OPEN ACCESS

Manuscript ID:
ASH-2024-12017828

Volume: 12

Issue: 1

Month: July

Year: 2024

P-ISSN: 2321-788X

E-ISSN: 2582-0397

Received: 13.04.2024

Accepted: 25.06.2024

Published: 01.07.2024

Citation:
Umamaheswari, M., and R. Ranjana. "Aspect Based Sentiment Analysis Using Deep Learning Algorithm: A Review." *Shanlax International Journal of Arts, Science and Humanities*, vol. 12, no. 1, 2024, pp. 41–46.

DOI:
https://doi.org/10.34293/sijash.v12i1.7828

Aspect Based Sentiment Analysis using Deep Learning Algorithm: A Review

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Abstract
Compared to broad sentiment analysis, aspect-based sentiment analysis (ABSA), which aims to predict the sentiment polarities of the designated features or entities in text, can produce more precise results. Product reviews and social media comments are examples of texts that can be used to identify and analyze sentiments. Another type of text analysis is known as sentiment analysis subtask, or ABSA. Deep learning methods have demonstrated efficacy in managing the intricacy of natural language and obtaining subtle emotions linked to many facets of a good or service. Deep learning has become increasingly popular in many applications, and in recent years, both the academic and industry communities have given ABSA a great deal of attention. Overall, ABSA's deep learning efforts have been successful in advancing sentiment analysis skills, which has given rise to important insights into how consumers view and respond to various features of goods and services. Deep learning-based methods are probably going to have a big impact on how sentiment analysis apps develop in the future as technology keeps developing. The size of the dataset, the task's difficulty, and the computer resources available all play a role in the deep learning method selection. To attain optimal performance, many state-of-the-art ABSA models pretrain on huge corpora and then fine-tune on task-specific datasets.

Keywords: Aspect Based Sentiment Analysis (ABSA), Sentiment Analysis, Deep Learning, Convolution Neural Network (CNN) and Recurrent Neural Network (RNN))

Introduction

The abundance of user-generated content on the internet has made sentiment analysis an essential method for gaining understanding of people's emotional states. Recently, the fields of computational linguistics [11] and semantic Web research have placed a great deal of emphasis on aspect-level sentiment analysis. Aiming for two distinct objectives, aspect extraction and sentiment classification of product evaluations and sentiment classification of target-dependent tweets, is the current focus of sentiment analysis research on improving granularity at the aspect level. Deep learning algorithms have emerged as a viable way to achieve these aims since they can capture both syntactic and semantic features of text without requiring high-level feature engineering, as is the case with previous methods

In this research, we aim to give a comparative evaluation of deep learning for aspect-based sentiment analysis, with the purpose of contextualizing different approaches. At the phrase or document level, traditional sentiment analysis research primarily forecasts the overall sentiment toward a sentence or document. It is anticipated that a single emotion will be conveyed over the one topic in the given text in order to generate the prediction, albeit this may not always be the case in practice.

As a result, during the past ten years, there has been an increasing emphasis on the requirement to identify more detailed aspect-level thoughts and feelings, also known as aspect-based sentiment analysis (ABSA).

An entity or a particular feature of an entity replaces the sentence or document as the concerned target on which the mood is expressed in the ABSA problem. The technique of generating a detailed opinion summary at the aspect level is called ABSA, and it provides useful, fine-grained sentiment information for applications that follow. ABSA identifies various aspect-level sentiment elements, including sentiment polarities, opinion terms, [17] aspect terms, and aspect categories. In early ABSA works, the initial step is to individually identify each sentiment part. One challenge that predicts the sentiment polarity for a particular aspect within a text is the aspect sentiment classification task. On the other hand, the work on aspect term extraction (ATE) [20] aims to extract every aspect term that is referenced in the text that is given.

Aspect set C, which is predefined for each specific area of interest, is intended to accommodate aspect category C, which describes an entity's unique aspect. For example, aspect categories in the restaurant industry could be food and service.

Aspect term A stands for an opinion target that is expressly indicated in the text that is supplied, like "pizza" in the sentence "The pizza is delicious." When the objective is implicit (e.g., "It is overpriced!"), the aspect term might be predictable as distinct, as in "null."

Opinion term O is the phrase used by the opinion holder to communicate how they feel about the target. For instance, the opinion phrase "delicious" appears in the running example "The pizza is delicious."

Sentiment Polarization P refers to how a sentiment is oriented relative to an aspect term or category, typically falling into the positive, negative, and neutral

Literature Review

Sentiment analysis, according to Haoyue Liu et al. (2020), is the process of looking at, analyzing, extrapolating, and making conclusions from subjective materials. Sentiment analysis was used by businesses to understand public opinion, conduct market research, evaluate brand reputation, identify consumer experiences, and examine the influence of social media. It can be categorized as document, sentence, or aspect-based based on the various needs for aspect granularity [5]. Their paper included a compilation of the recently proposed methods for handling an aspect-based sentiment analysis problem.

Deep learning techniques, conventional machine learning techniques, and lexicon-based techniques are the three most often used methodologies. In their survey piece, they provided a comparative summary of the most recent deep learning approaches. Several commonly used benchmark data sets, evaluation criteria, and the efficacy of existing deep learning approaches were discussed. Finally, a presentation and discussion of current issues and possible study areas for the future were offered.

In his study, Kaustubh Yadav (2021) described how "Aspect Based Sentiment Analysis" (ABSA), a subfield of natural language processing, focuses on practically segmenting the input into aspects before extracting the sentiment data. It was widely acknowledged that context-specific information was provided by ABSA [2] rather than by general sentiment analysis. further included a comparative analysis and looked into the various ABSA techniques. The survey article offered a thorough analysis and comparison of several options. It was simple to divide into pieces that gave a thorough rundown of the process.

In his survey study, Wenxuan Zhang et al. (2022) explained that the survey's goal was to provide a comprehensive overview of the aspect-based sentiment analysis problem, encompassing its various tasks, methodologies, current challenges, and potential future developments. They initially provided the context of ABSA study using the definition, popular modeling paradigms, and the four sentiment aspects of ABSA. Subsequently, they thoroughly examined every ABSA task and its corresponding solution, emphasizing the latest advancements for the compound ABSA [9] problems. Meanwhile, they summarized example techniques of several modeling paradigms [9] for each task and categorized prior studies according to the sentiment elements involved, giving a clear picture of current development. Additionally, they discussed how the application of trained language models to the ABSA problem has greatly enhanced several different ABSA tasks and looked at both their advantages and disadvantages. Finally, they talked about a few current problems and promising future developments in that industry.

In his survey article, Linan Ziu (2022) addressed how user-generated content on various Internet platforms was growing at a rapid pace and how it contained crucial information that supports decision-making. However, it is still challenging to adequately extract this information because there was so much of it. Sentiment analysis, therefore, offered an answer to this problem by illuminating people's perspectives on the objective of the opinion. Their article's objective was to provide a thorough overview of deep learning-based aspect-based sentiment analysis. They began by giving a quick overview of the aspect-based sentiment analysis, or ABSA, task. The general structure of the ABSA job was then described from two perspectives: the task modeling process [13] and significant subtasks. Finally, certain concerns regarding sentiment analysis were brought up and quickly covered, with a focus on aspect-based sentiment analysis.

Objectives and Research Methodology

A. Objectives

1. Because it directly focuses on sentiments rather than linguistic structure, the Aspect-Based Sentiment Analysis (ABSA) aids in a better understanding of the Sentiment Analysis problem [3].
2. A lot of solid research choose to carry out simply aspect extraction or categorization; those who combine sentiment analysis and aspect detection [14] have not yet reached peak effectiveness. A combination strategy that can handle both jobs and produce more widespread sentiment analysis at the aspect level is required.
3. To successfully complete the Aspect Extraction (AE) procedure
4. How to implement Aspect Sentiment Analysis (ASA) and develop a sentimental computation model that thoroughly examines all the emotional aspects.

B. Research Methodology

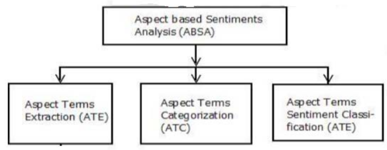

Figure 1 Organization of ABSA minor tasks

To arrive at the final results, ABSA techniques go through three stages: sentiment evolution (SE), aspect extraction (AE), and aspect sentiment analysis (ASA) [7]. The structure of the ABSA minor jobs is shown as a tree in Figure 1.

During the Aspect Term Extraction stage, the aspects' polarity—which may be implicit or explicit—is extracted. Moreover, ATE can be used to extract aspect words, objects, and even aspects based on the Opinion Target Expression (OTE) [4]. However, in the second stage of aspect term categorization (ATC), emotion polarity is classified as a predefined characteristic, object, or entity. Additionally, ATC [18] is responsible for identifying links, connections, and context-specific interconnections between different data elements, as target, object, aspect, and relationships between different data components, such as target, object, aspect, and sentiment words, that are context-specific. The last step in the ABSA process, Aspect Terms Sentiment Classification, establishes the dynamic nature of people's perceptions of various events. It is believed that social environments and personal experiences are the primary causes of SE.

Usually, the sentences yield two different kinds of aspects: implicit and explicit. Explicit elements are those ideas in the stated statement that explicitly designate targets. On the other hand, the ingredients are indirectly mentioned in the case of implicit SA. The second stage of the ABSA process is called aspect term categorization, or ATC, in which sentences that share comparable traits are joined to form categories. Every category represents a certain element, sometimes referred to as the aspect category. The last stage of the ABSA method, known as aspect term sentiment classification, determines the polarity of the sentence or phrase after aspect terms are extracted and categorized from them.

Deep Learning Algorithm for Absa

A. RNNs, or Recurrent Neural Networks

Recurrent neural networks (RNNs) are engineered to process sequential data by preserving a concealed state that retains details from prior inputs. This makes them appropriate for sentiment analysis and other tasks involving long-term dependency. The widely used RNN[15] model has demonstrated remarkable capability in numerous NLP assignments. Utilizing sequential information is the fundamental concept underlying it. We assume that every input in a typical neural network is independent of every other input. This is an unrealistic assumption for a lot of tasks. The words in front of a word must be known in order to forecast the word that will come after it in a sequence. RNN uses its prior knowledge to execute the identical operations on every element in a sequence. Although an RNN [8] can use any length of sequenced data in theory, in practice it can only review a limited number of earlier stages. Given the quantity a neural network's set number of input layers, the variable length of input must be processed either recursively or recurrently. The RNN achieves this by splitting the variable length input into a number of small, equal-length chunks, which are subsequently fed into the network. For instance, a sentence is handled as a collection of words when dealing with it. After that, we fed the sentence into the RNN one word at a time until it was complete. Finally, RNN generates a similar output.

Application in ABSA: RNNs are useful for modeling word dependencies within sentences, capturing the feelings and context around particular elements.

B. LSTM, or Long Short-Term Memory Networks

The vanishing gradient issue is solved by LSTMs, a kind of RNN that makes it possible for them to identify long-term dependencies in sequential data. To extract pertinent information from input sequences, LSTM [11] selectively modifies cell and hidden states based on input, prior state, and forget gate. Long-term dependencies are maintained by the cell state, whereas relevance is managed by the output gate. Sequences input for aspect extraction and ABSA can be represented as word embeddings, with aspect terms or sentiment labels being understood as the output. Long-range contexts, complicated dependencies, and variable-length inputs and outputs can all be modeled by LSTM.

Application in ABSA: Long Short-Term Memory (LSTM) models well contextual information across extended sequences, which makes them a good choice for encoding complex emotions about certain features.

C. GRU, or Gated Recurrent Unit

By merging the memory cell and hidden state, GRUs, another type of RNN, simplify the architecture. Unike the LSTM unit the GRU [1] controls the flow of information without employing a memory unit which makes it more efficient with uncompromised performance compared to LSTM. Moreover, GRU lessens the issue of vanilla RNN's vanishing gradients [12] and gradient explosions.

Application in ABSA: GRUs provide a trade-off between expressive capacity and processing efficiency when utilized for sequential modeling in ABSA applications.

D. CNNs, or convolutional neural networks

While one-dimensional convolutions allow CNNs to be used to sequential data, such as text, they are best recognized for their efficiency in image processing. CNN-based networks [19] do not model targets independently for explicit representation in context. CNNs [11] are efficient because they can mine semantics in contextual windows, which allows them to extract meaningful local patterns, or n-grams. Maintaining sequential order and modeling contextual information over vast distances are challenging, though.

Application in ABSA: CNNs are useful for extracting features associated with particular components of a phrase because they can capture local dependencies in the input data.

E. Transformer Models (such as GPT and BERT)

Transformer models are becoming more and more well-known due to their capacity to simultaneously record contextual data for the whole input sequence. For instance, BERT is optimized for particular tasks after being pretrained on sizable corpora. To understand the contextual links between words inside a sentence, these models are trained on existing data. Two popular methods for transformer models in aspect extraction are either employing the model as a feature extractor [16] and training a different classifier on top of the extracted features, or fine-tuning a pre-trained model on annotated data. All things considered, transformer models have demonstrated a great deal of potential in aspect extraction and will probably be a major focus of future study.

Application in ABSA: State-of-the-art outcomes in ABSA [6] have been attained by BERT, GPT, and other transformer-based models by capturing complex contextual information and interactions between features and feelings.

F. Gaps in Deep Learning Algorithms

The choice to employ Deep Learning (DL) techniques to ascertain aspect sentiments has evolved significantly, with a great deal of academics adopting this strategy. But the drawback of DL methods is that, in order to outperform other approaches, they need a very huge amount of data. Because the data models are complicated, training is very costly. Since choosing the best deep learning tools necessitates understanding of topology, training methodology, and other factors, there is no set theory to guide you in this process. Additionally, the majority of specialists use CNN, LSTM, and BI-LSTM approaches, all of which have gradient vanishing and overfitting [10] issues. Moreover, using it to train the DL architecture comes at a hefty expense.

G. Performance metrics in ABSA

Aspect-Based Sentiment Analysis (ABSA) models are often evaluated using a number of metrics [3] to see how well the model captures attitudes related to particular textual aspects or features.

Performance Metric	Description	Formula
Accuracy	The percentage of aspect-level feelings accurately categorized relative to the total number of aspects	(Number of Correct Predictions) / (Total Number of Aspects)
Precision	the proportion of positively or negatively projected sentiments that were accurately forecasted to all positively or negatively predicted feelings	(true positives) / (true positives + false positives)
Recall	The ratio of accurately predicted positive or negative feelings to the total number of real positive or negative thoughts	(true positives) / (true positives + false negatives)
F1 Score	The harmonic mean of recall and precision, which offers a ratio of the two measurements.	2 x {(precision x recall) / (precision + recall)}
Weighted F1 Score	The F1 score calculated for each class and then weighted by the number of instances in each class	∑class(weightclass×F1class) / (Total number of instances)

Conclusion

We present aspect-based sentiment analysis (ABSA) in this survey. Initially, we outlined the ABSA job, which consists of three subtasks: aspect term sentiment analysis, aspect term categorization, and aspect term extraction. Next, we talked about several deep learning algorithms that ABSA can employ. Lastly, we talked about performance indicators that ABSA can use.

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