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Enhancing Absa Using Dynamic Encoding

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Abstract - Aspect-Based Sentiment Analysis (ABSA) provides a fine-grained approach to understanding opin-ions by extracting aspect–opinion–sentiment relation-ships from text. It is particularly valuable in domains such as product reviews, customer services, banking, and social media, where identifying specific strengths and weaknesses is essential. The subtask of Aspect-based Sentiment Triplet Extraction (ASTE) extends ABSA by simultaneously identifying aspect terms, corresponding opinion expressions, and their sentiment polarities. This work proposes an improved ABSA framework that integrates pre-trained language models (PLMs) with a pruned syntactic encoding mechanism to efficiently capture both local and global contextual dependencies. Additionally, a dynamic encoding strategy is introduced to overcome the limitations of traditional local encod-ing, which often fails to capture long-range relation-ships between aspects and opinions. The combination of syntactic pruning and dynamic encoding enhances the association between aspect and opinion terms, leading to more accurate sentiment classification. Experimental evaluations on benchmark ABSA datasets are expected to demonstrate that the pro-posed model achieves higher accuracy and robustness compared to existing methods. This approach effec-tively combines syntactic structure and contextual un-derstanding, improving interpretability and performance in aspect-level sentiment prediction tasks.

Keywords : Aspect-Based Sentiment Analysis (ABSA), Aspect based Sentiment Triplet Extraction (ASTE), Pre-trained Lan-guage Models (PLMs), Dynamic Encoding, Opinion Mining, Sentiment Classification, Natural Language Processing (NLP).

I. INTRODUCTION

Aspect-Based Sentiment Analysis (ABSA) finds sentiment polarity and opinion statements pertaining to particular aspects mentioned in a review [8]. It is widely used in domains such as e-commerce and hospitality for understanding cus-tomer opinions [7]. Aspect Term Extraction (ATE), Opinion Term Extraction (OTE), and Aspect Sentiment Classification (ASC) are the main subtasks of ABSA [3], [4]. Aspect-based Sentiment Triplet Extraction (ASTE) jointly extracts aspect, opinion, and sentiment triplets [1], [2]. We train and evaluate the model on the SemEval Restaurant dataset [11]. The model integrates Pre-trained Language Models with syntactic pruning and semantic parsing techniques [1], [6]. Dynamic encoding improves long-range dependency learning and contextual un-derstanding [2], [5].

Our approach taps into Pre-trained Language Models (PLMs) and blends them with a Pruned Syntactic Encoding mechanism. This combo does a good job picking up both the small details and the bigger picture in review texts [1], [6].On top of that, the model uses a Dynamic Encoding strategy to solve the problems that old-school local encoding methods run into—like missing connections between distant aspect-opinion pairs in longer, more complicated sentences [2]. This approach makes the model easier to understand, tougher, and more accurate. Plus, it delivers really detailed sentiment insights, which come in especially handy for analyzing restaurant reviews [4], [5].

II. LITERATURE REVIEW

Recent advances in natural language processing (NLP) and deep learning have significantly enhanced the performance of Aspect-Based Sentiment Analysis (ABSA). Traditional sentiment analysis methods, based on statistical or classical machine learning approaches such as Support Vector Machines (SVM) and Na¨ıve Bayes, primarily focused on sentence- or document-level sentiment prediction. However, these mod-els failed to capture the fine-grained relationships between specific aspects and their associated opinions, limiting their interpretability in domain-specific contexts such as restaurant reviews.

To address these limitations, neural network–based models, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) architectures, were introduced to capture sequential and contextual dependencies. While these models improved sentiment classification accuracy, they often struggled to maintain long-range contextual understanding, especially in sentences containing multiple aspect–opinion pairs. This motivated the adoption of transformer-based Pre-trained Language Models (PLMs) such as BERT, RoBERTa, and MPNet, which have demonstrated exceptional contextual encoding capabilities through self-attention mechanisms.

Aspect-based Sentiment Triplet Extraction (ASTE) has further advanced ABSA by jointly extracting aspect terms, opin-ion terms, and sentiment polarities within a single framework, reducing error propagation seen in pipeline models. Recent re-search has explored integrating syntactic dependency informa-tion and graph-based representations with PLMs to strengthen aspect–opinion association and improve interpretability. Tech-niques such as Graph Convolutional Networks (GCNs) and attention-based mechanisms have been employed to capture structural dependencies in review text.

Despite these developments, challenges remain in efficiently modeling complex linguistic structures and handling domain-specific variability in restaurant reviews. The proposed ap-proach in this project leverages a Pruned Syntactic Encoding mechanism to retain meaningful dependency relations while reducing noise, combined with Dynamic Encoding to capture long-range contextual dependencies. These enhancements are expected to improve the precision of aspect–opinion–sentiment triplet extraction and enhance model robustness across bench-mark datasets such as SemEval.

Further sections of this study provide detailed analyses of key research contributions, summarizing methodologies, datasets, and performance results from prior work in ABSA and ASTE domains.

1. Pruning Self-Attention With Local and Syntactic Dependencies for Aspect Sentiment Triplet Extraction (Li Yuan and Jin Wan, 2025): This study introduced a Pruned Syntactic Transformer (PSTransformer) built on top of BERT embeddings to improve Aspect Sentiment Triplet Extraction (ASTE). The model replaced the standard Transformer layers in BERT with PSTransformer layers to combine both local and syntactic dependency information. A refining strategy was incorporated to optimize sentiment triplet prediction. Exper-iments on benchmark datasets, including LAP14, REST14, REST15, and REST16, achieved 69.64% accuracy on restau-rant reviews and 60.52% on laptop reviews. While outperform-ing standard baselines, the model struggled to handle long-range dependencies between aspect and opinion terms [1].

2. Large Language Models Enhanced by Plug-and-Play Syntactic Knowledge for Aspect-Based Sentiment Analysis (Yuanhe Tian and Xu Li, 2025): This work proposed a memory-based syntactic knowledge plugin for Large Lan-guage Models (LLMs). The plugin encodes various linguistic and syntactic features, integrating them into LLMs through a specialized hub module. The approach was evaluated on LAP14, REST14, REST15, REST16, and MAMS datasets, achieving 82.3% accuracy and surpassing previous baselines. The study demonstrated that enriching LLMs with syntactic knowledge improves contextual understanding. However, the experiments were limited to English datasets, restricting mul-tilingual generalization [2].

3. Syntactic and Semantic Aware Graph Convolutional Network for Aspect-Based Sentiment Analysis (Junjie Chen and Hao Fan, 2024): This model combined syn-tactic and semantic information using Graph Convolutional Networks (GCNs) to enhance structural and contextual un-derstanding in ABSA. The network used syntactic graphs to represent dependencies and semantic GCN layers to capture contextual meaning. Attention mechanisms and aspect mask-ing integrated the two types of information before sentiment classification. On LAP14, REST14, REST15, and REST16 datasets, the model achieved an average accuracy of 82.44%, outperforming strong baselines. However, it was limited by its dependence on explicit syntactic and semantic inputs without broader contextual adaptation [3].

4. ElHBiAt: Electra Pre-Training Network Hybrid of BiLSTM and Attention Layer for Aspect-Based Sentiment Analysis (Amin Ghanee Nezhad and Kia

Jahanbin, 2024): ElHBiAt utilized the Electra pre-trained network as its back-bone. The embeddings generated by Electra were passed to BiLSTM layers to extract bidirectional sequence information and long-term dependencies. Two attention layers were ap-plied to enhance context focus. The model was trained on cross-domain datasets, including LAP14, REST14, REST15, REST16, SEntFiN-v1 (finance), and drug reviews. It achieved 86.84% accuracy on the drug dataset and above 80% on other domains. Despite strong results, the model struggled with contextual sensitivity in financial texts and distinguishing multiple sentiment scopes within a single sentence [4].

5. **Enhanced Local and Global Context Focus Mech-anism Using BART Model for Aspect-Based Sentiment Analysis (Sunitha Suresh and K. Sharmila, 2024):** This study proposed a BART-based model leveraging both local and global context mechanisms to improve ABSA perfor-mance. The architecture dynamically attends to local context for detailed sentiment cues while maintaining global context for broader sentence-level understanding. Evaluations on the ACL 2014 Twitter and SemEval 2014 Laptop datasets showed improved accuracy over existing transformer-based models. However, the model's primary focus on social media data limited its applicability to more formal or domain-specific text [5].

6. Semantic Parsing for Aspect-Based Sentiment Anal-ysis (Muhammad Aqeel and Francesco Setti, 2025): This research integrated Semantic Parsing Trees with a Relational Graph Attention Network (RGAT) to enhance semantic under-standing for ABSA. By modeling the relationships between words through dependency and semantic relations, the model improved sentiment classification accuracy on the SemEval 2014 Restaurant and Twitter datasets. The approach consis-tently outperformed traditional ABSA models, but perfor-mance degraded when handling rare or unseen semantic rela-tions, indicating a need for broader knowledge generalization [6].

7. Advancing Aspect-Based Sentiment Analysis in Course Evaluation: A Multi-Task Learning Framework With Selective Paraphrasing (Shahla Gul, Kashif Saleem, Muhammad Asif, Fazal-e-Amin, and Muhammad Imran, 2024): This paper introduced a multi-task learning (MTL) framework incorporating selective paraphrasing as a data aug-mentation technique to enhance ABSA in course evaluation contexts. The model leveraged nuanced paraphrasing control to improve robustness and generalization when analyzing stu-dent feedback. Experiments on educational feedback datasets showed significant improvements in recall compared to stan-dard ABSA models. However, the lack of syntactic tree-based grammatical representation limited the model's linguistic in-terpretability [7].

III. SYSTEM OVERVIEW

The proposed system for Aspect-Based Sentiment Anal-ysis (ABSA) follows a multi-stage architecture that in-tegrates syntactic and semantic encoding for precise as-pect–opinion–sentiment extraction. The framework consists of five primary modules: Input Sentence, Word-Piece Tok-enizer, BERT Embedding, Pruned Syntactic Transformer, and Refining. Figure ?? illustrates the architecture and flow of information across these components.

A. Input Sentence (Review)

This is the raw textual input, typically a user review or opinionated sentence. It contains aspect terms (e.g., "battery") and sentiment expressions (e.g., "excellent") that the model aims to analyze. The sentence is unstructured at this stage and serves as the foundation for syntactic and semantic processing. It initiates the pipeline for aspect-based sentiment extraction, where understanding both word meaning and grammatical relationships is essential. The input is passed downstream for tokenization and embedding, enabling the model to interpret context and sentiment polarity effectively.

B. Word-Piece Tokenizer

The tokenizer breaks the input sentence into subword units using the WordPiece algorithm. It handles rare or unknown words by splitting them into recognizable fragments (e.g., "unhappiness" → "un", "##happiness"). Special tokens such as [CLS] (start of sentence) and [SEP] (separator) are ap-pended to guide BERT's attention mechanism. This step ensures compatibility with BERT's vocabulary and enables fine-grained semantic control. Tokenization preserves mean-ing while allowing the model to generalize across diverse linguistic inputs, particularly in domain-specific datasets like restaurant reviews.The tokenizer breaks the input sentence into subword units using the WordPiece algorithm used in BERT [13].

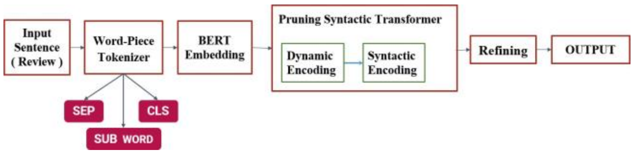

Fig. 1. System Architecture

C. Bert Embedding

This module transforms tokenized inputs into contextualized word vectors using the pre-trained BERT model. Each token is mapped to a high-dimensional embedding that reflects its semantic and syntactic role within the sentence. BERT's bidi-rectional architecture captures dependencies in both forward and backward directions, enabling richer contextual under-standing. These embeddings serve as the foundation for the syntactic transformer and downstream sentiment classification. They encode linguistic cues such as part-of-speech patterns, dependency relations, and polarity signals, facilitating nuanced interpretation of aspect–opinion pairs.This module generates contextual embeddings using the BERT model [13].

D. Pruned Syntactic Transformer

The Pruned Syntactic Transformer (PSTransformer) en-hances BERT by replacing its final transformer layers with a syntactically pruned attention mechanism. It consists of two major components:

1. **Dynamic Encoding**: Captures long-range dependencies between words, useful for interpreting nested clauses and distant aspect–opinion relations.

2. **Syntactic Encoding**: Models grammatical dependencies through attention masks or dependency trees. Pruning selectively removes redundant attention paths, reducing computational complexity while retaining essential syn-tactic information.

The Pruned Syntactic Transformer is based on syntactic prun-ing and transformer attention mechanisms [1].

E. Refining Module

The final stage processes outputs from the syntactic trans-former and applies a Softmax function to compute sentiment probabilities for each aspect. Aspect masking ensures that only relevant tokens contribute to the sentiment classification. The refining process iteratively adjusts weights based on prediction feedback, improving sentiment and aspect alignment accuracy.

The output is a set of interpretable sentiment triplets (e.g., *(battery, excellent, positive)*) that summarize user opinions across all aspects. This completes the ABSA pipeline, pro-viding fine-grained, explainable sentiment insights tailored to specific domains such as restaurant or product reviews.

IV. METHODOLOGY

The proposed technique for Aspect-Based Sentiment Anal-ysis (ABSA) includes seven consecutive units that aim to transform the raw text into the understandable sentiment outputs. [8] The first point is that each stage is necessary in the process to guarantee the correct extraction of as-pect–opinion–sentiment, the performance of the model, and the clarity of the results.

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A. Step -1) Data Collection

The primary step is to gather raw textual data from di-verse sources like restaurant and product reviews, customer feedback, and social media posts. The intent is to fabricate a varied and representative dataset that encompasses both aspect terms and sentiment expressions. Data collection can be accomplished by utilizing public APIs, web scraping, or benchmark datasets such as the SemEval Restaurant dataset. The amassed data is stored in neat formats like CSV or JSON files. High-quality and domain-specific data will offer ample linguistic coverage thus establishing a solid foundation for model training and evaluation.Benchmark datasets such as the SemEval Restaurant dataset are used for training and evaluation [11].

B. Step -2) Data Preprocessing And Cleaning

Raw textual data is, in most cases, noisy as it contains HTML tags, emojis, typos, and inconsistent casing. The mod-ule removes unwanted parts and standardizes the input by different methods, such as lowercasing, stopword removal, punctuation stripping, and lemmatization. Tokenization and normalization prepare the text for embedding creation. The preprocessing stage also involves the removal of duplicates, the dealing with missing values, and the filtering of the irrelevant entries. In supervised learning, labeled data is utilized for the annotation of aspects and their corresponding sentiment polarities. This step is done with the help of libraries like NLTK, spaCy, and pandas that ensure the text is clean and consistent, thus improving the model's learning quality and generalization.

C. Step -3) Embedding Conversion

In the following step, the clean pieces of text are changed into numbers or vectors from the embeddings produced by BERT. Each token is embedded in a high-dimensional space

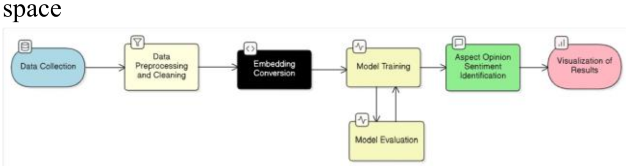

Fig. 2. System Methodology

that not only looks at the grammar but also considers the context of the token. In contrast to fixed embeddings like Word2Vec or GloVe, the BERT embeddings are dynamic and dependent on the context, so that even the same word can have different meanings depending on the words that surround it. These vectors in context are the input to the next phase of model training which thus equips the system to efficiently grasp sentiment-bearing expressions and aspect relationships.Traditional embeddings such as Word2Vec and GloVe generate static word vectors, while BERT produces contextual embeddings [9], [10], [13].

D. Step -4) Model Training

The training phase is about adjusting the BERT-based ABSA model to be more accurate. The model is taught to link aspect terms to the respective sentiment polarities (positive, negative, or neutral). The training set is used to update transformer-based architectures, and hyperparameters like learning rate, batch size, and dropout are adjusted to get the best results. To lessen the prediction errors, the model implements loss functions like cross-entropy, while validation steps are also there to hinder overfitting. This step is what essentially turns the system into a powerful analytical tool to understand intricate sentiment patterns in the new data.The model is trained using cross-entropy loss and backpropagation optimization techniques [13].

E. Step -5) Model Evaluation

The model performance is gauged through indicators such as accuracy, precision, recall, and F1-score after the whole training is over. This evaluation is done on a test set that is different from the training to ensure that the performance measure is unbiased. Errors like the confusion matrices and ROC curves are the instruments that are called upon to check classification quality and point out biases towards particular sentiment classes. The use of cross-validation also brings forth information about the stability of the model. The evaluation results serve as a stimulus for refinement by retraining, hy-perparameter tuning, or data augmentation among which the model then ensures strong generalization in various review samples.

F. Step -6) Aspect–Opinion–Sentiment Identification

This module involves using the trained model on fresh or previously unseen text data to derive aspect terms, opinion phrases, and the sentiments linked to them. The system discov-ers "food quality" (aspect) coupled with "excellent" (opinion) and a sentiment polarity. To find the relevant dependencies

between words, the model uses attention mechanisms and aspect masking. The result comprises the organized triplets— *(aspect, opinion, sentiment)* — that allow a detailed under-standing of the user thoughts on different aspects from just one review.

G. Step -7) Visualization Of Results

The last module presents the sentiment analysis done in an engaging manner and the dashboards with interactivity enabled are built by using Streamlit and other visualization libraries such as Plotly and Matplotlib. Among the features shown on the dashboard are sentiment distribution, aspect frequency, and polarity confidence scores. The real-time input feature empowers users to interactively evaluate the model and instantly see the changes in sentiment predictions. The visualization is the point where the technical output of the model meets the user interpretation and thus it is a tool that can be used by decision-makers in domains like customer experience analysis or business intelligence to gain insights that are actionable.The results are visualized using Streamlit dashboards and visualization libraries [12].

V. MATHEMATICAL MODEL OF THE SYSTEM

A. Input Simplification In Model Design

The proposed system can be formally represented as a triple of sets:

$$S = \{I, F, O\}$$

where:

- S denotes the complete system for Aspect Sentiment Triplet Extraction (ASTE).
- I represents the set of input elements provided to the system.
- F represents the set of functions or processes that transform the input into meaningful outputs.
- O denotes the set of outputs generated by the system.

The input set I is defined as:

$$I = \{I_1\}$$

$$I_1 = \text{Input Review}$$

Here, I1 corresponds to the raw textual data — typically customer or restaurant reviews — that contain aspect terms (e.g., “service,” “food,” “ambience”) and sentiment expressions (e.g., “great,” “poor,” “excellent”). These unstructured text inputs act as the foundation for subsequent natural lan-guage processing operations such as tokenization, embedding, and sentiment extraction. The function set F represents the core processing mechanisms responsible for transforming the input text into interpretable aspect–opinion–sentiment relationships. Mathemati-cally, this can be expressed as:

$$F = \{f_1, f_2, f_3, f_4, f_5\}$$

where:

- f1 = Tokenization and Preprocessing Function
- f2 = Embedding Generation using BERT
- f3 = Syntactic Pruning and Dynamic Encoding
- f4 = Sentiment Classification Function

1. f5 = Aspect–Opinion–Sentiment Triplet Extraction

These functions collectively model the transformation

pipeline from unstructured text to structured sentiment knowl-

edge.

B. Model Output Representation Improvement

The output set O represents the system’s result, formally defined as:

$$O = \{O_1\}$$

$$O_1 = \text{Set of Sentiment Triplets } (T)$$

$$T = \{(a_i, o_i, s_i) \mid a_i \in A, o_i \in O, s_i \in S\}$$

where:

- ai represents an extracted aspect term (e.g., “food,” “service”).
- oi represents an associated opinion term (e.g., “delicious,” “slow”).
- si represents the predicted sentiment polarity (positive, negative, or neutral).

Thus, each triplet (a_i, o_i, s_i) encapsulates a complete semantic relation between an aspect, its descriptive opinion, and the sentiment orientation. The entire output set O_1 contains all such triplets extracted from the input corpus.

Formally, the transformation of the system can be expressed as:

$$F : I \rightarrow O \quad F(I1) = O1$$

F (Input Review) = Set of Sentiment Triplets $\{(a, o, s)\}$

The input set I is defined as:

Theoretical Explanation

The mathematical model abstracts the end-to-end functioning of the ABSA system. The input (I_1) consists of unstructured textual data, which undergoes several transfor-mations through the functional pipeline (F). Each functional stage—tokenization, embedding, syntactic encoding, and sen-timent classification—acts as a mapping that progressively enriches the input representation.

The final output (O_1) provides a structured interpreta-tion of the review by extracting aspect–opinion–sentiment triplets. This representation enables fine-grained sentiment understanding rather than overall polarity detection, allowing domain-specific insights (e.g., “food–delicious–positive” or “service–slow–negative”).

Hence, the mathematical model defines the ABSA system as a deterministic mapping that transforms linguistic inputs into semantically interpretable sentiment triplets:

$$S = \{I, F, O\}, F(I) = O$$

where I = Review Text,

O = Extracted Aspect–Opinion–Sentiment Triplets.

VII. CONCLUSION AND FUTURE WORK

The designed Aspect-Based Sentiment Analysis (ABSA) system adeptly combines deep learning via BERT, a syntactic pruning method, and a trendy visualization tool like Streamlit to extract fine-grained sentiments from restaurant reviews. The system is capable of correctly detecting aspect–opinion–sentiment triplets, thus giving businesses the insight into users' opinions and the supporting data that can be used for decision making. They will concentrate on broaden-ing the dataset to encompass multi-domain and multilingual review corpora in order to enhance the model's ability to generalize in the next steps.

By using Large Language Models (LLMs) such as GPT and domain-adaptive transformers, the system can be further improved to have better contextual understanding and sentiment reasoning. Besides, there are possible enhancements such as having a real-time sentiment streaming dashboard, efficiently utilizing syntactic pruning through an adaptive attention mechanism, and employing cross-domain transfer learning to increase the model's robustness. Moreover, the system could be converted into a comprehensive sentiment in-telligence platform with potential applications in e-commerce, hospitality, and customer experience management.

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