Aspect Level Sentiment Analysis for Different Domain using Deep Learning Approach

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***Abstract* — Nowadays, sentiment analysis is an important decision-making tool for the extraction of human emotional state on the social media. It is a popular research area in Natural Language Processing (NLP) and widely used in recommender system, market research, prediction on political domain, social media monitoring, etc... Sentiment analysis (also called as opinion mining, text mining, emotional AI, etc...) is the process of algorithmically identifying whether the opinion in a news articles, social media posts and comments, forums, movie reviews as a positive, negative or neutral. In the past decades, there are many research works for sentiment analysis by using machine learning techniques like Naïve Bayes (NB), SVM, etc… Nowadays, deep learning models are implemented in Artificial intelligence applications to gain better performance. The main objective of this paper is to classify the sentiment polarity for the aspect of the given target entity as a positive, negative, or neutral. There are so many challenges and issues in SA. Among them, extracting the right feature for classification is the most important challenge in SA. To solve this problem, this paper proposes to build a convolutional neural network (CNN) model with the gating control mechanism for aspect level sentiment analysis using gating control technique in order to be more accurate and efficient in aspect filtering.**

Keywords— Aspect Level Sentiment Analysis (ALSA), Natural Language Processing (NLP), Deep Learning, Convolutional Neural Network (CNN)

I. INTRODUCTION

Nowadays, sentiment analysis is a popular and active research field in natural language processing (NLP) for finding sentiments of people for a specific product, services films, news, organizations and so on. It aims to mine the public opinions or attitudes expressed in written text. There are so many challenges and issues in sentiment analysis. The first one is it can't handle if the available data amount is huge. The other is extracting the right features for classification is the most challenges in sentiment analysis. Research goal is to classify the given document into positive, negative or neural (neutral means "no opinion") by building a convolutional neural network for sentiment model and finally compare the obtained results are outperformed than other learning methods. This paper aims to classify the sentiment polarity for the aspect of the given target entity as a positive, negative, or neutral by using convolutional neural network using gating method in order to be more accurate and efficient in aspect filtering and to compare obtained results are outperformed than other deep learning methods.

The rest of the paper is organized as follows: Section 2 presents the related work of the sentiment analysis using various methods. Section 3 discusses about the theory background includes sentiment analysis, deep learning and convolutional neural network. Section 4 presents experimental settings. Finally, section 5 concludes the study with the summary of the main points of the presented research.

II. RELATED WORK

Sentiment analysis is a well-studied topic in social media analysis and become an important decision-making tool to classify the sentiment or opinion of the user on the Web. In the past decades, there has been a lot of works for sentiment analysis using supervised learning like Naïve Bayes or Support Vector Machines (SVM) shown best results in sentiment analysis. In recent years, deep learning approaches has shown state-of-the-art results for sentiment analysis.

Deep Learning is the part of machine learning process and it is based on learning data representations. Unlike machine learning, deep learning can be trained on supervised, unsupervised and semi-supervised learning. Deep learning can be applied in NLP, speech and audio recognition, computer vision, machine translation, social media filtering and many more.

Reference [1] present a deep learning model called Recursive Neural Network (RNN), a fully labeled parse trees to represent the movie reviews (from rottentomatoes.com). The nodes of the tree are words or the groups of words, which means that we not only need the labels of the whole sentences, but also get the labels of each words and the group of words. To solve this RNN problem, this system aims to use Convolutional Neural Network. CNN only need the labels of the whole sentences instead of the fully labeled parse tree. In [2], a series of experiments with convolutional neural network trained on top of pre-trained word vectors for sentence-level classification tasks were presented. They show that a simple CNN with little parameter tuning and static vectors achieves excellent results on multiple benchmarks. [3] proposes empirical hyper parameter tuning for sentence classification on Yelp 2017 dataset. Reference [4] presents CNN for sentence classification by focusing on only one CNN layer. It can apply only a simple one-layer CNN to real world sentence classification tasks. [5] proposes Twitter sentiment analysis with deep convolutional neural network by initializing the parameter weights of the CNN . They apply the model on SemEval 2015 Twitter Data Analysis. By providing the network with good initialization parameters can have a significant impact on the accuracy of the trained model. The authors in [6] presents the studies about CNN on text classification to exploit the 1D structure of text data. They tested the model on IMDB movie reviews, electronics product reviews from Amazon review dataset and RCV1 topic categorization.

III. THEORY BACKGROUND

In this section, we present background knowledge about sentiment analysis, deep learning, and convolutional neural network.

A. Sentiment Analysis

The Sentiment analysis can be classified as

- Document Level
- Sentence Level
- Aspect Level

Document level gives the whole document polarity and only considers the opinion of only one opinion holder. Sentence Level SA can distinguish the opinion of the whole sentence. But there are more than one aspect or feature in a sentence, neither document nor sentence level can't tell the polarity of the detail aspect exactly. For example, *Food is great but service is horrible.* In this example, sentiment polarity about aspect "food" is positive but polarity for aspect "service" is negative in a sentence. If we ignore the aspect information, it is hard to determine for the whole sentence. So, this paper aims to classify opinions about specific aspects at aspect level because document and sentence level can't handle each of the aspect exactly.

B. Deep Learning

Nowadays, deep learning techniques are becoming an AI's powerful tool to solve complex problems. It is a kind of machine learning algorithms which uses multiple layers for feature extraction and transformation. The "deep" in deep learning refers to the number of layers (more than three layers including input and output) so qualifies as "deep" learning. The following figure shows that the deep learning approach can solve and give better performance than machine learning methods. If the more data are fed into the model, deep learning can handle and give the best performance than machine learning methods.

The preferred method for sequence of words or sentence is recursive or recurrent neural network methods like LSTM or GRU(Gated Recurrent Units). However, CNN is shown the best result in feature extraction. For this reason, CNN is chosen for the development of our model.

TABLE I. ASPECT AND SENTIMENT IN A EXAMPLE SENTENCE

Aspect	Sentiment
Food	Positive
Service	Negative

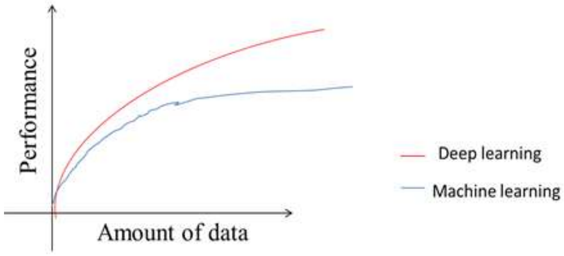

Figure 1. Deep learning Vs Machine learning.

C. *Convolutional Neural Network (CNN)*

CNN is widely used in image and video analysis, checkers game and biomedical image classification, etc… It is very famous for its great performance, especially in image recognition and computer vision. However, to the best of our knowledge, text classification using CNN is rarely used in the literature. Most of text classification are using recurrent and recursive neural network approach. So, this paper presents to build a sentiment model using convolutional neural networks (CNN) model and gives the best performance.

In this paper, we define the following 7 components for our CNN sentiment model:

- Word Embedding
- Convolution
- ReLU activation
- Pooling
- Flattening
- Fully connected
- Softmax output layer

Firstly, we collect review data from different data sources and pass the input into word embedding layer because CNN can't understand the sentence directly. In order to adopt the deep learning approach for the NLP task, we need to transform into a numerical form so that it can feed input data into the neural network layers.

The first layer of CNN is word embedding layer. In this layer, the texts are transformed into sentence matrix, and resized with the maximum size, after that, multiplied by the size of the vector of each word. In this case, review maximum size we used is 100. Finally, the dimensionality of the given sentence is s x d, where d is the size of the vector (in this case GloVe). We tested with different vector size (50, 100, 150, 200) and 100 is the best choice.

The embedding layer takes a sentence S = [w_1, w_2… w_n] and output the corresponding matrix S = [v_1, v_2, …, $_{vi}$] Є $R^{n\times k}$,

Let v_i Є R^k is the word vector for word w_i.

k= length for each word.

n= length of the sentence with padding.

Example Sentence,

S = {'Camera is good in M8'}

|V|= {'Camera','is', 'good','in', 'Mi8'}, where the size of vocabulary may be very large (e.g., 100K)

X= [10000 | 01000 | 00100 |00010 | 00001]

There are so many techniques of embedding word into corresponding vectors, such as Word2vec, GloVe, etc… Among them, GloVe with 100 dimensional is used in this paper.

Fig.1 shows that how word vectors are closely connected and occupied in a 2D chart. Example sentences are:

{'Camera is good in Mi8.'

'This iPhone is expensive.'

'Packaging is so nice in iPhone ',

'Battery last in Mi8.'

'Wonder design of Nokia.'}

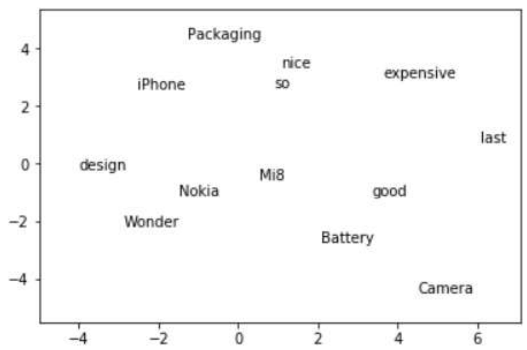

Figure 2. Word Vectors for example sentences

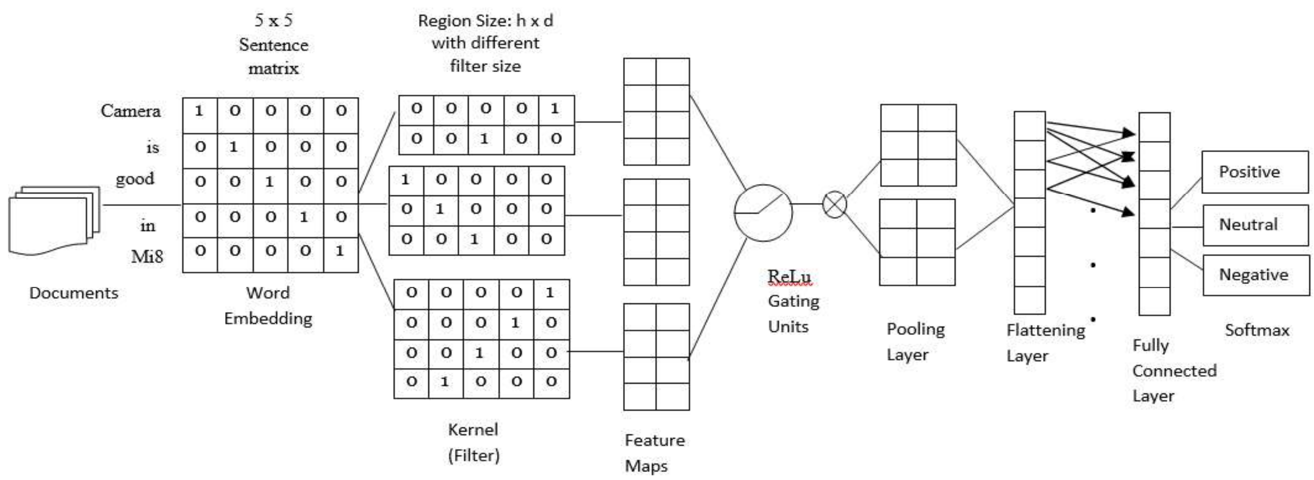

Figure 3. Proposed Convolutional Neural Network Model for Aspect Level Sentiment Analysis

After that, the dataset is divided into 2 parts, training and testing. We used 80% for training and 20% for testing. Some dataset are labelled by five classes or five stars rating. So, we repaired and mapped this five classes into 3 polarity classes (positive, neutral or negative) for sentiment prediction.

In the convolution layer, sliding the window from the beginning of the word matrix till the end with multiple filter sizes (tested with filter region size 2,3,4,5 and size=3 is the best choice for our work). Convolution layer with multiple filters can effectively extract n-gram features. After the convolution, feature maps are generated.

$$c = [c_1, c_2, \ldots, c_n]$$

Standard CNN doesn't consider for the aspect term. So, this paper proposes CNN approach with the gating units to extract the aspect information. After the convolution layer, ReLU gate is applied for filtering aspects. One of the advantages by using gating mechanism is to speed up the training time. With the given aspect information, they can extract the aspect-specific sentiment information for sentiment prediction. The gating unit controls the sentiment information from the feature map and then forwards it to the pooling layer. For the pooling layer, we used MaxPooling which extracts the maximum value ĉ=max{c} as the feature corresponding to one particular filter. Features extracted from the pooling layers are concatenated and used as an input to the flattening layer. Flattening is the process of converting all the results of 2 dimensional arrays into a single long continuous linear vector. Finally, Softmax layer computes the probability of class c and output the polarity for each aspect in the given sentence. Standard convolutional neural network doesn't consider for the aspect term. So, we propose CNN based approach with the gating units to extract the aspect information. For the gating units, we use ReLU to extract the right features.

TABLE II. DIFFERENT DOMAINS AND THEIR ASPECTS

Domain	Aspects	Sentiment Type
Restaurant	Staff	Positive, Neutral, or Negative
	Service	
	food	
	Price	
	ambience	
	misc	
Hotel	Service	Positive, Neutral, or Negative
	Staff	
	Price	
	Location	
Laptop	Windows	Positive, Neutral, or Negative
	Price	
	Operating System	
	Hard Drive	
	Gaming	
	Speed	
	Speaker	
	Touchpad	
	Build-in Camera	
	Battery	
	Headphones	
	Mouse	
	Keyboard	
	Power Supply	

IV. Experiment

A. Dataset

TABLE III. DATASETS FOR DIFFERENT DOMAINS AND THEIR ASPECTS

No	Datasets	No. of records	Description
1	Amazon	3 Million	Product
2	Yelp 2015	560,000	Restaurant
3	SemEval 2016	Approx 6K	Restaurant, Laptop,Hotels
4	IMDB	50,000	Movie reviews
5	MR (rottentomatoes.com)	10,662	Movie reviews
6	Standford Sentiment Treebank	11,855	Movie reviews

For the data, we use public datasets like IMDB, amazon, yelp, , etc... After collecting the dataset, we merge these all datasets and shuffle them randomly and divided them into 2 parts: training (80%) and testing (20%) sets.

IMDB dataset is a benchmark dataset for sentiment classification. The task is to determine the polarity of the movie reviews are positive, negative or neutral. For the classification, we used 50,000 movie reviews data taken from IMDB.

Before classifying the sentiment over the review data, we firstly performed a pre-processing step. In this stage, we remove the empty lines, punctuation marks, parenthesis and other special characters.

B. System Requirements

For the development of our sentiment model, the Keras framework was used for the best performance. Keras is an open source neural network library written in Python and runs on top of Tensorflow, CNTK or Theano as backend. It was chosen due to its high level API and it assists in the development of deep learning models, providing high-level building blocks. So, it is not necessary to perform low-level operations such as product tensor and convolutions. Nevertheless, it needs a specialized and optimized tensor manipulation library to do so, we used Tensorflow as backend. It is an open-source symbolic tensor manipulation framework developed by Google. Keras can run seamlessly on both CPU and GPU. The following table shows the system and version requirements of our sentiment model in Keras.

TABLE IV. SYSTEM REQUIREMENTS FOR OUR SYSTEM

No	System requirements	Version	Description
1	Python	3.6.8:: Anaconda Inc.	High-level, interpreted and general-purpose dynamic programming language
2	Anaconda	1.9.6	Enterprise-ready, secure and scalable data science platform
3	Jupyter Notebook	5.5.0	Web application to create statistical modeling, machine learning, etc…
4	Tensorflow	1.10.0	An open-source machine learning library to develop neural network model.
5	Keras	2.2.2	High-level neural network API running on top of Tensorflow. Runs seamlessly on CPU and GPU.

TABLE V. ACCURACY ON DIFFERENT DATASETS

Model	Amazon	Yelp2015	SemEval2016	IMDB	MR	SST
Proposed System	78.8	81.5	88.2	86.4	85.2	87.5
LSTM	75.9	81.6	87.9	85.5	83.7	87.5
Bi-Directional GRNN	78.9	78.9	88.1	80.2	84.9	83.6

C. Result and Discussion

Firstly collect review data from different data sources like IMDB, Amazon, Yelp, , etc… and pass the data into word embedding layer. The texts are vectorized with one-hot encoded vector and these vectors are passed into the CNN layers to extract the aspect and polarity for sentiment prediction. For the implementation, this system use Python 3.6, Tensorflow version 1.10.0, and Keras 2.2.2. The operating system must be 64-bit. To boost the performance, this system uses fine-tuned and pre-training word embedding. We tested with word vectors of different size (50, 100, 150, and 200). For the evaluation, we compiled the model with binary cross-entropy for the loss function and the proposed method gets higher accuracy than other neural network methods: LSTM and Bi-directional GRNN as shown in Table V.

V. Conclusion

In conclusion, aspect level sentiment is an important task for many social media analytics, medial, political, market research, etc… This system aims to extract an aspect of the target entity and its associated sentiment on different domain. Because of the achievement of deep learning, more and more researchers are trying to solve the challenging sentiment analysis task by using deep learning algorithms. This paper presents to build an aspect level sentiment model using convolutional neural networks approach for the better performance. Here, we used the ReLU activation function for the aspect extraction. It solved the challenge of implicit feature extraction faces in machine learning approach. Our future work aims to build the CNN model of ALSA in Myanmar Language.

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