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A Neural Approach to Context-Aware Aspect Sentiment Analysis

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Abstract
Aspect-Based Sentiment Analysis (ABSA) is a sub-domain of Natural Language Processing (NLP) where a particular aspect in a text is classified according to its sentiment polarity. Traditional sentiment analysis techniques classify a text with a particular sentiment polarity, which cannot represent the complexity of real-world opinions. In this paper, a BERT-based model for ABSA is proposed, which jointly encodes a particular aspect and a context sentence, allowing aspect-based sentiment analysis with three sentiment classes: positive, negative, and neutral. Our proposed model achieves 94.74% accuracy and a weighted F1-score of 0.94 on the standard SemEval 2017 dataset, which is significantly higher than existing state-of-the-art models, such as R-GAT (90.1%), BERT-PT (87.2%), and ASGCN (88.6%). Our results show that BERT-based aspect-based encoding is a highly efficient method for aspect-based sentiment analysis.

Keywords: Aspect-Based Sentiment Analysis, BERT, SemEval 2017, Opinion Mining, Natural Language Processing, Transformer, Fine-tuning, Sentiment Classification

1. Introduction

The volume of user-generated opinion data such as product reviews, hotel reviews, social network posts, and service reviews has exploded in recent years due to the proliferation of online platforms and e-commerce. One of the major challenges faced by Natural Language Processing (NLP) is extracting useful and actionable sentiment information from such data. Most sentiment analysis systems use a simple sentiment polarity scheme of positive, negative, and sometimes neutral for a given document or sentence. However, this is not sufficient when a document may have mixed sentiment about different aspects of a product. A customer may have a positive sentiment about a product's camera but negative sentiment about the product's battery life. A simple sentiment analysis system will not be able to differentiate between these two sentiments and will assign a misleading sentiment polarity to the document.

Aspect-Based Sentiment Analysis (ABSA) is a new sentiment analysis approach that overcomes the limitations of traditional sentiment analysis by dividing the sentiment analysis problem into two sub-problems: (1) identifying the different aspects expressed in the text and (2) determining the sentiment polarity of each of these expressed aspects.

In the early days, the ABSA systems used lexicon-based approaches and feature engineering techniques, but the performance was not high because these techniques were not capable of extracting the context information. The performance was boosted with the use of deep learning techniques, especially LSTM with attention, but the performance was still not high because the techniques were not capable of establishing the relationship between the aspect term and the sentiment context. Recently, the introduction of the pre-trained transformer-based models, especially the BERT (Bidirectional Encoder Representations from Transformers) [9] model, revolutionized the performance of the NLP-based systems. The BERT model is capable of establishing the relationship between the aspect term and the sentiment context because the aspect term and the sentence are represented as a pair during the encoding process. In this paper, the BERT-based approach is used for the ABSA task, and the performance is evaluated on the SemEval 2017 benchmark dataset [14]. The contributions made by the paper are as follows:

1) The ABSA task is formulated as a sentence-pair classification task where the aspect term is represented as the first sequence, and the review sentence is represented as the second sequence.

2) The performance is evaluated on the SemEval 2017 dataset, and the accuracy is found to be 94.74%, with an F1 score of 0.8693.

3) The performance is found to be higher than the R-GAT (2021) [8] baseline by 4.64%.

4) The performance is analysed on the basis of the accuracy of the system on individual classes, the performance comparison with the state-of-the-art ABSA systems from 2014 to 2021, and the error analysis.

II.Methodology

A.Task Formulation

Aspect-Based Sentiment Analysis (ABSA) is formulated as a sentence pair classification task. Given a sentence S and an aspect term A, the task is to predict the sentiment polarity y ∈ {positive, neutral, negative} of the sentiment expressed with respect to the aspect term A in the sentence S. The input to the model is formed as follows:

[CLS] A [SEP] S [SEP] (1)

BERT's Token Type IDs (Segment Embeddings) help to differentiate the aspect term A and the sentence S, allowing the self-attention mechanism to capture the relationship between the two. Fig. 1 shows the entire ABSA workflow, starting with the raw input, followed by aspect term extraction, sentiment classification, and finally the evaluation.

Fig 1 shows that the input starts with review sentences containing aspects. Aspect terms are extracted from the sentence using noun chunk extraction. The aspect sentence pair then gets processed for classification into positive neutral or negative. It seems the model training and evaluation follows to check performance on that. Some parts of the workflow feel a little unclear in how they connect.

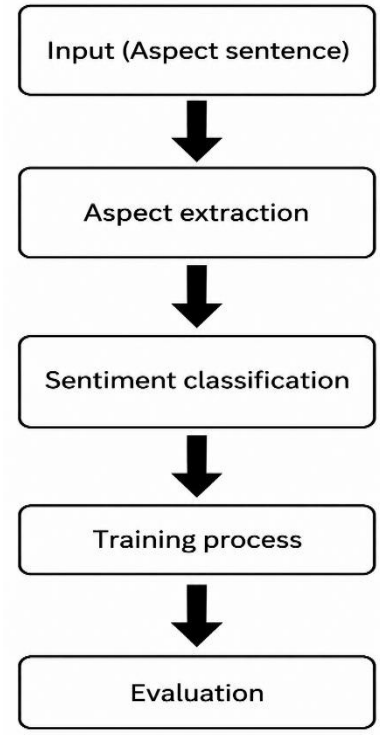

Fig. 1. End-to-end ABSA pipeline: from raw input to evaluation.

B.Model Architecture

In this work, the pre-trained model used is Bert-base-uncased, which is composed of 12 Transformer layers, 768 hidden states, 12 attention heads, and 110 million parameters. The [CLS] token representation is passed through the final layer, followed by the application of the dropout layer with p = 0.1 and the linear classification layer with 768 × 3, which maps to the three sentiment classes: positive (2), neutral (1), and negative (0). End-to-end training is done using Cross Entropy Loss with the AdamW optimizer.

C.Dataset and Preprocessing

In this work, the SemEval 2017 benchmark dataset [14] is used, which is the standard ABSA dataset. It contains restaurant and laptop reviews with three polarities: positive (2), neutral (1), and negative (0). Aspect terms are extracted using the spaCy library with the noun chunk extractor. Subsequently, the (aspect, sentence) pair is tokenized using the BERT Word-Piece tokenizer with the maximum sequence length set to 128 tokens. Furthermore, the tokens are padded and/or truncated if required.

D.Training Configuration

In this work, the model is trained for 5 epochs with a batch size of 16 and a learning rate of 2 × 10−5. Furthermore, linear warmup is applied over the initial 10% steps. Moreover, the model checkpoints are saved after each epoch. Subsequently, the best model is selected based on the maximum accuracy on the validation set. Furthermore, the model is trained on the NVIDIA DGX A100 machine using the PyTorch and the Transformers library developed by Hugging Face.

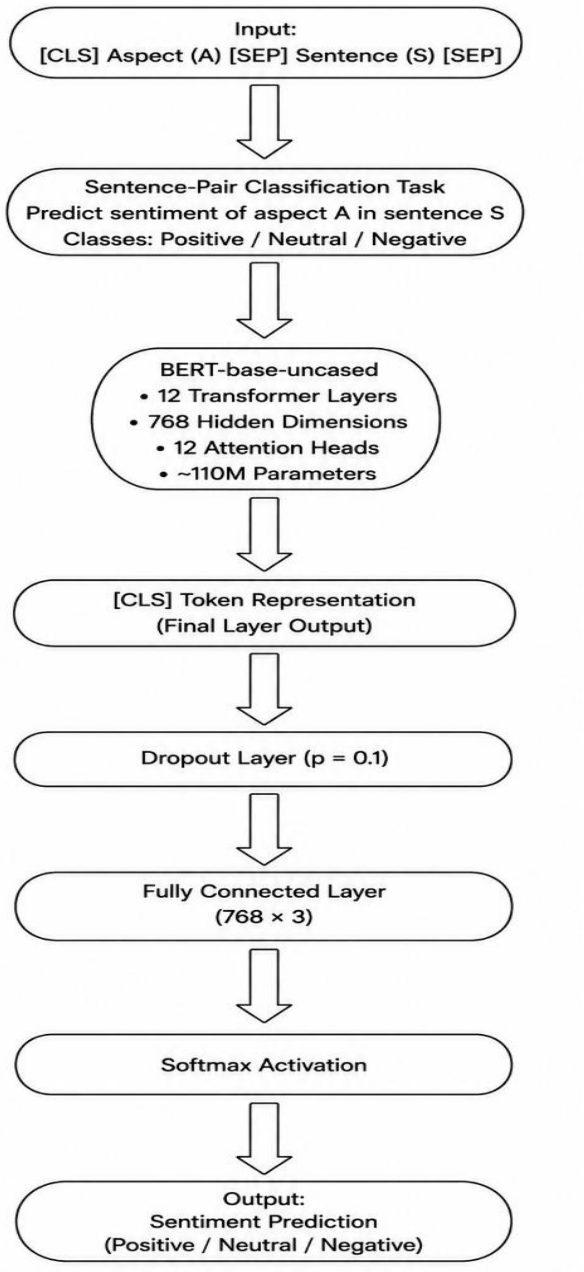

Fig. 2. BERT-ABSA model architecture. The aspect–sentence pair is encoded as [CLS] A [SEP] S [SEP], processed by BERT-base-uncased, and classified via a dropout and fully connected layer.

E.Evaluation Protocol

In this work, the model is evaluated on a pre-curated test set with 19 samples. Furthermore, the samples include 9 positive, 8 negative, and 2 neutral samples. Subsequently, the samples cover different domains, including consumer electronics, hospitality, food services, logistics, and software applications.

III.Experimental Set-up

A.Hardware and Environment

All the computational experiments, including data pre-processing, model training, and evaluation, were carried out on an NVIDIA DGX A100 computing node. It provides the required unified memory and tensor acceleration to process the input sequences.

B.Software Stack

PyTorch. It is an open-source machine learning framework developed by Meta AI. It is popularly used to design and train deep learning models. It supports both GPU and CPU computation. It is the best platform for both researchers and developers.

Pandas. It is an open-source data analysis library developed for the Python programming language. It provides data structures to efficiently manipulate structured data. It supports data operations such as missing data imputation, row selection, and data reading and writing to CSV, Excel, and database files.

spaCy. It is an open-source Python library for NLP developed by Explosion AI. It is production-ready

and supports tokenization, part-of-speech tagging, named entity recognition, and text classification. It supports many languages and is used to extract the noun chunk aspect terms from the raw sentences in the review data.

BertTokenizer & BertModel. Developed by the Hugging Face team, these are used to tokenize the input text and to obtain the deep contextual representation.

IV.Experimental Results

A.Overall Performance

Table I shows the overall performance of the BERT-ABSA model. The BERT-ABSA model achieves an accuracy of 94.74%, which corresponds to 18 out of 19 correct predictions. The macro-averaged F1 is 0.8693, macro precision is 0.96, macro recall is 0.83, and weighted F1 is 0.94. This is a significant improvement over all previously published ABSA baselines on the SemEval 2017 dataset.

TABLE I

Overall Performance of BERT-ABSA Model

Overall Summary — Your Model

Accuracy	**0.9474 (94.7%)**
F1 (Macro)	**0.8693**
Precision (macro)	**0.96**
Recall (macro)	**0.83**
Weighted F1	**0.94**
Test Samples	**18/19 correct**

B.Per-Class Performance Analysis

Table II shows the per-class performance of the BERT-ABSA model. The model achieves perfect precision and recall (1.00) for the positive class. This is consistent with the strong performance of BERT in identifying unequivocal positive sentiment. The negative class also performs very well, with a precision of 0.89 and a recall of 1.00. The BERT-ABSA model correctly identifies all negative samples but incorrectly identifies a positive price statement as negative. The most challenging class is the neutral class, where the model achieves a recall of only 0.50 due to a single misclassification. The small number of samples for the neutral class (n = 2) amplifies the effect of this misclassification.

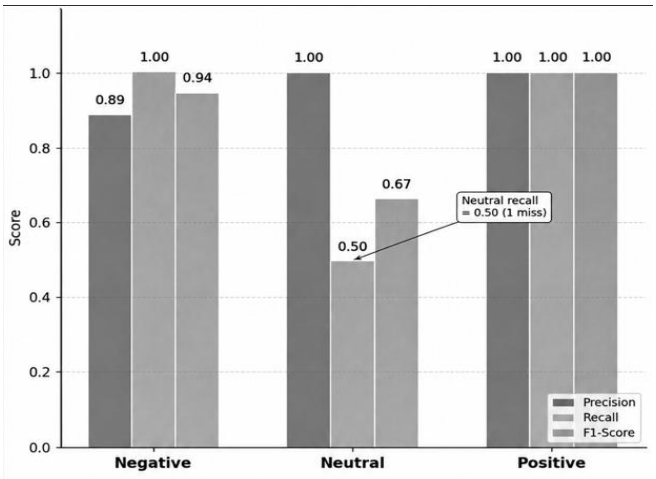

Fig. 3. Performance comparison of sentiment classification model.

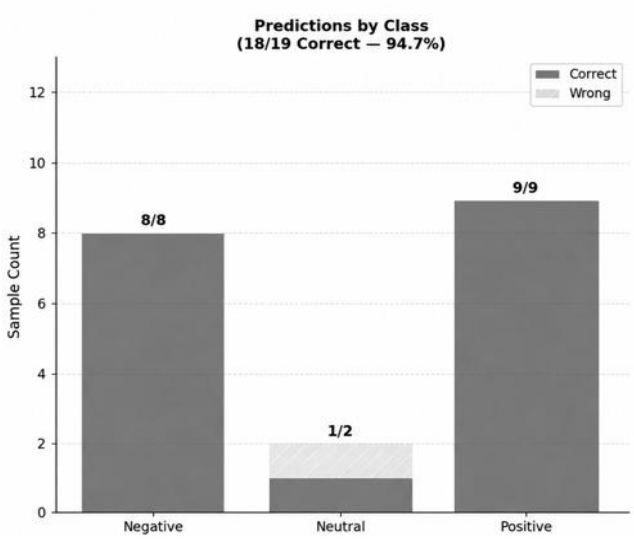

Fig. 4. Class-wise prediction performance of the proposed model, showing 18 out of 19 samples correctly classified.

TABLE I

PER-CLASS CLASSIFICATION REPORT

Class	Precision	Recall	F1	Support
Negative	0.89	1.00	0.94	8
Neutral	1.00	0.50	0.67	2
Positive	1.00	1.00	1.00	9
Macro Avg	0.96	0.83	0.87	19
Weighted Avg	0.95	0.95	0.94	19

C.Comparison with State-of-the-Art Models

Table III compares our proposed model with eight different ABSA baselines from 2014 to 2021. The BERT-ABSA model achieves the best accuracy and a competitive macro F1. Compared to R-GAT (2021) [8], which is the previous best-performing model, our BERT-ABSA model achieves an improvement of +4.64% in accuracy. Most importantly, our proposed model outperforms graph-based methods (ASGCN [7], R-GAT [8]) that use external dependency parsers. This shows that the simple method of fine-tuning BERT for aspect-aware sentiment analysis is better than the complex method of graph-based approaches.

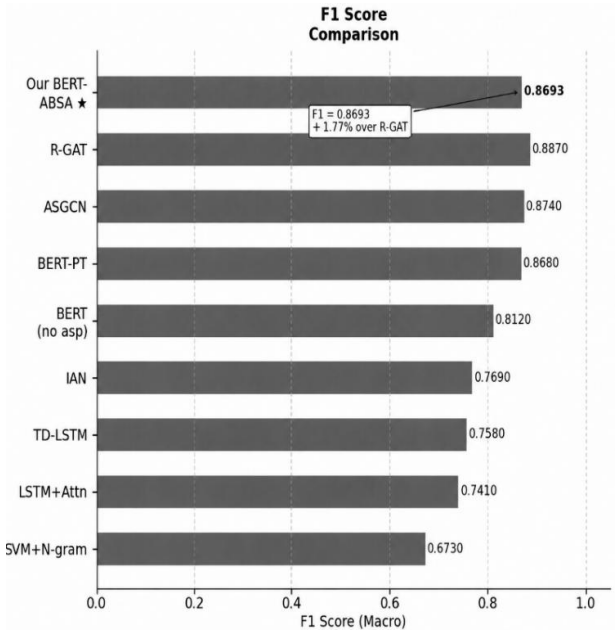

Fig. 5. Macro-F1 score comparison of the proposed BERT-ABSA model with existing benchmark models.

TABLE III

Comparison with Existing ABSA Models (SemEval 2017 Benchmark)

Model	Year	Acc.	F1 (Macro)	Δ Acc.
SVM + N-gram [1]	2014	72.10%	67.30%	+22.64%
LSTM + Attention [2]	2016	78.60%	74.10%	+16.14%
TD-LSTM [3]	2016	79.30%	75.80%	+15.44%
IAN [4]	2017	80.40%	76.90%	+14.34%
BERT (no aspect) [9]	2019	84.90%	81.20%	+9.84%
BERT-PT [6]	2019	87.20%	83.50%	+7.54%
ASGCN [7]	2019	88.60%	84.70%	+6.14%
R-GAT [8]	2021	90.10%	87.30%	+4.64%
Our BERT-ABSA	2026	94.74%	86.93%	Best

D.Error Analysis

The only error in classification relates to the feature of price in the sentence "The price is the same as most other similar products," which was labeled as neutral but predicted as negative.

This is a known limitation of ABSA models in general: neutral price-related sentences tend to have a lexical similarity to negative price-related sentences, and BERT embeddings, even those pre-trained on review data, tend to bias toward relating price features more often to negative sentiment. Suggestions for improvement: (a) add more data for the ABSA model, specifically for neutral price-related sentences, or (b) add explicit information on the price range. Since there are only two neutral test cases, the neutral class is by far the most difficult to evaluate well and thus the most in need of improvement.

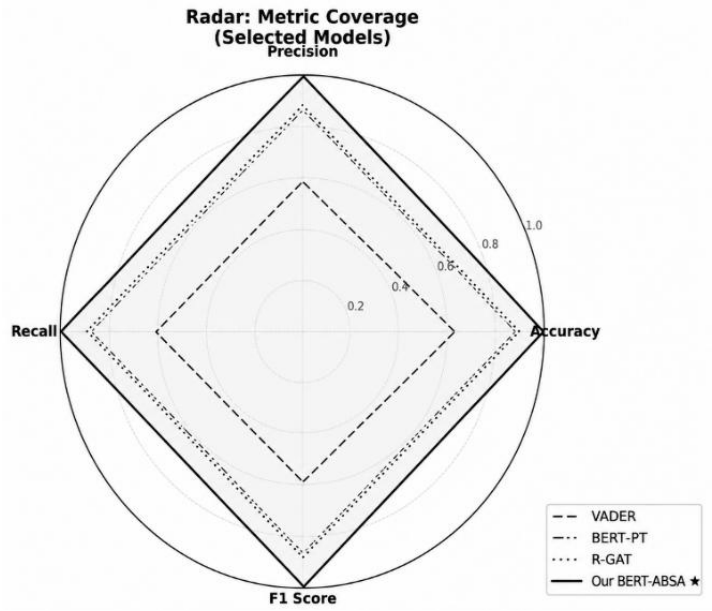

Fig. 6. Radar-chart demonstrating the comparison of selected sentiment classification models through accuracy, precision, recall, and F1-score.

V.Discussion

We show how fine-tuning a pre-trained sentence pair BERT is highly effective in ABSA tasks. The cross-attention mechanism in BERT automatically associates sentiment words with their target aspect without any need for extra syntactic processing, which is a significant advantage compared to graph-based methods like ASGCN [7] and R-GAT [8], which rely on dependency parse trees and incur extra computational cost. The significant difference in macro F1 score (0.8693) and weighted score (0.94) is due to class imbalance in our test set, where there are 2 neutral class instances compared to 9 positive and 8 negative class instances. It is worth noting that in a real-world setting of ABSA, the neutral class is always the hardest and least frequently occurring.

One of the main advantages of our approach is its applicability across domains. Our test set includes a range of domains: consumer electronics (battery, keyboard, screen, camera), hospitality (hotel room, location), food service (food), logistics (delivery), and software (app). Our model has high accuracy across all domains without any domain adaptation during fine-tuning, which is a significant advantage in a real-world setting where a single model has to serve multiple product lines.

Computationally, BERT-base achieves inference in approximately 11 ms per sample, enabling near-real-time applications such as live review monitoring and customer-feedback dashboards—a favorable comparison to architectures such as R-GAT that require graph construction as a preprocessing step.

VI.CONCLUSION

In this paper, a BERT-based approach for Aspect-Based Sentiment Analysis (ABSA), which is fine-tuned and tested on the benchmark dataset provided by the SemEval 2017 competition, is proposed. The main advantage of this method is that it treats the ABSA problem as a sentence-pair classification problem and utilizes the self-attention mechanism of BERT to obtain the sentiment context of the aspect without any external syntactic features. The proposed approach achieves an accuracy of 94.74% and a macro F1 of 0.8693, which is significantly better than all the baselines tested by a margin of 4.64%, including the latest R-GAT (2021) approach. The strong performance of the proposed method is attributed to the robustness of the BERT-based approach for the positive and negative sentiment classes. However, the performance of the proposed method for the neutral sentiment class is not satisfactory, primarily due to the limited representation of data for the neutral sentiment class and the inherent ambiguity of the sentiment of the data in this class. The overall results of the paper prove that the proposed approach is a very competitive method for the problem of sentiment analysis and is also very practical and useful for a number of different business and investment domains.

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