Abstract

Aspect based sentiment analysis (ABSA) can provide more detailed information than general sentiment analysis, because it aims to predict the sentiment polarities about the given aspects or entities from text. We summarize previous approaches into two subtasks: aspect-category sentiment analysis (ACSA) and aspect-term sentiment analysis (ATSAs).

Previous approaches predict the sentiment polarity of the concerned targets via long short-term memory (LSTM) and attention mechanisms. We propose a model based on convolutional neural networks (CNN) and gating mechanisms, which is more accurate and efficient. First, the novel Gated Tanh-ReLU Units (GTRU) can selectively output the sentiment features according to the given aspect or entity. The architecture is much simpler than attention layer used in the existing models. Second, the computations of our model could be easily parallelized during training, because convolutional layers do not have time dependency as in LSTM layers, and gating units also work independently.

Problem Definition

A number of models have been developed for ABSA, but there are two different subtasks, namely aspect-category sentiment analysis (ACSA) and aspect-term sentiment analysis (ATSAs).

- ACSA is to predict the sentiment polarity with regard to the given aspect, which is one of a few predefined categories and may not show in the text.
- ATSAs is to identify the sentiment polarity concerning the target entities that appear in the text instead, which could be a multi-word phrase or a single word.

For example, “average to good Thai food, but terrible delivery.”

- ACSA: <service, ?>  ->  negative
- ATSAs: <Thai food, ?>  ->  positive

Models

Our model Gated Convolutional network with Aspect-based Sentiment Analysis (GCAE) is built on convolutional layers and gating units. The model has two convolutional layers on the top of the embedding layer, whose outputs are combined by novel gating units. Convolutional layers with multiple filters can efficiently extract n-gram features at many granularities on each receptive field. The proposed Gated Tanh-ReLU Units (GTRU) have two nonlinear gates, each of which is connected to one convolutional layer. The convolutional features \(a_i\) receive additional aspect information \(a_a\) with ReLU function; while the other features \(s_j\) are responsible for extracting sentiment features. The gate outputs are then multiplied. GTRU can selectively extract aspect-specific sentiment information for sentiment prediction.

For ATSAs task, where the aspect terms consist of multiple words, we extend our model to include another convolutional layer for the target expressions.

Since each component of the proposed model could be easily parallelized, it has much less training time than the models based on LSTM and attention mechanisms.

In the above equations, \(X\) is the feature matrix of the given sentence. \(\mathbf{w}_s\) is the embedding vector of the given aspect word. \(\mathbf{W}, \mathbf{V}, \text{ and } b\) are the parameters.

Experiments

We conduct experiments on public datasets from SemEval\(^6\) workshops. The sentences which have different sentiment labels for different aspects or targets in the sentence are more common in review data than in standard sentiment classification benchmark. Therefore, to access how the models perform on review sentences more accurately, we create small but difficult datasets, which are made up of the sentences only having one or different sentiments on different aspects/targets. For example,

- Average to good Thai food, but terrible delivery.
  - food  ->  positive
  - Average to good Thai food, but terrible delivery.
  - delivery  ->  negative

We use restaurant review data from SemEval 2014 Task 4. There are 5 aspects: food, price, service, ambience, and misc; 4 sentiment polarities: positive, negative, neutral, and conflict. By merging restaurant reviews of three years 2014 - 2016, we obtain a larger dataset called “Restaurant-Large”.

We compare our model with ATAE-LSTM\(^5\), TD-LSTM\(^5\), JAN\(^5\), RAM\(^5\), and SVM from SemEval report\(^6\) which uses six additional sentiment lexicons.

Conclusions

In this paper, we proposed an efficient convolutional neural network with gating mechanisms for ACSA and ATSAs tasks. GTRU can effectively control the sentiment flow according to the given aspect/target information, and two convolutional layers model the aspect and sentiment information separately.

We prove the performance improvement compared with other neural models by extensive experiments on SemEval datasets. How to leverage large-scale sentiment lexicons in neural networks would be our future work.

References

1. Yeqian Wang, Minyi Huang, Xianzhi Ju, and Ji Zhao. 2018. Attention-Based LSTM for Aspect-Level Sentiment Classification. In EMNLP, pages 808-818.

Contact

Wei Xue
Florida International University, Miami, FL, USA
Email: wxue004@cs.fiu.edu

Addenda

1. We define sentiment analysis as the process of determining the attitude expressed in a piece of text. This can include identifying positive, negative, or neutral sentiments.
2. We use the term aspect to refer to a specific topic or feature of a product or service, such as food, price, or service.
3. We use the term target to refer to the specific aspect or feature that is being evaluated.
4. We use the term sentence to refer to a complete statement or group of statements that convey a specific sentiment.
5. We use the term aspect-based sentiment analysis to refer to the process of analyzing the sentiment of a sentence with respect to a specific aspect or target.
6. We use the term aspect-category sentiment analysis (ACSA) to refer to the process of analyzing the sentiment of a sentence with respect to a specific category of aspects.
7. We use the term aspect-term sentiment analysis (ATSAs) to refer to the process of analyzing the sentiment of a sentence with respect to a specific term of an aspect.

For more information, please visit our website: [Aspect Based Sentiment Analysis with Gated Convolutional Networks](https://example.com).