Aspect Based Sentiment Analysis with Gated Convolutional Networks

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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 (ATSA).

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 (ATSA).

- 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.
- ATSA 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."*

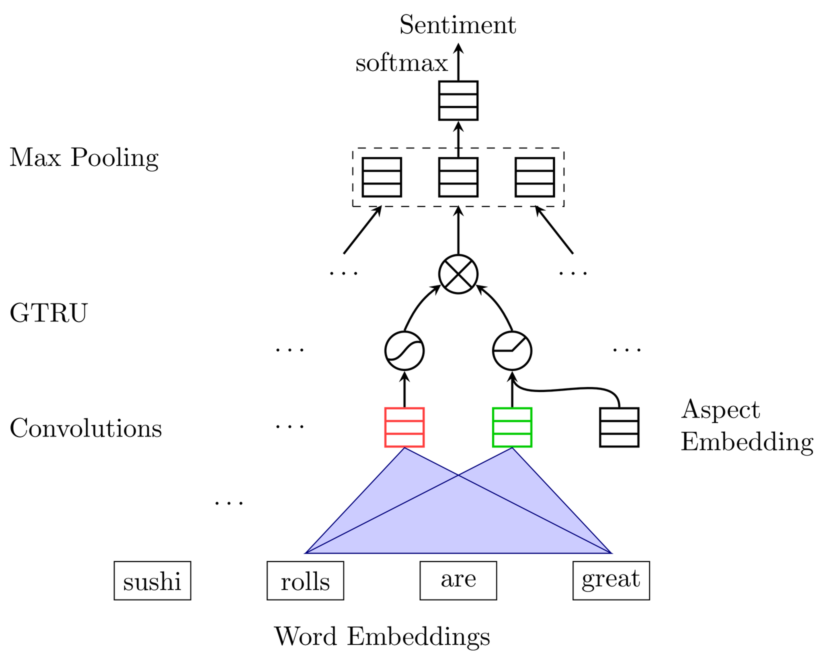
- ACSA: <service, ?> -> negative
- ATSA: <Thai food, ?> -> positive

Models

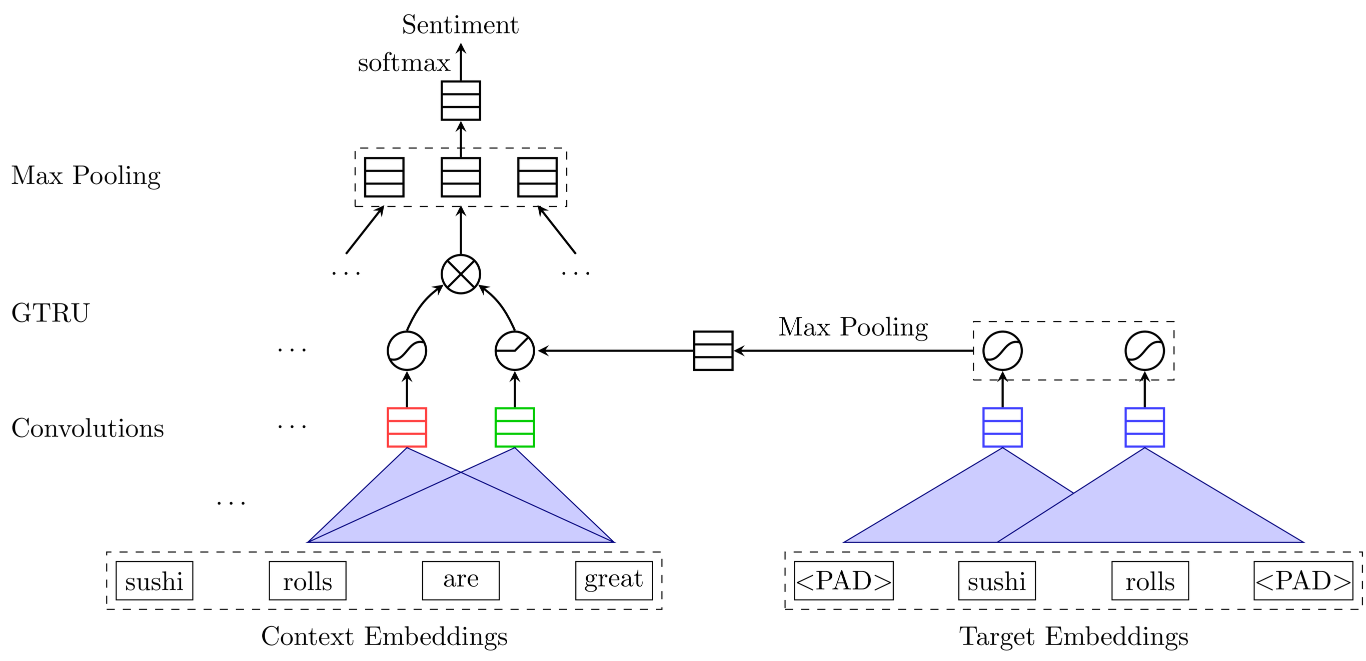
Our model Gated Convolutional network with Aspect Embedding (**GCAE**) is built on **convolutional layers** and **gating units**. The model has two convolutional layers on the top of the embedding layer, whose outputs are combined by novel gating units. Convolutional layers with multiple filters can 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 $\boldsymbol{v}_a$ with ReLU function; while the other features s_i are responsible for extracting sentiment features. The gate outputs are then multiplied. GTRU can selectively extract aspect-specific sentiment information for sentiment prediction.

Models



GCAE for ACSA task



GCAE for ATSA task

$$a_i = \mathrm{relu}(\mathbf{X}_{i:i+k} * \mathbf{W}_a + \mathbf{V}_a \boldsymbol{v}_a + b_a)$$
$$s_i = \tanh(\mathbf{X}_{i:i+k} * \mathbf{W}_s + b_s)$$
$$c_i = s_i \times a_i$$

Gated Tanh-ReLU Units (GTRU)

For ATSA 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, $\mathbf{X}$ is the feature matrix of the given sentence. $\boldsymbol{v}_a$ is the embedding vector of the given aspect word. $\mathbf{W}$, $\mathbf{V}$, and b are the parameters.

Model	ATSA
ATAE	25.28
IAN	82.87
RAM	64.16
TD-LSTM	19.39
GCAE	3.33

The time to converge in seconds on ATSA task. All models are implemented in PyTorch and executed with a 1080Ti GPU.

Models	Restaurant-Large		Restaurant 2014	
	Test	Hard Test	Test	Hard Test
SVM*	-	-	75.32	-
SVM + lexicons*	-	-	**82.93**	-
ATAE-LSTM	83.91±0.49	66.32±2.28	78.29±0.68	45.62±0.90
CNN	84.28±0.15	50.43±0.38	79.47±0.32	44.94±0.01
GCN	84.48±0.06	50.08±0.31	**79.67±0.35**	44.49±1.52
GCAE	**85.92±0.27**	**70.75±1.19**	79.35±0.34	**50.55±1.83**

The accuracy of all models on ACSA task. Each experiment is repeated for five times.

Experiments

We conduct experiments on public datasets from SemEval[5] 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 opposite 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 of 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[1], TD-LSTM[2],IAN[3], RAM[4], and SVM from SemEval report[5] which uses six additional sentiment lexicons.

Models	Restaurant		Laptop	
	Test	Hard Test	Test	Hard Test
SVM*	77.13	-	63.61	-
SVM + lexicons*	**80.16**	-	**70.49**	-
TD-LSTM	73.44±1.17	56.48±2.46	62.23±0.92	46.11±1.89
ATAE-LSTM	73.74±3.01	50.98±2.27	64.38±4.52	40.39±1.30
IAN	76.34±0.27	55.16±1.97	68.49±0.57	44.51±0.48
RAM	76.97±0.64	55.85±1.60	68.48±0.85	45.37±2.03
GCAE	**77.28±0.32**	**56.73±0.56**	**69.14±0.32**	**47.06±2.45**

The accuracy of all models on ATSA subtask.

Conclusions

In this paper, we proposed an efficient convolutional neural network with gating mechanisms for ACSA and ATSA 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.

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