi-

				filtered CNN in modeling sentence representation.
5	Bo Pang, et al	Sentiment Analysis on minimum cuts using subjectivity summarization [8]	2004	In this paper sentences are analyzed and classified as 'thumbs up' and 'thumbs down'. To determine this they use machine learning method that uses text categorization.
6	Andrew L.Maas, et al	Learning word vectors for sentiment analysis.[1]	2011	In this paper, they use a model that uses a mix of supervised and unsupervised techniques to learn word vector and the accuracy is approx 82%
7	Siwei Lai, et al	Recurrent Convolutional neural networks for text classification.[10]	2015	Use of recurrent structure to prevent less noise compared to traditional windowing network. It employs a max-pooling layer which captures key components in the text.
8	Maira Gatti, et al	Deep Convolutional Neural network for sentiment analysis of the short text. [9]	2014	Use of deep convolutional neural network to extract information from character to sentence level data for performance of sentiment analysis of the short text. The results of their paper compare RNTN and it is as effective with an accuracy of 85.7%.

4. Conclusion

It is observable that the work done in this paper focuses on obtaining a higher accuracy through varied methods of sentiment analysis. We can conclude that the higher rate of testing obtained, higher is the accuracy obtained, better performed of the system. We implement using Naive Bayes method for performance of sentimental analysis.

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