B.Comp. Dissertation

A BERT-Based Framework for Targeted Sentiment Analysis

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Abstract

Sentiment Analysis In the report, we distinguish the differences between the general sentiment analysis and Targeted Sentiment Analysis. Future more, we analyze the existing problems of Targeted Sentiment Analysis. To address these problems, we proposed a new BERT-based framework to solve the targeted sentiment analysis problem. Based on the framework, we introduce some auxiliary training methods to improve the accuracy of the results. To illustrate the existing methods' robustness problem toward new unseen targets, we introduce a new data set setting, which explicitly make the targets in the training set and test set to be different. Then, we use the adversarial training methods to enhance the robustness of our framework training. Overall, our framework behave better than the state of the art in the traditional targeted sentiment analysis setting and showed robustness in the new re-split data set setting.Finally, we describe the future work in targeted sentiment analysis.

Subject Descriptors:
C5 Computer System Implementation
G2.2 Graph Algorithms

Keywords:
Targeted Sentiment Analysis, robustness, BERT, adversarial training, auxiliary training

Implementation Software and Hardware:
Python, Pytorch, RTX 2080TI

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Chapter 1

Introduction

The sentiment analysis is a specific task under the text classification.

Many problems exist in computer science. In this project, we studied one particular important problem and propose a solution for it.

1.1 Background

In this section, we briefly discuss the history and background of the targeted sentiment analysis problem. A detail literature survey is presented in Chapter 2.

The sentiment analysis was proposed The problem we study in this report is an important one. This problem is first proposed in 1990 in the context of graph theory (smith90graph). Zhang gives thec first algorithm to the problem and applied it to solve several problems in artificial intelligence (zhang91aizhang92ai). More recently, a slightly different formulation of the problem is studied independently (kovsky92diffali94diff). None of this previous work uses the technique that we propose in this project. Thus, we believe that our algorithm is novel.

1.2 The Problem

In this section, we formally defined the problem. We adopt the definition given by Kovsky (kovsky92diff).

1.3 Our Solution

1.4 Report Organization

Chapter 2

Related Work

2.1 Text classification

2.2 Aspect Based Sentiment Analysis

2.3 Pre-trained models

Chapter 3

Problem and Algorithm

3.1 Formal Description of Problem

Given a text sequence with n words text=$\{w_1, w_2, w_3, w_4, ..., w_n\}$ and a target with m words, target text= $\{t_1, t_2, t_m\}$ with its begin position b, the problem is to classify the sentiment polarity $polarity = \{positive, neutral, negative\}$ towards the given target in the context. We followed the SemEval 2014 Task 4(Pontiki, Galanis, Pavlopoulos, Papageorgiou, Androutsopoulos, & Manandhar, 2014)

3.2 Design of Algorithm

3.3 A general framework for Targeted Sentiment Analysis(TSA)

3.3.1 BERT for text classification

As a powerful pre-trained universal language model, BERT can be used in various downstream tasks. To utilize bert, we have several direct ways:

1. Using BERT embeddings as the input of sequence
2. Fine-tuned BERT by [CLS] classification token.

To enhance the performance, (sun2019finetune) have several methods for text classification:

Trick for text classification

1. Various fine tuning methods

    (a) Within-task pre-training

    (b) In-domain pre-training

    (c) Cross-domain pre-training

2. Different learning rates are used for different layers of Bert

Those methods only consider the sentence-level classification. For TSA, the classification problem is more fine-grained, hence we will introduce our BERT-based framework for TSA.

BERT for TSA

As described in the related work, BERT-SPC (Song, Wang, Jiang, Liu, & Rao, 2019) repeat the target words at the end of context sentence.

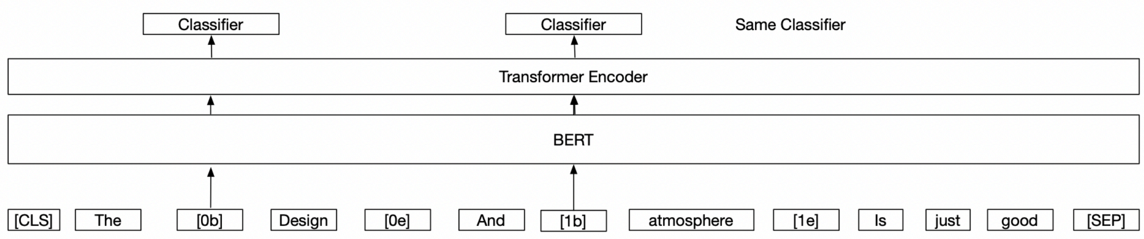

Figure 3.1: Our framework for TSA

For original bert, the most direct way to utilize bert

As show in the image 3.1, we add the begin token and end token around the target. In our initial experiments, we add the same token for different targets in the context sentence. However,

3.4 Auxiliary training methods for TSA

3.5 Adversarial training methods for Robustness of TSA

Chapter 4

Evaluation

4.1 Implementation Details

Our experiment is based on the code of ABSA-Pytorch. We release our code in TSA-Pytorch.

4.2 Experimental Setup

4.2.1 Targeted Sentiment Analysis

4.2.2 Domain Adaption' effect on Targeted Sentiment Analysis

4.2.3 Robustness of Targeted Sentiment Analysis Algorithms

4.3 Visualization

4.3.1 Pre-trained BERT Visualization

4.3.2 Fine-tuned BERT Visualization

4.3.3 Conclusion from Visualization

4.4 Results

Table 4.1: Test results on three typical data sets.

	Models	Twitter		Restaurant		Laptop	
		Accuracy	Macro-F1	Accuracy	Macro-F1	Accuracy	Macro-F1
RNN baselines	TD-LSTM	0.7080	0.6900	0.7563	-	0.6813	-
	ATAE-LSTM	-	-	0.7720	-	0.6870	-
	IAN	-	-	0.7860	-	0.7210	-
	RAM	0.6936	0.6730	0.8023	0.7080	**0.7449**	**0.7135**
Non-RNN baselines	Feature-based SVM	0.6340	0.6330	0.8016	-	0.7049	-
	Rec-NN	0.6630	0.6590	-	-	-	-
	MemNet	0.6850	0.6691	0.7816	0.6583	0.7033	0.6409
AEN-GloVe ablations	AEN-GloVe w/o PCT	0.7066	0.6907	0.8017	0.7050	0.7272	0.6750
	AEN-GloVe w/o MHA	0.7124	0.6953	0.7919	0.7028	0.7178	0.6650
	AEN-GloVe w/o LSR	0.7080	0.6920	0.8000	0.7108	0.7288	0.6869
	AEN-GloVe-BiLSTM	0.7210	**0.7042**	0.7973	0.7037	0.7312	0.6980
Ours	AEN-GloVe	**0.7283**	0.6981	**0.8098**	**0.7214**	0.7351	0.6904
	BERT-SPC	**0.7355**	**0.7214**	**0.8446**	**0.7698**	**0.7899**	**0.7503**
	AEN-BERT	**0.7471**	**0.7313**	**0.8312**	**0.7376**	**0.7993**	**0.7631**

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Chapter 5

Conclusion

In our work,

5.1 Contributions

5.2 Future Work

5.2.1 Domain adaptation for BERT(Post-training BERT)

The post-training bert can achieve better in the specific domain's sentiment analysis. In p

5.2.2 Self-Supervised BERT training methods

References

Pontiki, M., Galanis, D., Pavlopoulos, J., Papageorgiou, H., Androutsopoulos, I., & Manandhar, S. (2014). SemEval-2014 task 4: Aspect based sentiment analysis. *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014)* (pp. 27–35), Dublin, Ireland, August, 2014: Association for Computational Linguistics.

Song, Y., Wang, J., Jiang, T., Liu, Z., & Rao, Y. (2019). Targeted sentiment classification with attentional encoder network. *Lecture Notes in Computer Science*, , 2019, 93–103.

Appendix A

Code

Appendix B

Proofs

In this appendix, we present alternate, longer, but more interesting proof of correctness of our algorithm. This proof is based on induction and proof by contradiction.