Instruct-DeBERTa: A Hybrid Approach for Enhanced Aspect-Based Sentiment Analysis with Category Extraction

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Abstract

Aspect-based sentiment Analysis (ABSA) is an advanced NLP task that identifies sentiments related to specific aspects of a product or service, offering more detailed consumer insights than general sentiment analysis. The proposed research introduces a hybrid model, `Instruct-DeBERTa`, which combines `InstructABSA` for aspect term extraction (ATE) and `DeBERTa-V3-baseabsa-V1` for aspect sentiment classification (ASC). Using datasets from SemEval Restaurant 2014,2015,2016 and SemEval Laptop 2014, the model demonstrated improved performance across domains. Further enhancements included category classification using cosine similarity, linear layers with ReLU activation, regularization methods, and optimized attention heads for the hospitality domain. These improvements address existing model limitations, providing a comprehensive solution for analyzing consumer feedback, valuable for enhancing customer satisfaction and product development.

1 Introduction

Aspect-based sentiment Analysis (ABSA) extracts opinions on specific product or service aspects, offering deeper insights than traditional sentiment analysis, which focuses on overall sentiment (Mudalige et al., 2020; Rajapaksha et al., 2020, 2021). Early lexicon-based methods struggled with context, while machine learning required manual feature extraction. Deep learning models like RNNs and LSTMs improved ABSA with auto-feature learning (Jayasinghe et al., 2021; Rajapaksha et al., 2022; Samarawickrama et al., 2022) but had difficulty with complex syntax. Transformer models, especially BERT, revolutionized ABSA by using attention mechanisms for better contextual understanding, greatly improving aspect extraction and sentiment classification. Variants like `RoBERTa` and `DeBERTa` have further enhanced performance. In this paper, we introduce a novel model named `Instruct-DeBERTa` and apply several enhancements to improve its performance, achieving state-of-the-art results for the joint task of Aspect Term Extraction (ATE) and Aspect Sentiment Classification (ASC) on SemEval datasets. Experiments conducted using datasets extracted from the SemEval 2014-2016 restaurant reviews (Res-14, Res-15, Res-16), and the SemEval 2014 laptop dataset (Lap-14) demonstrate the remarkable performance of `Instruct-DeBERTa` in the field of accurately detecting aspects and sentiment classification.

2 Methodology

In this study, we developed an aspect-based sentiment analysis pipeline utilizing transformer-based models to automatically extract aspects and analyze sentiments in textual data. The pipeline is composed of two primary stages: aspect extraction and sentiment classification. For these two stages, we utilized the best models for each task that we found through our thorough literature review. `Instruct-DeBERTa` fuses the current state-of-the-art `InstructABSA` developed by Scaria et al. (2024) for ATE and `DeBERTa-V3-baseabsa-V1` by Yang et al. (2023) for ASC into one single unified model for doing the joint task of ATE and ASC.

Next the performance of the `Instruct-DeBERTa` model was optimized for Aspect-Based Sentiment Analysis (ABSA) in the hospitality domain using datasets Res-14, Res-15, and Res-16. A new mechanism for category classification was introduced, leveraging a cosine similarity-based methodology to categorize aspect terms into predefined categories without explicit training on categorized datasets. The visualization of relationships between aspects and categories was done using t-SNE and Voronoi diagrams.

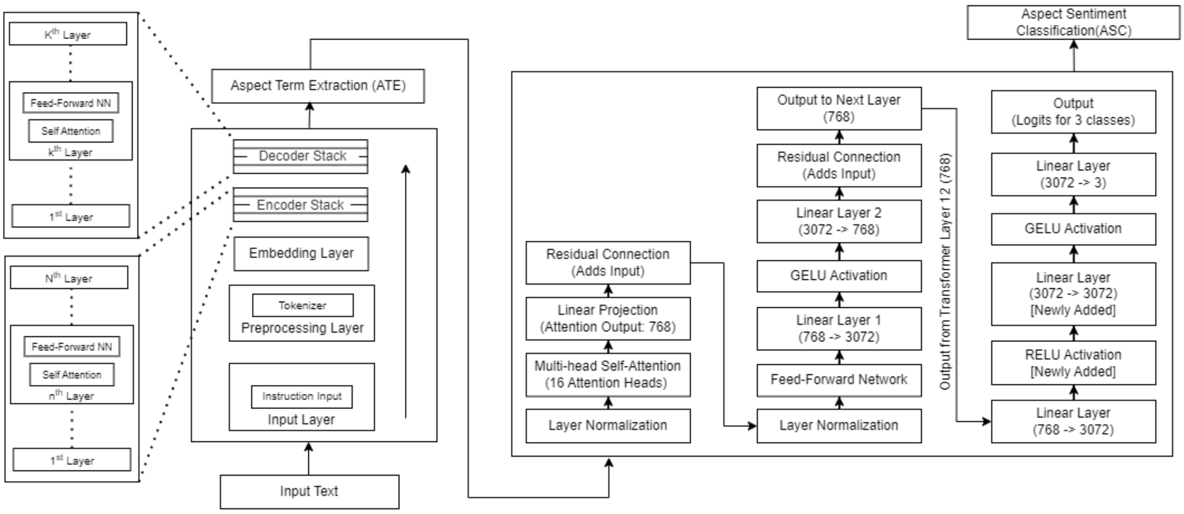

Figure 1: Complete Structure of the final improved version of `Instruct-DeBERTa`

Model	F1 Score (%)					
	Res-14		Res-15		Res-16	
	ATE	ASC	ATE	ASC	ATE	ASC
InstructABSA (Scaria et al., 2024)	92.10	–	76.64	–	80.32	–
DeBERTa-V3-base-absa-v1.1 (Yang et al., 2023, 2021)*	–	90.94	–	89.55	–	83.71
DeBERTa-V3-base-absa-v1.1-Improved version	–	**91.62**	–	**86.79**	–	**85.88**
Instruct-DeBERTa (Single task)*	91.39	88.63	75.13	81.26	77.79	79.35
Instruct-DeBERTa-Improved version (Single task)	**91.39**	**89.22**	**75.13**	**81.14**	**77.79**	**80.61**
Instruct-DeBERTa (Joint task)*	80.78		–		–	
Instruct-DeBERTa-Improved version (Joint task)	**81.64**		**68.93**		**72.23**	

Table 1: F1 scores for the selected models individually and when pipe-lined. *These F1 scores were taken from (Jayakody et al., 2024).

Several architectural modifications were made to improve the model, such as adjusting dropout rates, adding a linear layer with ReLU activation for better aspect extraction, and fine-tuning parameters like attention heads. Regularization techniques like L2 regularization and optimized dropout rates were used to prevent overfitting. These adjustments improved performance, specifically the weighted F1 score for some datasets, though performance gains were marginal in certain cases, like the aspect term extraction task.

3 Results

Our hybrid model, `Instruct-DeBERTa`, outperformed all other million parameter models on most datasets for the ATE-ASC joint task. The initially developed model outperformed the previous best performing models as `Grace` (Luo et al., 2020) and `Span` (Hu et al., 2019). The improvements to the `Instruct-DeBERTa` model, including adding a linear layer with ReLU, regularization, and tuning attention heads, led to enhanced performance across several datasets. For Res-14 and Res-15, the weighted F1 scores improved as in Table 1. In terms of aspect categorization, t-SNE was used to visualize relationships between aspect terms and their categories in 2D space. Voronoi diagrams were generated to clearly map aspect terms to predefined categories like cleanliness and room service in the hospitality domain. This categorization was manually verified with an accuracy of 85%. These visualizations clarified the relationships between aspect terms and categories.

4 Conclusion

The hybrid `Instruct-DeBERTa` model combines `InstructABSA` for aspect extraction and `DeBERTa-V3-baseabsa-V1` for sentiment classification. Recent adjustments—adding a linear layer, ReLU, regularization, and optimizing attention heads—boosted F1 scores, especially in the hospitality domain, without retraining. The model is also capable of classifying aspect categories, boosting accuracy for ABSA.

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