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Project Title:	Fine-tuning Aspect Based Sentiment Analysis with Transformer based models
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Date of Submission	20/02/2024

This document contains the Literature Review of the similar works (papers) that has been proposed and published before on the related topic.

Fine-tuning Aspect Based Sentiment Analysis with Transformer based models

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***Index Terms*—Sentiment Analysis, Natural language processing, Aspect based sentiment analysis (ABSA), Transformer based pre-trained models, text classification, XLNet, RoBERTa, ALBERT, SpaCy, Textblob.**

I. Introduction

Sentiment analysis is the field that uses natural language processing and text classification to identify, identify, and extract emotions from opinionated data that is already available. It is a technique for interpreting the sentiments in the text that is also becoming more difficult in many research fields, such as data mining, due to the quick rise in the quantity of web pages that contain reviews of products and services.The reviewed papers collectively delve into aspect-based sentiment analysis (ABSA) within the news domain, employing a fusion of rule-based aspect extraction and deep learning methodologies, including Bidirectional Long Short-Term Memory (BiLSTM) and Convolutional Neural Networks (CNN). They confront challenges such as sentiment prediction's class imbalance and underscore the significance of capturing both local and global contextual cues for precise analysis. Despite methodological variances, the papers share a common objective of refining sentiment analysis by combining rule-based strategies with sophisticated deep learning models. Moreover, they underscore the necessity for further exploration to tackle issues like class imbalance and to assess the potential of pre-trained models like BERT for bolstering ABSA performance in news-oriented contexts.

II. Literature Review

II-A Aspect Based Sentiment Analysis

The methodologies used in the paper [1] involve categorizing ABSA methods into two main categories: Transformer-based ABSA and Graph Neural Network (GNN)-based ABSA. For Transformer-based ABSA, the paper [1] discusses the architecture of the Transformer model, which employs stacked self-attention and fully connected layers for both the encoder and decoder. It also presents related solutions that utilize Transformer models for ABSA, such as methods proposed by Sun et al., Jiang et al., and Li et al. On the other hand, for GNN-based ABSA, the paper explains the architecture of Graph Convolutional Networks (GCN) and how they operate on graph structures to capture syntactic and long-range word dependencies. The paper lists six public datasets commonly used for ABSA tasks, covering various domains and languages which includes online consumer comments and targeted sentiment analysis data. The experimental results from related studies that demonstrate the effectiveness of these approaches in handling ABSA tasks on benchmark datasets are presented. Some challenges and gaps identified in the paper include the need for further research in domain adaptation, the scarcity of high-quality and diverse datasets, especially in languages other than English, and linguistic problems such as noise in the datasets due to emojis, grammar mistakes, and misspellings.The paper concludes by highlighting the importance of addressing the identified challenges and gaps in future research. It suggests that future work could focus on improving domain adaptation techniques, curating more diverse datasets in multiple languages, and developing robust models to handle linguistic problems in ABSA tasks. Additionally, the paper encourages exploring novel related tasks within sentiment analysis and continuing research efforts in this field.

Paper [2] involves in developing the BERT-SAN model, a multi-task BERT framework for aspect-based sentiment analysis. It utilizes a pre-trained BERT model with a Self-Attention Network (SAN) as a task-specific layer, addressing two correlated sub-tasks: aspect relatedness prediction and aspect-based sentiment analysis. Two datasets, REST-14 and REST-Large, are used for aspect-based sentiment analysis, containing restaurant reviews with varying aspects and sentiment classes. The BERT-SAN model achieves superior performance on both datasets compared to competitive models, demonstrating the highest accuracy for aspect-based sentiment analysis. Multi-task learning with BERT-SAN also outperforms single-task learning. One gap identified is the potential extraction of irrelevant opinion words by the model, suggesting a need for further refinement to improve relevance. Future work includes refining the model to address irrelevant opinion word extraction, further fine-tuning for performance enhancement, and exploring zero-shot learning techniques to predict sentiment with new aspects. These improvements aim to advance the BERT-SAN model for aspect-based sentiment analysis.

Paper [3] proposes machine learning models to analyze movie reviews and predict both aspects and sentiments. Specifically, the aspect prediction is performed using Logistic Regression and Decision Tree models, while sentiment analysis is conducted using Logistic Regression and Multinomial Naïve Bayes models. The dataset used in the research paper is the IMDB movie review dataset, consisting of 50,000 rows with 25,000 representing positive polarity reviews and 25,000 representing negative polarity reviews. Each row contains a movie review and its corresponding sentiment label. The results of the research indicate that Decision Tree achieved a higher accuracy of 98% for aspect prediction, while Logistic Regression attained an accuracy of 92%. For sentiment analysis, Logistic Regression outperformed Multinomial Naïve Bayes with an accuracy of 93% compared to 91%. One potential gap in the research is the lack of exploration into unsupervised techniques for aspect extraction using association. Additionally, the research focuses solely on single-aspect predictions per review, whereas multiple aspects could be mentioned in a single review, potentially leading to a loss of information. For future work, the research paper suggests implementing a neutral sentiment class to categorize reviews with a neutral tone. Furthermore, the project could be expanded to allow for multiple aspects per review to capture more detailed information. Finally, deep learning models such as RNN and LSTM could be explored to compare their performance against existing machine learning models. These enhancements would improve the granularity and accuracy of aspect-based sentiment analysis on movie reviews.

The research paper [4] utilizes a combined approach of rule-based aspect extraction and BiLSTM for aspect-based sentiment analysis (ABSA) in the news domain. The methodology involves Data Preprocessing; Aspect Term Extraction which is a rule-based approach employed, involving noun chunk extraction, candidate aspect selection, and candidate similarity filtering; Word Embeddings - Pre-trained Word2Vec embeddings are used to convert the data into numerical form, capturing semantic relatedness of words; Sentiment Polarity Prediction- A Bidirectional Long Short-Term Memory (BiLSTM) network predicts sentiment polarity with a three-point granularity (positive, negative, neutral). The researchers utilized the ”PerSenT” dataset, containing crowd-sourced annotations of sentiments in news articles at document and paragraph levels. Performance Metrics: The model achieved macro-f1 scores of 42% on the standard test set and 39% on the frequent test set. Confusion Matrix : The model showed good accuracy in identifying positive sentiment but struggled with neutral and negative sentiments due to class imbalance. Comparison with Benchmark Models : The proposed model demonstrated comparable performance to benchmark models, particularly in negative sentiment prediction. The model's performance in predicting negative sentiment was limited by class imbalance in the training dataset. The Future work could be Experimenting with fine-tuning transformers like BERT is recommended for improved performance. Exploring different class balancing approaches is suggested to address the challenge of class imbalance and enhance the model's performance, especially in predicting negative sentiment.

The proposed methodology in the paper [5] integrates three key operations: mining semantic features, transforming extracted corpus using Word2vec, and implementing CNN for opinion mining. The hyperparameters of CNN are tuned using Genetic Algorithm (GA). Datasets from various domains such as hotel reviews, automobile reviews, and movie reviews were collected using web scraping techniques from specific websites. The experimental results show that the proposed technique achieved better performance compared to state-of-the-art techniques with an accuracy rate of 95.5%, precision rate of 94.3%, recall rate of 91.1%, and f-measure rate of 96.0%. Although the proposed method demonstrated high accuracy and performance, there are still areas for improvement. For instance, future work could focus on integrating parallel computing to enhance computational speed and exploring metaheuristic-related features to further optimize the model. Future research directions include integrating parallel computing to speed up computation, exploring metaheuristic-related features to optimize the model further, and developing a web-based ontology framework automation to incorporate sentiment analysis on social sites.

II-B Transformer Models

Paper [6] proposes a novel two-step method for aspect-based sentiment analysis (ABSA) that effectively extracts aspects and classifies their sentiment. It leverages a hybrid feature set (lexical, syntactic, sentiment-related) and applies particle swarm optimization (PSO) to select a more informative subset. An ensemble of three classifiers (Maximum Entropy, Conditional Random Field, Support Vector Machine) then classifies the sentiment of extracted aspects. This two-step approach achieves significant improvements on standard datasets (SemEval-2014 Restaurant, SemEval-2015 Laptop) compared to baselines, demonstrating its effectiveness across different domains. Future work could explore advanced deep learning techniques, reduce model complexity, improve interpretability, and enhance generalizability.

In paper [7] the BERT-IAN model delves into the realm of aspect-based sentiment analysis (ABSA), deciphering what people feel about specific aspects mentioned in reviews. The pre-trained BERT model excels at understanding the meaning and emotion embedded within words, providing a rich contextual foundation for both the aspect itself and the surrounding sentiment.This is where BERT-IAN shines. It goes beyond simply understanding individual element ,analyzes how the aspect and sentiment interact, capturing the subtle nuances of how they influence each other.Equipped with the comprehensive understanding from BERT and the focused attention mechanism, the model accurately predicts the sentiment (positive, negative, or neutral) associated with the specific aspect.

The "Sentiment-Aware Transformer Using Joint Training" [8] paper introduces an innovative model for aspect-based sentiment analysis (ABSA), addressing the limitations of traditional sentiment analysis by simultaneously tackling aspect term extraction (ATE) and sentiment classification (SC). Leveraging a Transformer architecture, the model effectively captures the semantic meaning of words and the sentiment they convey, with the integration of sentiment lexicons enhancing its sentiment-awareness. Results across datasets demonstrate superior performance compared to baseline models, showcasing its proficiency in accurately identifying aspects and classifying sentiment. However, the authors acknowledge challenges such as limited training data, suggesting that diversifying domains and languages could enhance generalizability. Overall, the paper presents a promising advancement in ABSA, emphasizing the importance of joint training and sentiment-awareness in achieving state-of-the-art results, while also highlighting avenues for future research and refinement.

The paper [9] presents a novel approach to aspect-based sentiment analysis (ABSA), leveraging Convolutional Neural Networks (CNN) and Multi-Hierarchical Attention mechanisms to delve deeper into the sentiment expressed towards specific aspects within reviews. By focusing on local features and different levels of information, the model demonstrates notable improvements in performance on standard datasets like SemEval-2014 Restaurant and SemEval-2015 Laptop, showcasing its ability to accurately identify and analyze sentiment for individual aspects. However, the authors highlight several areas for further exploration, including refining the model to handle complex sentence structures and long-distance dependencies, integrating contextual information from external sources or dialogue history to improve sentiment understanding, and investigating more advanced attention mechanisms to enhance the model's ability to capture crucial aspect-sentiment relationships. Addressing these areas could enhance the proposed approach's effectiveness in uncovering nuanced sentiment within text data, potentially leading to even more precise sentiment analysis in various application.

Li Li in their research paper [10] introduces a Transformer-based Relation Detect Model for Aspect-based Sentiment Analysis (ABSA), offering a nuanced approach to understanding the intricate connections between aspects and sentiment in text. By leveraging Transformer Encoder neural networks and a Relation Detection Module, the model not only identifies aspects and their associated sentiment but also explicitly models the relationships between them, providing deeper insights into why certain sentiments are expressed towards specific aspects. These include broadening the exploration of relation types to better handle complex sentence structures, integrating domain-specific knowledge to improve performance in specialized fields, and emphasizing explainability and interpretability to provide users with valuable insights into the model's reasoning. Overall, Li Li's proposed approach represents a significant advancement in ABSA, with opportunities for further refinement to enhance its effectiveness and applicability across diverse domains.

Paper [11] "Aspect-Based Sentiment Analysis Using Local Context Focus Mechanism with DeBERTa" addresses key challenges in ABSA by proposing a novel approach that integrates the DeBERTa pre-trained language model (PLM) with a Local Context Focus Mechanism (LCFM). Traditional ABSA methods often struggle with capturing long-range dependencies, handling complex sentence structures, and generalizing to new domains. By leveraging DeBERTa's contextual understanding capabilities and LCFM's focused attention on local context, the model aims to provide more accurate sentiment analysis for specific aspects mentioned in text. This innovative approach demonstrates the potential to enhance ABSA accuracy and reliability, particularly in scenarios involving intricate sentence structures and diverse domains.

The paper "Aspect-Based Sentiment Analysis Using Local Context Focus Mechanism with DeBERTa" [12] addresses key challenges in ABSA by proposing a novel approach that integrates the DeBERTa pre-trained language model (PLM) with a Local Context Focus Mechanism (LCFM). Traditional ABSA methods often struggle with capturing long-range dependencies, handling complex sentence structures, and generalizing to new domains. By leveraging DeBERTa's contextual understanding capabilities and LCFM's focused attention on local context, the model aims to provide more accurate sentiment analysis for specific aspects mentioned in text. This innovative approach demonstrates the potential to enhance ABSA accuracy and reliability, particularly in scenarios involving intricate sentence structures and diverse domains.

III. SUMMARY

Furthermore aspect-based sentiment analysis using transformer-based models like BERT, RoBERTa, and GPT, several innovative features might be explored. First, the development of hybrid transformer architectures could leverage the strengths of each model, combining BERT, RoBERTa and GPT capabilities. Aspect-level fine-tuning strategies could focus specifically on relevant parts of the model for targeted adaptation. Domain-specific adaptation through fine-tuning on domain-specific datasets or incorporating domain knowledge during training could improve performance in specific domains. Multi-task learning could optimize sentiment analysis also with related tasks like aspect extraction or opinion summarization. Transfer learning across domains could adapt pretrained models to low-resource domains. These methods could combine predictions from multiple models to enhance performance and mitigate individual biases. These approaches will collectively offer promising results to advance aspect-based sentiment analysis with transformer-based models, while improving accuracy, robustness, and efficiency.

TABLE I
FINDINGS AND REVIEW OF PAPERS

Paper Title	Methodology	Dataset	Result	Gap	Remarks
[1]	Rule-based aspect extraction combined with BiLSTM for sentiment prediction	PerSenT dataset	Macro-f1 score of 42% on standard test set and 39% on frequent test set	Class imbalance affecting negative sentiment prediction	Proposed model outperforms most benchmark models except BERT Classifier
[2]	Rule-based aspect extraction coupled with BERT model	Customer review dataset	Achieved higher accuracy and F1-score compared to baseline models	Limited exploration of domain-specific sentiment lexicons	Demonstrates the effectiveness of BERT in ABSA tasks
[3]	Rule-based aspect extraction integrated with transformer-based models	SemEval dataset	Improved F1-score for aspect extraction compared to traditional methods	Lack of consideration for aspect-level sentiment classification	Demonstrates the potential of transformer-based models in ABSA
[5]	Integrating semantic feature mining, Word2vec transformation, and CNN with GA tuning	Various domains: hotel, automobile, movie reviews	95.5% accuracy, 94.3% precision, 91.1% recall, 96.0% f-measure	Future work: Integrate parallel computing, explore metaheuristic features	High accuracy and performance compared to state-of-the-art techniques
[6]	Two-step: Feature selection (PSO) + Ensemble classification (ME, CRF, SVM)	SemEval-2014 Restaurant, SemEval-2015 Laptop	Improved performance in ATE and SC compared to baselines	Deep learning, model complexity reduction, interpretability, generalizability	This model works on diverse datasets
[7]	BERT + Interactive Attention Mechanism	SemEval-2014 Restaurant, SemEval-2015 Laptop	Improved performance compared to baselines	Domain adaptation, sentiment beyond words, model interpretability	Looks best when working with BERT
[8]	Joint training of Transformer with sentiment-awareness	SemEval-2014 Restaurant, SemEval-2015 Laptop	Improved performance compared to baselines	More diverse training data, reduced model complexity, task-specific training	NA

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