Title	Text Generation Model Enhanced with Semantic Information in Aspect Category Sentiment Analysis
Author(s)	Tran, Tu Dinh
Citation	
Issue Date	2023-09
Type	Thesis or Dissertation
Text version	author
URL	http://hdl.handle.net/10119/18748
Rights	
Description	Supervisor:白井 清昭, 先端科学技術研究科, 修士(情報科学)

Text Generation Model Enhanced with Semantic Information in Aspect Category Sentiment Analysis

2110422 TRAN, Tu Dinh

Sentiment Analysis (SA) is a task of identifying opinions expressed in a piece of text, especially in order to determine whether the writer's attitude toward a particular topic or product is positive, negative, or neutral. Although SA is performed on various types of texts such as a document and a sentence, recently, people have paid more attention to aspect-level sentiment analysis. Aspect Category Sentiment Analysis (ACSA), which is one of the main subtasks of Aspect-based Sentiment Analysis, intends to detect the polarity of the conveying emotions on the aspect within the input text. It is helpful to understand the writer's opinions in detail especially when a review sentence contains multiple aspects with different polarity.

The typical approaches solve ACSA as a text classification task. They concentrate on improving the quality of the representation of contextual information by using better language models and extracting selectively aspect-related information with attention mechanism. However, some previous studies point out that fine-tuning language models for text classification is not effective since the majority of language models are pre-trained on text generation tasks. Therefore, a method called "BART generation" is proposed to solve ACSA as the text generation task, which is based on the outstanding language model called Bidirectional and Auto-Regressive Transformers (BART). This model accepts review sentences as input and generates target sentences that clearly express the polarity toward a given aspect. The target sentence is yielded by filling an aspect category and sentiment word into a predefined template. It outperformed the other classification models for ACSA. However, BART generation faces difficulty in capturing relations between opinion words and aspect words as well as extracting aspect-related information in sentences containing multiple aspects.

To solve these problems, the goal of this study is to propose a method that leverages Abstract Meaning Representation (AMR) for capturing relations between opinion words and aspect words as well as enhancing the aspect-related information extraction within the BART generation method. AMR is the semantic representation that expresses the meaning of a sentence as a rooted, directed, and labeled graph. AMR can provide a better way to model word relations that are difficult to extract within a sentence. Besides, since AMR assigns the same graph for multiple sentences with the same meaning, it can help to alleviate data sparsity in ACSA. To encode the AMR graph, Graph Attention Networks (GAT) is used to obtain the embedding of nodes, which is updated by applying the attention mechanism. A new Cross-Attention module for AMR is added in each decoder layer to incorporate the semantic information in the AMR graph into our text decoding phase. In this study, the pre-trained AMRBART is used as the AMR parser to obtain the AMR graph for the given review sentence. To calculate the attention to the AMR, the nodes in the AMR graph and the words in the sentence should be aligned. This alignment is determined by the pre-trained AMR aligner LEAMR.

Furthermore, two new regularizers are introduced to improve the allocation of Cross-Attention weights over the AMR graph. The first one is the identical regularizer, which compels the Cross-Attention weights of AMR nodes and the Cross-Attention weights of their aligned words in the review sentence to be equal as much as possible. The second is the entropy regularizer, which enables the model to only pay attention to a few AMR-related nodes. With the new regularizers, we expect to help the model correctly extract aspect-related information from the AMR graph

Since our model follows BART generation, it is based on the Transformer framework with a stack of encoder-decoder layers whose parameters are initialized by the pre-trained language model BART. However, the parameters of the newly introduced GAT module and AMR Cross-Attention layers should be initialized randomly. In practice, we find it challenging to fine-tune our model consisting of the modules initialized by the different ways. Therefore, we propose to pre-train the whole model again using in-domain texts. The pre-training is done by text-denoising task that is used for the pre-training of BART. That is, our model is pre-trained to reconstruct a complete review sentence from a corrupted sentence that is created by applying token masking, text infilling, and text deletion.

We evaluate the performance of our model on three datasets: Rest14, Rest14-hard, and MAMS. Rest14 is a dataset of restaurant reviews, where the most of reviews have only one aspect. Rest14-hard is a modified version of the Rest14 dataset that only includes sentences with multiple aspects in the test set. The training and development sets are the same as the original Rest14 dataset. Since the test set of Rest14-hard is small, we also adopt MAMS where all sentences in the training, development, and test sets contain multiple aspects. For each dataset, the proposed model is trained and evaluated five times with different random initialization of the parameters. In terms of evaluation metric, we utilize mean accuracy together with standard deviation which is denoted as "mean$\pm$(std)".

Our model achieves $91.2 \pm (0.258)$, $78.1 \pm (0.258)$, and $84.6 \pm (0.453)$, which outperforms the state-of-the-art method (BART generation) by 0.7, 0.7, 1.5 percentage points on Rest14, Rest14-hard, and MAMS, respectively.

These results prove the effectiveness of incorporating the semantic information from AMR into the text generation model. In addition, the large improvement in MAMS proves that our regularizers can help the model to extract useful aspect-related information more appropriately even when there are multiple aspects in a sentence.

The ablation study is conducted to fully investigate the effect of each module within our model. We remove the identical regularizer, the entropy regularizer, both regularizers or pre-training procedure, then train the models. Compared to the full model, the accuracy scores of all ablated models are degraded. It means that each component plays an important role in the overall performance of our model. Additionally, we visualize the attention scores of AMR Cross-Attention layers in our full model and the model without both regularizers for a few sentences. It shows that our regularizers successfully increase the attention weights over important nodes. Furthermore, we conduct error analysis. The results indicate that our model faces obstacles in extracting aspect-related information for coarse-grained aspects like “miscellaneous”.

Despite the promising results, our model still has some problems. The main challenge is to alleviate the gap between the pre-trained language model and the new components that are added to incorporate semantic information from AMR. Although the pre-training using in-domain texts is applied to tackle this problem, it seems insufficient. Further studies should concentrate on overcoming this limitation to achieve stable performance. In addition, the potential of our approach to incorporate semantic information given by AMR into the deep learning model should be further investigated. That is, we will evaluate the performance of our model in other subtasks of sentiment analysis such as Aspect Category Detection or Aspect-based Sentiment Analysis.