Applying Deep Learning Approach to Targeted Aspect-based Sentiment Analysis for Restaurant Domain

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Abstract

Sentiment analysis is a well-studied topic in social media analysis and it becomes an important decision-making tool to classify the opinion of user on the Web. In a few years ago, there are so many research works for sentiment analysis using machine learning. Nowadays, deep learning models are implemented in AI applications to gain better performance. This paper proposes to extend the traditional LSTM approach by adding the external knowledge. LSTM is a kind of recurrent neural network (RNN) and it can learn the past and future information. Unlike traditional RNN, it can capture the long sequence of text. With the LSTM cell, SenticNet is used as an external knowledge, to improve the accuracy in classification. We termed SenticNet multi-attentive LSTM (MA-LSTM). The results from the SenticNet MA-LSTM are classified as positive, negative or neutral and finally, compare the results with other state-of-the-art LSTM methods: standard LSTM, TD-LSTM, TC-LSTM, AE-LSTM, and ATAE-LSTM. *To our knowledge, this is the first work for using multi-attention LSTM with external knowledge in targeted aspect-based sentiment analysis task.*

Key Words- Targeted ABSA, Long Short Term Memory, multi-attentive LSTM (MA-LSTM), SenticNet, Natural Language Processing (NLP), Deep Learning

1. Introduction

Sentiment analysis is a popular research area in NLP for finding the opinions of people on a specific product, services, movie reviews, and so on. It has been widely used in recommender systems, market research, and prediction on social media. Sentiment analysis is a suitcase research problem. It needs to solve many NLP tasks like text normalization, POS tagging, text chunking, lemmatization, subjectivity detection, sarcasm detection, aspect extraction, and polarity detection. Among them, aspect extraction is the most important task in sentiment analysis. If we ignored, the accuracy will reduce in the classification. With the development of deep learning, RNN approaches have gotten remarkable results in sentiment classification, machine translation, image classification and speech recognition. In this paper, a neural network sentiment model is built by using multi-attentive LSTM approaches combining with the SenticNet. The main aim of this paper is to predict the targeted aspect, classify the relevant polarity and compare the result with other LSTM methods.

The remainder of the paper is organized as follows: Section 2 presents the related work of the ABSA tasks using LSTM based methods. Section 3 discusses the methodology about ABSA, long short-term memory and attention mechanism. After that, Section 4 explains the proposed system architecture, and Section 5 analyzes for the experiments. Finally, Section 6 presents a summary of the main points of the presented study.

2. Related work

This section presents several research works related to targeted sentiment analysis, ABSA and LSTM method. There are so many research works for sentiment analysis using LSTM approach like TDLSTM (target-dependent LSTM) and TCLSTM (Target Connection) to determine the sentiment target in the whole sentence.

In [1], the authors present an attention-based LSTM Network for aspect-level sentiment classification. They initialized with Glove pre-trained word vectors on an unlabeled corpus, sized 840 billion. They used 300 hidden layers and experiment on Theano with the SemEval 2014 dataset and show state-of-the-art performance on aspect-level sentiment classification. The authors in [2] apply the target-dependent LSTM (TD-LSTM) approach for sentiment classification on the Twitter benchmark dataset and compare the results with feature-based SVM, adaptive recursive neural network and lexicon-enhanced neural network. In [3], the authors present the creation of new ABSA annotated dataset that is developed on Foursquare[1] restaurant review data. They manually annotate a completely new dataset from comments. These comments are about 215K user reviews during the period from 2009 to 2018. [4] describes the SemEval 2016 task 5 on ABSA which is an extension of 2014 and 2015. It provides a total of 39 datasets and the datasets are prepared in XML format.

[1]https://foursquare.com/toledonews/list/restaurant-reviews

The evaluation ran into two phrases. In the "Phase A", the participants were asked to return separately the aspect categories (Slot1), the (Slot2), and the {Slot1, Slot2} tuples for SB1. For SB2, the respective the text-level categories are identified. In the "Phase B", the gold annotations for the test sets of Phase A are provided and the participant had to be returned the sentiment polarity values (Slot3). For the polarity detection, they trained with SVM classifier with a linear kernel. To evaluate sentiment polarity in Slot3, they use accuracy measurement. For the evaluation of Slot1, Slot2 and {Slot1, Slot2}, they use F1 score measurement. [5] presents the AttectiveSpace 2, a vector space model that allows for reasoning on natural language concepts by reducing the dimensionality of affective commonsense knowledge. This model allows the semantic feature of concepts that are clustered according to their semantic and affective relatedness. [6] proposes an attention-based LSTM model and they did experiments on SemEval 2014, 2015, and 2016 datasets. They present two novel approaches. The first approach is encoding a target to capture the semantics of the target expression because the target is an essential one when attention weights are computed. The second approach is to construct syntactic-based attention model which focuses on small subset words that are close to the target. The results show that the attention-based LSTM improves the accuracy and Macro-Fi score by incorporating two proposed methods. In [7], the authors propose the targeted ABSA which solves the challenges of both ABSA and target sentiment analysis by using the commonsense knowledge. They conduct experiments on SentiHood and subset of SemEval 2015 datasets. There are 3,862 sentences for single target and 1,353 sentences for multiple targets. They didn't consider the NULL targets, so they got the high performance for their method.

According to our reviews, standard LSTM does not meet well on the targeted ABSA task. Therefore, this paper proposes to integrate multiple attention model to standard LSTM for targeted ABSA and it enhances the accuracy. To our knowledge, out task, targeted aspect-based sentiment analysis using multiple attentive LSTM with the external knowledge is the first work in all related works.

3. Methodology

In this section, ABSA, standard LSTM and attention mechanism will be presented.

3.1. Aspect-based sentiment analysis

There are many research works of sentiment analysis at document and sentence level. Although these two levels can keep complete and in-depth results, aspect level has achieved much attention in these years because aspect extraction is the most important issue in sentiment analysis. Aspect is an attribute of the targeted entity. For example, price, service, view are aspects of the restaurant domain. If we didn't consider the aspect, it's hard to determine the sentiment for a target aspect. Therefore, this paper proposes to analyze the sentiment of the specific aspect at the aspect level because the above two level can't handle the specific aspect explicitly. The main aim of ABSA's task is to classify the sentiment polarity for a specific aspect.

3.2. Long-short term memory

LSTM is not only the most successful deep neural network for long sequences of data, but also it is good in learning implicit knowledge from the input data. Standard RNN has to solve many problems: it requires learning long-term dependencies, hard to train and it has the gradient vanishing or exploding problems when dealing with long sequences of data. In order to overcome the issues of RNN, LSTM was developed and achieved the better performance. LSTM network use special units. It includes a memory cell that can maintain information for the long term. The standard LSTM cannot detect which is the most important part to classify in sentiment analysis. In order to solve this problem, we proposes multiple attention LSTM mechanism to attend to the important part of a sentence. Rather than using single attention Model, multiple attention model can capture the attended words over and over again to capture the important aspects. Typical LSTM building block is shown in Figure 1. It is composed of a cell c_t, input gate i_t, output gate o_t, forget gate f_t and hidden output h_t.

3.3. Attention mechanism

The attention mechanism gives attention to the aspect of a specific target in the input sequence. In the ABSA task, the neural network model need to extract the aspect information for different aspects and combined with the attention mechanism can solve the problem of different polarity for different aspects in a sentence. The attention model for ABSA is shown in Figure 2.

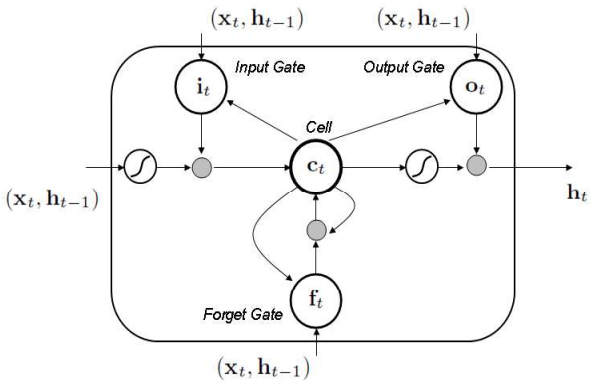

Figure 1. Long Short Term Memory

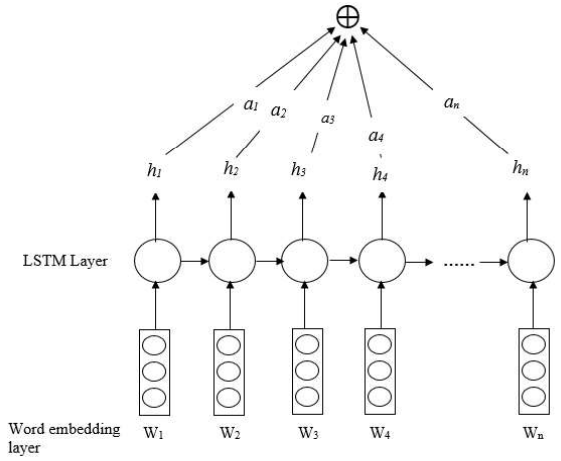

Figure 2. General Attention LSTM for ABSA task

4. The proposed system architecture

In this section, we explain the task definition, an overview of the proposed system, target level attention, MA-LSTM network and SenticNet.

4.1. Task definition

For the restaurant domain, a review may consist of a sequence of sentences, in which a sentence consists of a sequence of words and targets composed of m words, denoted as T= $\{t_1, t_2, ..., t_i, ..., t_m\}$, where t_i refers to the i^{th} word in the target expression. In our work, the task can be divided into two main subtasks. Initially, it extracts the aspect category that belongs to the predefined target *t*. After that, it detects the polarity with respect to the specific aspect that is associated with target t. In this paper, we define 12 aspect categories and more than 300 targeted aspects for the restaurant domain. Example sentences for targeted ABSA task are shown in Table 1.

4.2. Overview

Firstly, we collect restaurant review and pass these words into the embedding layer. A sentence S consists of a sequence of words. For example, S= $\{w_1, w_2, ..., w_i, ..., w_n\}$ consists of *n* words and an aspect, w_i. We need to convert input words into corresponding word vectors $\{v_1, v_2, ..., v_i, ... , v_n\}$ by using a look-up table, is known as the word embedding, as shown in Figure 2. We identify all the word vectors stacked in a word embedding matrix is:

$$W \in \mathbb{R}^{d \times |V|}, \quad (1)$$

where |V| is the vocabulary size and d is the dimension of the word vector.

Table 1. Example sentences for targeted ABSA

No.	Review text	Category	Target	Polarity
1.	Burgers with extra pickles, onion rings and the chocolate shake are the best ever!!!! :)	FOOD#QUALITY	Burgers	positive
		FOOD#QUALITY	Onion rings	positive
		DRINKS#QUALITY	Chocolate shake	positive
2.	There is just no respect shown by the general staff	SERVICE#GENERAL	staff	negative
3.	Good ambience and fast service!	AMBIENCE#GENERAL	ambience	positive
		SERVICE#GENERAL	service	positive

In our multi-attentive neural network architecture, we use two main components: sequence encoder and attention mechanism. Sequence encoder transforms the word embedding into a sequence of hidden outputs. After that, the attention model is built on top of it. The target level attention takes the hidden outputs of the target expression as input. And then, it encodes each word in the attention level. The target level attention model outputs weighted sum of hidden outputs as a vector representation of the given target expression. The output from the target level attention is the representation of the target. After that, the target embedding vector with the aspect embedding is used to calculate for the whole sentence. Finally, Softmax function is used to predict the targeted polarity as positive, negative and neutral. The overview architecture is shown in Figure 3.

4.3. Target level attention

In the targeted ABSA, a sentence may include multiple target-sentiment pairs. Therefore, the attention model is becoming an important part in the neural network model for the text classification. It captures the most important context of the sentence towards a target.

Using the attention mechanism, we calculate an attention vector for the target expression. A target t composed of n words in a sentence and can be described as T= $\{t_1, t_2, ..., t_i, ..., t_n\}$, where t_i refers to the position of i^{th} word in the target expression.

We calculate the target vector v_t as:

$$v_t = H'\alpha = \sum_j \alpha_j h_{t_i} \quad (2)$$

Where, target attention vector is distributed over the target word sequence T. The attention vector α takes the hidden outputs as input.

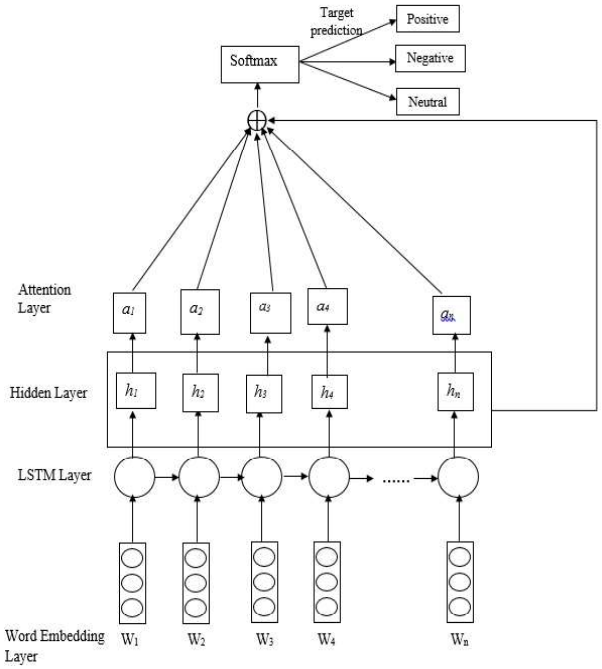

Figure 3. Multi-attentive LSTM for targeted ABSA

4.4. MA-LSTM

Recently, analyzing the sentiment towards a specific aspect and target have drawn much attention because it is dependent on a particular set of aspects and entities. Using a single attention layer, it can't find the complete information in the complicated sentences. Therefore, this paper proposes to use multiple attention mechanism to capture the most important context of the sentence. Our MA-LSTM network adds an attention mechanism to the LSTM cell. It includes two steps. For the first step, the sentence is encoded using the LSTM. An LSTM cell is made up of three gates (forget gate, input gate, and output gate) and a cell. It takes a sentence of sequence and the gates determine which information flow in and flow out at the current time step. The mathematical representation for an LSTM cell can be described as:

$$f_t = \sigma(W_f \,.\, [h_{t-1}, x_t] + b_f) \quad (3)$$

$$i_t = \sigma(W_i \,.\, [h_{t-1}, x_t] + b_i) \quad (4)$$

$$C_{t-1} = \tanh(W_C \,.\, [h_{t-1}, x_t] + b_C) \quad (5)$$

$$C_t = f_t \times C_{t-1} + i_t \times C_{t-1} \quad (6)$$

$$o_t = \sigma(W_o \,.\, [h_{t-1}, x_t] + b_o) \quad (7)$$

$$h_t = o_t \times \tanh(C_t) \quad (8)$$

where, x_t = input vector
h_{t-1} = output of the previous block
h_t = output of current block
C_{t-1} = memory cell from previous block
C_t = memory cell from current block
i_t = input gate
o_t = output gate
f_t = forget gate

W is for weight matrices and b is the bias vector. σ denoted as the sigmoid function and activation tanh function is used to calculate for the prediction. In order to consider the previous and next word in the sequence, we use bidirectional LSTM to encode the input word. Bidirectional LSTM can process the sequence of words in the original order and reversed order. The output of LSTM is computed based on the hidden states. The second step in MA-LSTM is multiple attention mechanism. In the first attention layer, it explores the concept level information and then finding the relevant target aspect in the second attention layer. Finally, the Softmax function is applied to generate the attention distribution over the words in the sentence. Softmax function can solve the multiclass problem where the range is between 0 and 1. The probability calculation for polarity class is shown in Equation 9.

$$y = Softmax\,(W_y \,.\, C + b_y) \quad (9)$$

Where, W_y is the weight matrix and b_y is the bias term.

4.5. SenticNet

This paper uses SenticNet knowledge to LSTM cells to get the best accuracy for the classification. SenticNet is a commonsense knowledge base that contains 50,000 concepts and it is associated with the set of effective properties. The affective properties provide not only concept-level phrases but also the semantic links to the aspects and related polarity. For example, the concept of "*rainbow trout*" has the property of "KindOf-food" and it is directly related to aspect "restaurant" or "food". However, the high dimensionality of SenticNet prevents it from being used in deep learning models. Therefore, we use AffectiveSpace [5] to map the concepts of SenticNet as low-dimensional representations. Based on this concept, we embed the concept-level information into a neural network to better classify both aspects and sentiment in the text. When we use the SenticNet, it can extract three main parts in a sentence: 1) concept extraction, 2) aspect extraction, 3) polarity detection For example, in a restaurant review "The restaurant is adorable and very clean". According to this sentence, we have firstly to extract concepts. The extracted concepts are shown in Figure 4.

Figure 4. Concepts extraction

After that, we need to extract aspects from these concepts. This example sentence tells us about the aspect "restaurant".

Figure 5. Aspects extraction

Finally, we detect sentiment polarity from the sentence. As shown in Figure 6, the sentiment polarity for this sentence is "positive".

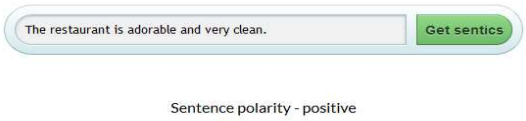

Figure 6. Polarity detection

5. Experimental Setting

This section explains about the dataset, experimental results, and evaluation, and finally, system requirements for this paper are presented.

5.1. Dataset

This paper we use the restaurant review data in Yangon under the category of local cuisine. The data are collected from the tripadvisor[2]. The dataset contains more than 20,000 sentences and we annotate these sentences according to the SemEval2016 ABSA challenge annotation guidelines. Each sentence contains annotations about opinion target, aspect category, and sentiment polarity. The aspect category and example of some target words are shown in Table 2.

The following review id, r_id=1 is an example for the annotated sentence for restaurant domain in XML format. In this paper, we add one more attribute "*sentiment_word*" to SemEval2016 ABSA challenge annotation.

Because of ABSA, there may be more than one opinion for different aspects in a sentence. The following example is an annotated review for more than one aspect and their related polarity.

```
<Review r_id="1">
  <sentences>
    <sentence s_id="1:0">
        <text> Excellent place for a coffee.</text>
    <Opinions>
      <Opinion   target="coffee"
                 category="DRINKS#GENERAL"
                 polarity="positive"
                 sentiment_word="excellent"
                 from="38" to="42"/>
    </Opinions>
    </sentence>
    <sentence s_id="1:1">
     <text> Nice ambience and the lighting is good
    </text>
  <Opinions>
    <Opinion   target="ambience"
               category="AMBIENCE#GENERAL"
               polarity="positive"
               sentiment_word= "nice"
               from="5" to="13"/>
    <Opinion   target="lighting"
               category="AMBIENCE#GENERAL"
               polarity="positive"
               sentiment_word= "good"
               from="22" to="30"/>
    </Opinions>
  </sentence>
 </sentences>
</Review>
```

Table 2. Aspect Categories and targets

	Aspect-Category	**Target**
1	AMBIENCE#GENERAL	Atmosphere, interior, music, seats, style, tables
2	DRINKS#QUALITY	Chocolate shake, coffee, lemon tea, passion tea, wine
3	DRINKS#PRICES	Aperitivos, beer, wine
4	DRINKS#STYLE_OPTIONS	Coffee, cups, wheat beer
5	FOOD#PRICES	Burger,salad, sandwich, sashimi, whole wheat pita
6	FOOD#QUALITY	Burgers, chips, double cheeseBK, mushroom, onion rings, pasta, steaks
7	FOOD#STYLE_OPTIONS	Cooked and grilled meals, dessert, presentation of food
8	LOCATION#GENERAL	Balcony, seaside deck, view, window
9	RESTAURANT#GENERAL	Address, bar, café, Grill'd
10	RESTAURANT# PRICES	place
11	RESTAURANT#MISCELLANEOUS	Happy hours, parking, place
12	SERVICE#GENERAL	Host, managements, service, staff,

Table 3 shows the collected number of review data for local cuisine.

[2]https://www.tripadvisor.com/Restaurants-g294191-Yangon_Rangoon_Yangon_Region.html

Table 3. Number of review data

No.	Review Data	No. of Instances / Sentences
1	Shan Kitchen	258
2	999 Shan Noodle House	2057
3	Taing Yin Thar	160
4	Lucky 7	288
5	Wai Wai Noodle Place	206
6	Rangoon Tea House	1599
7	Shan Yoe Yar	749
8	LinkAge Restaurant and Art Gallery	378
9	Jana Mon Ethnic Cuisine	230
10	Aung Mingalar Shan Noodle Restaurant	381

5.2. Results and analysis

For the evaluation, we tested our restaurant data on different models. Overall accuracies for each model are shown in Figure 7. As shown in the figure, our model, SenticNet MA-LSTM gets the state-of-the-art performance than the ATAE-LSTM which is the highest accuracy in all related works.

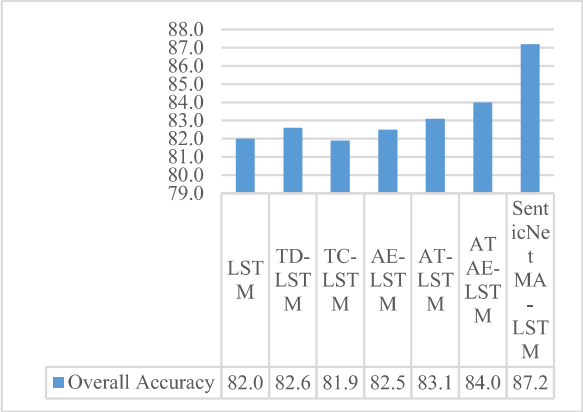

Figure 7. Accuracies for sentiment prediction on different model

5.3. System requirements

For the implementation, we use Keras framework 2.2.2 for better performance. It is a high-level neural network API and runs on top of Tensorflow, CNTK or Theano. We used Tensorflow version 1.10.0 as backend. It is an open-source symbolic tensor manipulation framework. Keras can run on both CPU and GPU.

6. Conclusion

As a conclusion, we proposed a deep neural sentiment model for targeted ABSA because aspect plays an important role in sentiment analysis. We modeled the extension of the standard LSTM model combining with the SenticNet knowledge for the restaurant domain. This system classifies the sentiment polarity for every detailed aspects of local cuisine around Yangon. So, the new customer can know the opinion of each aspect. Moreover, we add multiple attention mechanism to attend the sentiment-salient part of the sentence and generates the more accurate representation of the target. Experiments show that our model gets a higher accuracy than other models like *TD-LSTM, TC-LSTM,* AE-LSTM and ATAE-LSTM. Our model outperformed 3.2 % more by [1].

7. References

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