Deep Learning Approaches for Textual Sentiment Analysis

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ABSTRACT

Sentiment analysis is computational measurement of attitude, opinions, and emotions (like positive/ negative) with the help of text mining and natural language processing of words and phrases. Incorporation of machine learning techniques with natural language processing helps in analysing and predicting the sentiments in more precise manner. But sometimes, machine learning techniques are incapable in predicting sentiments due to unavailability of labelled data. To overcome this problem, advanced computational technique called deep learning comes into play. This chapter highlights latest studies regarding use of deep learning techniques like convolutional neural network, recurrent neural network etc. in sentiment analysis.

Keywords: Polarity, Deep Learning, Opinion Mining, sentiment analysis, convolution neural network, recurrent neural network

Introduction

Sentiment analysis is a subset of natural language processing used in association with text mining techniques for the extraction of subjective information from social media sources. Collection of documents, reviews, blog posts, data from microblogging sites like tweets from twitter, status and news articles. Basically sentiments are analysed for certain product, domain, people and try to quantify the polarity of that particular information. In other words, Sentiment analysis means mining of text for finding out the actual meaning/essence/attitude behind the text. It is also called as opinion mining. It is both science and art because of its complex context. Correct identification of hidden polarity behind the text is the key of success for any sentiment analysis task. Some of the reasons which make sentiment analysis a tough job in text are:

- Understanding the context of language for human is easy but teaching the same thing to machine is a complicated task.
- Vast variety of languages and grammar usage of every language is different.
- Usage of unstructured text like slangs, abbreviated form of text and grammar nuances make it more difficult to analyse.

Figure 1 shows the general framework of sentiment analysis. With the advent of web and social media lots of information is present for opinion mining like blog posts, data from microblogging sites, news posts etc. Most of this data is in textual form and for computation we need to transform it in to vector form. Natural language processing come up with loads of models like bag of words vector, vector space models, word embedding etc. Mining technique is chosen after that according to application for example if we want to analyse movie reviews we have rating and text as our dataset etc. Correct feature extraction is necessary for the training and testing accuracy of any machine learning model.

Now a days, deep learning models do not required hand coded features but they are data hungry techniques and need loads of data for training. Training is accomplished with the help of labelled data. After that trend or pattern is analysed by machine learning technique called knowledge. At last this knowledge with some mathematical function will be used for predictions of unlabelled data.

Sentiment analysis plays a greater role in gaining the overview of wider public opinion and social media interactive dataset is the best source for it. Gaining deeper insights from dataset make it more useful for forecasting applications like stock market in which correct sentiment identification make it more predictable for investors. Market research for maintaining the quality of product can be accomplished with the help of sentiment analysis. Opinion mining of customer review helps in knowing the current status of our product and its competitors.

Natural language processing (NLP) is one of the promising domain which makes our day to day life easier like keyboard auto completion, speech recognition, dictionary prediction etc. Amalgamation of machine learning with NLP brings awesome results in various applications and sentiment analysis is one of them. Sentiment analysis become talk of the town day by day because of its deep business insights which help in taking further decisions. Sentiment information is taken from customer reviews, posts from microblogging sites like twitter, rediff etc. and computational intelligence based techniques are applied for mining, analysing and forecasting of trend information.

Figure 1. General framework of sentiment analysis

Major limitation in sentiment analysis is the strict classification of polarity in to three buckets called positive, negative and neutral. While human emotions are not so quantifiable every time sometime it is ambiguous and chaotic in nature. While in future researchers are trying to move from one dimensional monotonous scaling of positive to negative to multidimensional scaling. Involvement of deep learning techniques opens a new line of research in sentiment analysis which is described in last part of this chapter. In next section we presented a simple case study of sentiment classifier using Naïve Bayes machine learning algorithm for understanding the general flow of model.

This chapter is arranged as follows. Second section tells about basic machine learning based sentiment analysis with the help of tabular representation. Third section discusses supervised based sentiment classifier. Fourth section is all about revolutionary change bought by next generation of learning (deep) techniques in accuracy of sentiment analysis with the help of existing studies followed by conclusion in the last section.

Case study of Naïve Bayes based sentiment classifier

In this small and simple case study our attempt was to make a sentiment classifier based on movie review dataset. In this model firstly we have labelled set of sentiments (positive, negative and neutral) used for training of classifier. After training of classifier unlabelled set of movie reviews are taken for testing. Naïve Baye's model was chosen as classifier for classification task. Let's have some basic idea about Baye's formula first:

$$P[a/b] = [P[b/a]*P[a]]/P[b] \qquad (1)$$

Equation 1st is the basic Bayes formula consist of b is the document and a is the class and objective is to find out the probability of class b given by document a. So numerator is composed of likelihood and prior information and denominator consist of normalization constant. Mapping of Bayes algorithm in this problem is followed as: Prior information is original label (L.H.S part) which model come to know at training time and after that testing is done on unlabelled reviews and try to predict the correct labels. Naïve Bayes works on this principle and termed as multinomial Naïve Bayes in text classification problems.

Natural language toolkit was used for importing dataset and further computations. Argmax function was employed which returns probability of polarity with respect to class and help in finding out the class of unlabelled reviews. Trained and fine-tuned model was employed on unlabelled data with best possible parametric setting for this model. Accuracy measure was used for assessment of overall performance. It was observed that seventy to seventy five percent of accuracy was achieved. Top ten words are shown with predicted labels in Table 1.

Accuracy obtained: 82%

Table 1. Most valuable information ten features

Word(unimaginative) = T	n: p = 8.3 : 1.0
Word(shoddy) = T	n : p = 6.9 : 1.0
Word(schumacher) = T	n : p = 6.9 : 1.0
Word(singers) = T	n: p = 6.4 : 1.0
Word(turkey) = T	n : p = 6.3 : 1.0
Word(suvari) = T	n : p = 6.3 : 1.0
Word(mena) = T	n : p = 6.3 : 1.0
Word(wasted) = T	n : p = 6.3 : 1.0
Word(atrocious) = T	n : p = 5.8 : 1.0
Word(justin) = T	n : p = 5.8 : 1.0

True = T, Negative = n, Positive = p

It can be concluded that basic machine learning techniques works good but doesn't have brilliant performance. Last three years of research shows a deflection towards NLP with deep learning. It is one of the emerging fields with enormous applications and improving accuracy. In this chapter our aim is to explain the drift of Basic learning based sentiment analysis to advanced learning based sentiment analysis. We tried to explain the power of deep learning based sentiment analysis with the help of detailed review of existing research studies.

MACHINE LEARNING BASED SENTIMENT ANALYSIS

Due to exponential increase in digital world (like social networking sites and online marketing sites) decision making becomes logical. In previous times people use their intution or data was not the biggest power that time. But now prediction becomes easy due to vast availability of data like reviews, blogs etc. Sentiment analysis is one of the major tool in business analytics because it helps in knowing the doamin , needs and trend of target users. Machine learning based approaches plays a great role in classification and analysis of sentiments for example labelling of unstructured reviews with the help of labelled one. Some of the machine learning based sentiment analysis studies are described and summarised with the help of table 2.

Table 2. Basic learning based sentiment analysis

Reference	Machine Learning Technique Used	Purpose
Neethu & Rajasree, 2013	Naïve Bayes , Support Vector Machine, Maximum Entropy, Ensemble learning	Classification efficiency is improved by using feature extraction technique
Maas et al., 2011	Vector space model, Probabilistic latent topic Model, Linear SVM	Extended unsupervised model with semantic information in association with lexical information
Gautam & Yadav, 2014	Naïve Bayes, Maximum entropy and Support vector machine, Semantic analysis	Naïve Bayes outperform maximum entropy and SVM in classification of reviews with the help of twitter dataset
Mudinas, Zhang, & Levene, 2012	Support Vector Machine, Sentiment strength detection.	Integrates lexicon and learning based approaches and shows better results on CNET and IMDB movie reviews as compared to individual learning or lexicon based models
Tripathy, Agrawal, & Rath, 2016	Stochastic Gradient Descent, Naïve Bayes, Maximum Entropy,	Text conversion in to vector is accomplished with the Combination of count vectorizer and TF-IDF, also compare N-Gram with POS techniques. It was shown that as N increases after two accuracy starts decreasing
Rosenthal, Farra, & Nakov, 2017	Support Vector Machine, word2vec	Cross lingual training was explored with the help of Arabic language and shows improved results in irony and emotion detection
Cambria, 2017	Gated Multimodal Embedding Long short term memory	Use of temporal attention layer proved to be very beneficial in dealing of acoustic and visual noise
Chen, Xu, He, & Wang, 2017	Divide and Conquer, Neural Network	Sentence level sentiment analysis was accomplished with convolutional neural network at sentence level
Appel, Chiclana, Carter, & Fujita, 2016	Naïve Bayes, Maximum Entropy	Semantic orientation of polarity was utilized with the help of NLP based hybrid technique and shows improved results than NB and ME
Kolchyna, Souza,	Support Vector machine, Naïve Bayes, Lexicon based ensemble method	Naïve Bayes and SVM outperforms the lexicon based methods

Treleaven, & Aste, 2015		
Toh & Su, 2016	Feed forward Neural Network	Two step approach was employed , single layer feed forward network for domain classification, DNN for sequential classification
Kanakaraj & Guddeti, 2015	Decision Tree, Random Forest, Extremely Randomized Trees	Experimented with ensemble based learning which have kind of approaches depend on application and training data provided.
Chalothom & Ellman, 2015	Naïve Bayes, Support Vector Machine, Senti Strength and Stacking	Different flavour of supervised and semi supervised ensemble classifiers was explored in association with lexicons and shows better results than BOW
Dey, Chakraborty, Biswas, Bose, & Tiwari, 2016	Naïve Bayes, K- Nearest Neighbour	Two supervised learning approaches were used by focussing on sentence polarity and subjective style on movie and hotel reviews. Results were application specific.

DEEP LEARNING BASED SENTIMENT ANALYSIS

Sentiment analysis aim is to analyse people's sentiments or opinions according to their area of interest. Sentiment analysis becomes a hot topic among researchers with the rapid growth of online generated data and equally powerful processing techniques like natural language processing, machine learning and deep learning etc. As we already discussed machine learning techniques in previous section in association with supervised learning based case study. Results are still not satisfactory with basic learning techniques. In this section we will study advance learning techniques called deep learning and studies which accomplished these techniques in sentiment analysis and opinion mining.

Word embedding is one of the crucial step in deep learning based sentiment analysis technique. As described in (Tang et al., 2016) "Word embedding is a representation in which each word is represented as a continuous, low-dimensional and real valued vector". Basic concept behind word embedding is the utilization of context information. For example words like good and bad will be mapped in to same space and beneficial in many NLP applications (POS tagging etc.) but proved to be a disaster in case of sentiment analysis because of their opposite polarity. Therefore, extra information called sentiment embedding is needed for increasing the effectiveness of word context. Semantic embedding is composed of labelled information called sentiment polarity and able to differentiate between words which have opposite polarity. The authors (Tang et al., 2016) uses two neural networks one for prediction (predict polarity of words) and another for ranking (provide real valued sentiment score for word sequence with fixed window size). Empirical study was carried out with three models (Dist + Ngrams, SVM+

Ngrams, SVM + Text Features) on twitter dataset. Effectiveness of sentiment embedding was experimented on three levels word, sentence and lexical. End results concluded sentiment embedding and proved to be a milestone on three levels; word level shows sentiment similarity between words, sentence level for discriminative features and lexical level for sentiment lexicon.

Another approach was proposed by (Chen, Sun, Tu, Lin, & Liu, 2016) for same problem: absence of sentiment information. This approach utilizes the document –level sentiment information which deals with complete information about a product instead of just local level text information. This model was built on hierarchical neural network in association with global user and product based information. Hierarchical long short term memory model was employed to generate sentence and document embedding. Sometime due to vague ratings and complex statement of reviews sentiment analysis degrades its accuracy. At that time user and product information played a significant role in improving the accuracy of model.

Customer reviews is one of the major factor for accessing the opinionated quality of any product. Traditionally it was accomplished with manual steps like lexicon construction, feature engineering etc. But revolutionary change in computation come up with deep learning techniques which reduces the human efforts of feature selection and make this work automated with high demand of large data. Deep learning techniques intrinsically learn mappings from large scale training data. The authors (Guan et al., 2016) proposed a new framework in association with deep learning which is composed of two steps. First one is to learn embedding from rating of customer reviews and second one is the addition of classification layer for supervised fine tuning of labelled sentences. Learning of embedding is based on the concept of sentences with same labels are ranked closer while sentences with opposite labels are ranked farther from each other. Weakly supervised deep learning embedding (WDE) was employed with the help of convolutional neural network. Effectiveness of WDE was measured with the help of amazon reviews and it was concluded that framework based on weakly labelled set of sentences outperforms existing baseline models.

Employment of deep learning in sentiment analysis make it easier to extract contextual information from complex short texts like reviews, posts of microblogging sites etc. Joint model was proposed by (Wang, Jiang, & Luo, 2016) was built with convolutional neural network (CNN) and recurrent neural network (RNN). CNN took the advantage of coarse grained local features while RNN learned via long term distance dependencies. Windows of different length and involvement of various weight metrics was employed in CNN and max pooling was used from left to right. Pipeline of framework was composed of word and sentence embedding after that convolutional and pooling layers, RNN layer support with concatenation layer and final output with softmax output. Results was computed on three benchmark datasets 1) Movie Review 2) Stanford sentiment treebank1 (SST1) with all kind of reviews 3) SST2 with binary labels only. This joint model outperforms the CNN and RNN models alone.

One of the best application which exploits deep learning is financial sentiment analysis. Stock price forecasting is of great interest for investors before investing their money. Financial sentiment analysis comes under financial technology also called as Fin Tech (Day & Lee, 2016) is one of the growing research field. Exploration of deep learning for improving accuracy of forecasting make it more interesting for investors. Stock attributes is composed of information like firm specific news articles, public sentiments which affects decision and impact of media information on firms. This means same information may leads to different decisions for different investors. Deep learning model was employed with three non-linear activation functions called Sigmoid, TanH and rectified linear Unit (ReLu). Result shows that inclusion of deep learning techniques proved to be a turning stone in increasing the forecasting accuracy of Fin Tech models.

Deep learning techniques are data hungry and therefore they work best in case of big data analytics. Big investment banks like Goldman Sachs, Lehman Brothers and Salomon brothers uses the financial advice as their backbone. StockTwits and SeekingAlpha is one of the growing social media for investors and stock information. Long short term memory, doc2vec and CNN model was employed by (Sohangir, Wang, Pomeranets, & Khoshgoftaar, 2018) for finding out the hidden knowledgeable patterns from StockTwits network. Performance was evaluated with accuracy, precision, recall, F-measure and AUC. It was concluded from results that CNN outperforms logistic regression, doc2ve and LSTM for StockTwits dataset.

Most of the sentiment analysis models are based on English generated texts, the authors (Vateekul & Koomsubha, 2016) evaluated the deep learning based sentiment analysis on Thai generated twitter data. Two efficient deep learning techniques was employed one is long short term memory (LSTM) and another is dynamic convolutional neural networks (DCNN) except maximum entropy. Effect of word orders was also taken in to consideration of experimental study. LSTM and DCNN outperforms basic machine learning models for Thai based twitter data. Comprehensive experimental study was carried out for parametric adjustments and results as computed on best parametric settings. It was concluded that DCNN followed by LSTM give best results and shuffling of word orders strongly influence sentiment analysis.

In traditional sentiment analysis (around 2005) statistical models used words with their sentiment scores called lexicons, as their features. But now a days due to involvement of word embedding, use of lexicons become invisible and almost obsolete. The authors (Shin, Lee, & Choi, 2016) tried to explore the combination of word embedding with lexicons. Weather it is a useful combination and if it is what is the best path of using both in association. Experimental study was carried out on two datasets SemEval-2016 Task 4 and Stanford sentiment treebank. Word2Vec from google skip-gram model and six types of lexicon embedding was employed. CNN in association with attention vectors (importance of each word and lexicon) was used as deep learning layer. Integration of lexicons with word embedding helps in improving the efficiency of traditional CNN model.

Sarcasm detection is one of the crucial task in sentiment analysis. Sarcasm consist of ambiguous and reversible statements whose polarity can’t be classified positive or negative easily. Therefore, powerful NLP techniques are required for analysis of sarcastic statements. CNN based deeper analysis of sarcastic tweets was accomplished by (Poria, Cambria, Hazarika, & Vij, 2016). CNN was used because it doesn’t need any hand crafted features and build its global feature set by taking local features which is good for learning context. Macro-F1 was used as efficacy measure and experiments was accomplished on both CNN and CNN-SVM in which extracted features from CNN, fed to SVM for classification.

Similar to sarcasm there is one more information called hate speech detection. It is useful in various business decisions. Hateful tweets are imposed of abusive language and a targeted domain may be product, gender, racism, Gay community etc. Multiple classifiers was employed by (Badjatiya, Gupta, Gupta, & Varma, 2017) in association with three deep learning embedding called Fast Text, CNN and LSTM for detection of hateful sentiments. Comprehensive analysis of numerous embedding was accomplished like TF-IDF values, Bag of words model, GLoVe model and deep learning based embedding. Precision, recall and F1 measure was used as evaluation metrics. It was observed that deep learning based embedding outperform baseline embedding models and gradient boosted decision tree shows best accuracy values.

Composition of sentiment plays an important role in detecting the sentiment polarity. Extended approach of layer-wise relevance propagation was used with recurrent neural network (RNN) (Arras, Montavon, Müller, & Samek, 2017). RNN was employed with one hidden layer of bi-directional long short term memory and five class sentiment prediction. Trained LSTM was compared on two decomposition methods sensitivity analysis and LRP. It was concluded from our experiments, LRP based LSTM supports best classification decision as compared to gradient based decomposition.

Lexical and syntactic features are one of the turning stones in improving the accuracy of sentiments. Unsupervised learning (Jianqiang, Xiaolin, & Xuejun, 2018) was used in association with latent contextual semantic relationship and co-occurrence relationship between tweets. Feature set was obtained through word embedding with n-gram features and polarity score of word sentiments. Feature set was propagated to deep convolution neural network was for training and prediction of sentiment labels. Accuracy and F1 measure on five twitter datasets (STSTd, SE2014, STSGd, SED, SSTd) clearly shows GloVe - DCNN model outperform baseline N-gram model, BoW and SVM classifier.

With the advent of deep learning models traditional approaches become invisible while they also have good computational powers. The authors (Araque, Corcuera-Platas, Sanchez-Rada, & Iglesias, 2018) explores combination of both traditional surface approaches and deep learning. Baseline model was formed with word embedding and linear machine learning approach. Ensemble of (classifiers and features) models was formed from these varied feature set and experimented on six public datasets. Friedman test was used for empirical verification of results and it was observed that ensemble of features and classifiers outperforms basic models.

One of the major issue in sentiment analysis is their language because not all tweets are monolingual, and at that time translation incurs extra cost. Machine learning based approaches needs extra effort of machine translation. Deep learning based models was proposed by (Wehrmann, Becker, Cagnini, & Barros, 2017) which learn latent features from all languages at the time of training. Word level and character level embedding was explored with CNN. Four different language tweets (English, Spanish, Potuguese and German) was analysed. Results was compared with machine translation based techniques with three polarities (Positive, Negative, Neutral) with the help of accuracy and F-Measure. Proposed approach works on character level networks so independent of machine translation technique, word embedding, less pre-processing steps and took only half of memory space. Summary of deep learning techniques used in sentiment analysis is presented Table 3.

Table 3. Deep Learning in Sentiment Analysis

Authors	**Algorithm**	**Dataset**	**Text 2 vec**	**Efficacy Measures**	**Language**
Tang et al., 2016	Sentiment Embedding+ KNN	Twitter Data (SemEval, RottenTomatoes)	WE, SE, word2veec	Accuracy	English
Guan et al., 2016	SVM,SVM+ NB, CNN	Amazon Customer Review	Word2vec	Accuracy, Macro F1	English
Wang et al., 2016	CNN,CNN+ RNN	Movie Reviews, Stanford Sentiment Treebank (SST1) and SST2	Word2vec	Accuracy	English
Chen et al., 2016	Hierarchical LSTM	IMDB, Yelp 2013, Yelp 2014	Sentence level embedding	Accuracy, RMSE	English
Day & Lee, 2016	Deep neural network with sigmoid, tanH and ReLu function	News data(Now News, Apple Daily, LTN and Money DJ finance)	Lexicon based embedding	ROI Heatmap	Chinese
Vateekul & Koomsubha , 2016	LSTM and DCNN	Thai tweet corpus	Word2vec	Accuracy	Thai
Shin et al., 2017	CNN	SemEval'16 Task 4 and SST	Word2vec, lexicon embedding	F1 score , Accuracy	English
Poria et al., 2017	CNN, CNN-SVM	Sarcastic tweets	Word2vec	F1 score	English
Badjatiya et al., 2017	CNN, LSTM	Hate related tweets	BOWV, N-gram, GloVe, FastText	Precision, Recall, F1 measure	English
Arras et al., 2017	Bi-directional LSTM	SST, movie reviews	Word2vec	Accuracy	English
Jianqiang et al., 2017	Deep convolution	STSTd, SemEval2014, Stanford twitter	GloVe, BOW	Precision, Recall, F1 score	English

	neural network	sentiment gold, SED, SSTd			
Araque et al., 2017	Ensemble of classifiers	Microblogging data and movie reviews	Word2vec, GloVe	F1 score	English
Wehrmann et al., 2017	CNN, LSTM	1.6 million annotated tweets	Word and character level embedding	Accuracy, F-measure	English, German, Portuguese, Spanish
Sohangir et al., 2018	LSTM, CNN	StockTwits posts	Doc2vec	Accuracy, Precision, AUC	English

Conclusion

Sentiment analysis is one of the evolving research area with an ample amount of applications and getting matured day by day. It is concluded from above studies that accuracy of sentiment analysis models are not up to the mark till now. One of the main reason behind lacking of accuracy is complex structure of data. While, it is also observed that drift from machine learning to deep learning techniques with natural language processing shows promising results. Unstructured nature of data is very difficult for training and accuracy achieved by basic machine learning algorithms were very low. Correct feature extraction is the heart of machine learning algorithms. But this problem is very much solved by the use of deep learning algorithms due to automatic selection of features with large availability of data. And it is estimated that understanding the contextual behaviour of data (ratings, reviews etc.) with deep learning and other computational techniques make it more likable for more applications in future.

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