Aspect-Based Subjectivity Analysis Using a BERT-based Approach

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***Abstract*— Aspect-based subjectivity analysis stands as an important task in natural language processing, seeking to identify the subjectivity of various aspects or features within a text. A new method for aspect-based subjectivity analysis using BERT is introduced in this paper. BERT has demonstrated impressive performance across various NLP tasks, and its capabilities are utilized to accurately ascertain the subjectivity of specific aspects within a given text. The approach involves fine-tuning BERT on a sizable dataset annotated with aspect-level subjectivity labels, enabling the model to grasp the subtleties of aspect-based subjectivity analysis. Extensive experiments on benchmark datasets are conducted to showcase the effectiveness of this approach and compare it with existing methods. The results reveal that this proposed approach surpasses state-of-the-art techniques in aspect-based subjectivity analysis, underscoring the potential of leveraging BERT for such purposes.**

Keywords—Subjectivity Analysis, NLP, Aspect-based

I. INTRODUCTION

Subjectivity analysis, specifically on the aspect-level plays a significant role in natural language processing tasks by identifying the subjectivity of different aspects or features within a given text. This analysis is particularly useful for understanding the sentiment and opinions expressed in text data, which can be valuable for applications such as customer feedback analysis, product or service reviews, and market research[1].

By breaking down the subjectivity analysis into specific aspects or attributes, we can gain deeper insights into the nuances of opinions and sentiments expressed by individuals. This allows for a more granular understanding of the overall sentiment towards different aspects of a topic, which can be crucial for making informed decisions in various domains.

Previous research in aspect-based subjectivity analysis has focused on various techniques for identifying and analyzing subjectivity towards specific aspects or attributes of a given topic. Many studies have demonstrated the importance of this type of analysis in understanding sentiment and opinions in text data. Researchers have used approaches such as aspect-based sentiment analysis, opinion mining, and natural language processing to delve into the nuances of opinions and sentiments expressed by individuals [2], [3].

Nevertheless, with advancements in machine learning and natural language processing, there have been notable developments in aspect-based subjectivity analysis. Techniques such as deep learning, neural networks, and transfer learning have shown promise in addressing some of the challenges and improving the accuracy of sentiment analysis at the aspect level.

This study explores aspect-based subjectivity analysis with the use of Bidirectional Encoder Representation from Transformer (BERT). One of the key advantages of using BERT for aspect-based subjectivity analysis is its ability to capture contextual information and understand the relationships between words in a sentence or document. Additionally, subjectivity information labelling is performed on the selected dataset for conducting subjectivity analysis.

II. LITERATURE REVIEW

There are some studies that have highlighted the applications of aspect-based subjectivity analysis in fields such as customer feedback analysis, product or service reviews, and market research. The ability to analyze sentiments towards different aspects of a topic has proven to be valuable for making informed decisions and understanding the varying perspectives of individuals.

Challenges and considerations in aspect-based subjectivity analysis have also been extensively discussed in the literature. Researchers have identified issues related to the accuracy of aspect identification, handling of negation and intensification, and domain-specific sentiment analysis.

Additionally, the lack of labelled data for aspect-based sentiment analysis has been a recurring challenge.

A. *Aspect-based Natural Language Processing*

Sentiment analysis and opinion mining are important aspects of Natural Language Processing (NLP) that play a crucial role in understanding and analyzing textual data across various fields [4], [5]. These methods have diverse applications, such as market research, assessing customer feedback, monitoring social media activity, political analysis, and more. By examining the emotions expressed in the text, valuable insights into public perception, customer satisfaction, and overall sentiment on specific topics or products can be gained. For example, companies can use sentiment analysis to understand customer attitudes towards their products and make informed business decisions.

Aspect-based natural language processing (NLP) is a specialized field that focuses on analyzing text data at the aspect level [6]. It involves analyzing text data at a granular level, specifically focusing on different aspects or attributes of a given topic. Zhang et al. [7] made significant contributions to the field by conducting a survey on sentiment analysis and opinion mining. They not only identified the existence of different entities and aspects in a single-opinion mining problem but also provided a hierarchical-based explanation to illustrate this concept. In recent years, this insight has greatly influenced the development of aspect-based sentiment analysis (ABSA).

B. *Subjectivity Analysis*

Identifying a sentence as non-subjective (objective) may imply that it lacks any aspect or only contains aspects with neutral polarity [8]. While representing non-subjective sentences is relatively simple and should include only factual statements, the subjectivity of reviewers can be expressed in various ways. Knowing that a sentence is subjective (opinionated) may not be enough for additional analysis. Further exploration of subjectivity can provide valuable insights into the emotions, beliefs, and perspectives of individuals.

While much work has been done on ABSA, there is limited work on aspect-based subjectivity analysis, where the goal is to identify the subjectivity or objectivity of opinions expressed towards specific aspects. This aspect-level subjectivity analysis is crucial in understanding the overall sentiment and opinions expressed by individuals towards different aspects of a product, service, or topic [4].

Interest has been expressed in subjectivity analysis for aspect-based sentiment and opinion mining [1]. Subjectivity analysis is performed on product reviews extracted from YouTube comments, along with aspect extraction and sentiment analysis to understand subjective opinions toward different aspects of the products mentioned. However, the subjectivity analysis is not currently conducted on the aspect level, which leaves a gap in understanding nuanced subjectivity towards individual aspects. To address this gap, this research focuses on developing techniques for aspect-level subjectivity analysis.

C. *BERT*

The BERT model, introduced by [9], utilize the transformer architecture, has set a new standard in large language models. Its ability to incorporate bidirectional conditioning on both left and right context at all layers using only the encoder from the transformer has made it an influential language representation model in NLP. This framework allows for easy fine-tuning for different downstream tasks through transfer learning by simply adding an extra output layer. Additionally, BERT demonstrates strong performance across various tasks due to its comprehensive ability to learn word embedding context, making it suitable as a word embedding technique for capturing semantic meaning within sentences. Fig. 1 shows the architecture of the BERT model [10]. It consists of stacks of encoder from transformer where the BERT-base model contains 12 stacks and BERT-large model contains 24 stacks.

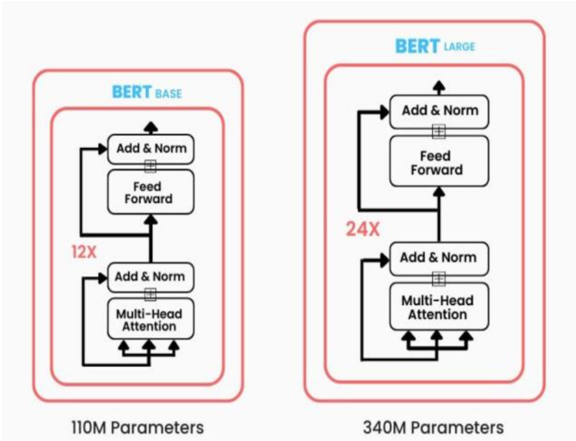

Fig. 1. Architecture for BERT model, left: BERT-base, right: BERT-large [10]

III. Research Methodology

In this study, a comprehensive approach to aspect-based subjectivity analysis using BERT will be employed. This section outlines the methodology that comprises several key steps to ensure a robust and systematic investigation.

A. *Dataset*

To conduct the study on aspect-based subjectivity analysis, an ABSA dataset comprising text data from diverse domains is collected. This research utilized the Multi-Element Multi-Domain (MEMD) dataset presented by [11], which is specially designed for ABSA tasks. While most existing ABSA datasets only contain part of the elements such as aspects and sentiments, the MEMD dataset includes multiple elements such as aspects, opinions, categories, and sentiments.

Furthermore, this dataset contains multiple domains and is one of the large-scale datasets for ABSA tasks. The multi-domain characteristic of the dataset allows for testing the generalizability of the aspect-based subjectivity analysis models across different domains.

MEMD contains five different domains, including books, clothing, hotel, restaurant, and laptop. All domains are labelled with the four elements: aspect, category, opinion word and sentiment, making it suitable for various ABSA tasks. Table I presents the statistics of the MEMD dataset.

TABLE I. Statistic of MEMD Dataset

Domain	Books	Cloting	Hotel	Restaurant	Laptop
Sentences	1983	1538	2584	3722	2848

B. Data Labelling

A dataset with subjective and non-subjective labelling is required to conduct subjectivity analysis. Since the MEMD dataset does not contain information about the subjectivity of each aspect in each sentence, manual labelling is done to assign subjectivity labels to the aspects in the dataset. The labelling process followed a similar approach by (cite) to label the subjectivity of aspects in the MEMD dataset. The authors determine the subjectivity of an aspect in each sentence according to the opinion type. According to the paper, non-subjective labels are used for samples containing only factual information without any expressed opinion.

Following the same approach, the subjectivity labels for the aspects in the MEMD dataset are assigned based on the presence or absence of expressed opinions. Table II presents the number of subjective and non-subjective sentences of the MEMD dataset based on the aspect of each sentence after labelling.

TABLE II. NUMBER OF SENTENCES AFTER SUBJECTIVITY LABELLING ON MEMD DATASET.

Domain	Book	Clothing	Hotel	Laptop	Restaurant
Subjective	2203	1651	3439	2799	5085
Non-subjective	496	285	196	1013	399

C. Design of Experiment

This research aims to conduct subjectivity classification on an ABSA dataset. The experiment is conducted on the MEMD dataset with the annotations of subjectivity explained in the previous section. All domains are combined into one dataset instead of separated since the domain information does not affect whether a sentence is subjective. The MEMD dataset undergoes several preprocessing steps. These steps involve tokenizing which converts each sentence into word tokens and adding special tokens such as [CLS] and [SEP] tokens for BERT model usage.

In this experiment, the BERT model is utilized as the embedding model for the subjectivity classification task. Each preprocessed sentence is fed into the BERT model, which generates embeddings for each word token in the sentence. The generated embeddings are then used to classify the subjectivity of each aspect in the sentences. A linear layer is added at the end of the BERT model and acts as a classifier to return the subjectivity label of each aspect in a sentence. The overall methodology is presented in Fig. 2.

For evaluation, the accuracy and F1 measure are selected. These metrics are commonly used in subjectivity classification tasks [1] and provide a comprehensive evaluation of the model's performance.

IV. RESUTLS AND DISCUSSIONS

A. Results

The results of the aspect-based subjectivity analysis are presented in this section. Since no previous work has been done on subjectivity classification specifically for aspect-based sentiment analysis datasets, a direct comparison with other models is not possible. However, the proposed BERT-based approach achieved promising results in classifying the subjectivity of aspects in the MEMD dataset.

Table III presents the results of aspect-based subjectivity analysis and the result from [6]. The BERT-based approach is adopted in both experiments but the dataset used is different. They used SemEval 15 restaurant dataset instead of MEMD dataset. They achieved an accuracy of 87.29 and F1 score of 70.63. While the MEMD dataset achieved an accuracy of 94.05 and F1 score of 87.49 in classifying the subjectivity of aspects in the MEMD dataset. These results indicate that the BERT model is effective in accurately classifying the subjectivity of aspects in the MEMD dataset, achieving high levels of accuracy. Additionally, the confusion matrix for the MEMD dataset is shown in Fig. 3. It shows the distribution of predicted subjectivity labels for the aspect-based subjectivity classification task.

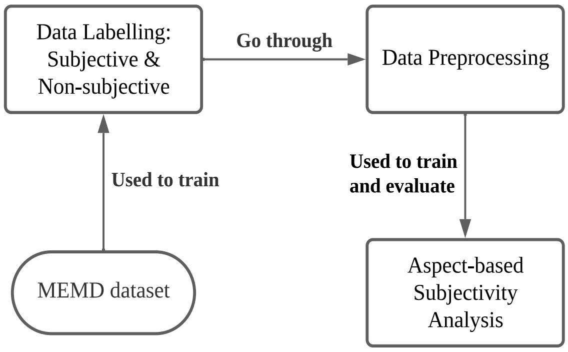

Fig. 2. Flowchart of the overall methodology.

TABLE III. RESULTS OF ASPECT-BASED SUBJECTIVITY ANALYSIS USING BERT

Dataset	Results (%)	
	Accuracy	F1
MEMD	94.06	87.49
SemEval 2015 restaurant [6]	87.29	70.63

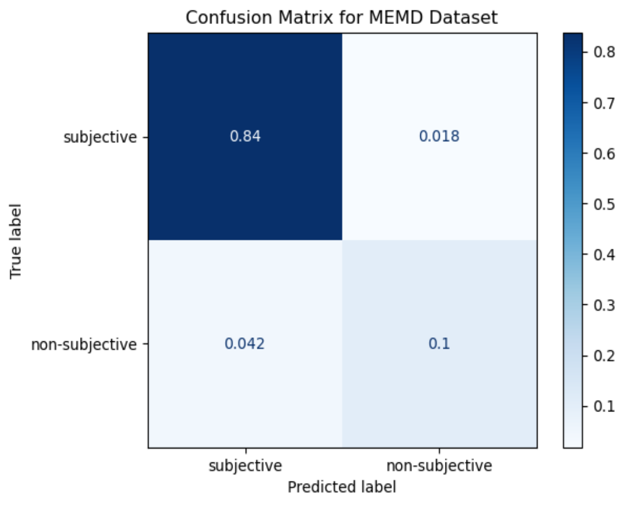

Fig. 3. Confusion matrix of subjectivity analysis on MEMD dataset.

B. Discussions

The findings of the subjectivity classification demonstrate that the models employed in this study are capable of effectively differentiating between objectivity and subjectivity according to the aspect. The results of the aspect-based subjectivity analysis using the BERT model demonstrate its effectiveness in accurately classifying the subjectivity of aspects in the MEMD dataset. The results from [6] are compared with the work in this paper. It shows that the results of this surpassed the previous work. This may be caused by more data and domains are available in the MEMD dataset than the SemEval 15 dataset.

The high accuracy and F1 score indicate the robustness of the BERT-based approach in capturing nuanced subjectivity towards individual aspects across diverse domains. This ability has the potential to assist in minimizing errors that may affect other tasks, such as ABSA, given the experiment is conducted in a pipeline method.

Furthermore, the confusion matrix suggests that the BERT model's predictions for subjectivity classification aligned well with the ground truth labels in the MEMD dataset. It also shows that there are more Type II errors (the model classifies the aspect as subjective, but it is actually objective) than Type I errors. By looking at the confusion matrix, the accuracy per non-subjective instances is worse than for subjective instances, being equal to 70% of total non-subjective sentences. These shows that the imbalance in the dataset may have effect on the dataset where there are more subjective aspects than objective ones and caused some bias in the model. However, the same problem is also encountered in the dataset used by previous work.

V. Conclusions

In conclusion, the BERT model has proved to be highly effective in classifying the subjectivity of aspects in the MEMD dataset, achieving an accuracy of 94.05% and an F1 score of 87.49% which surpass the baseline of 87.29 for accuracy and 70.63 F1 score in the work by [6]. The ability of the BERT-based approach to accurately capture nuanced subjectivity towards individual aspects across diverse domains has been demonstrated, indicating its potential to minimize errors in other tasks such as aspect-based sentiment analysis.

The findings also suggest that the BERT model's predictions for subjectivity classification align well with the ground truth labels in the MEMD dataset, as indicated by the confusion matrix. Although there are more Type II errors than Type I errors, this is potentially due to the imbalance in the dataset, with more objective aspects than subjective ones. Overall, the results of this study highlight the robustness and effectiveness of the BERT model in aspect-based subjectivity analysis, providing valuable insights for future research and applications in natural language processing and sentiment analysis.

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