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Advancing Aspect-Based Sentiment Analysis through Enhanced Contrastive Learning Techniques

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Abstract: Aspect-Based Sentiment Analysis (ABSA) is a method used to find out how people feel about specific parts (aspects) of something like the "features" of a laptop or the "service" at a restaurant within a sentence. It plays a big role in analyzing opinions in reviews. Recently, contrastive learning has become popular in improving ABSA. This learning method helps the system learn better by comparing examples like learning to tell the difference between a good and a bad review more clearly. This paper looks at two common contrastive learning methods for ABSA: Sentiment-Based Supervised Contrastive Learning: This method uses the actual sentiment labels (like "positive" or "negative" or "neutral") to teach the model what to focus on. Augmentation-Based Unsupervised Contrastive Learning: This method creates new versions of the same sentence to help the model understand the meaning, without using sentiment labels.The paper also introduces four new methods to make ABSA even better: Prompt-Based Contrastive Learning (PromptCL): Uses AI models to create paraphrased sentences with the same meaning, helping the system learn from different ways of saying the same thing. Aspect-Specific Adversarial Contrastive Learning (ASACL): Slightly changes words near the aspect being analyzed, so the model becomes better at handling confusing or noisy inputs. Hierarchical Contrastive Learning (HiCL): Looks at both the whole sentence and specific parts to learn more complete understanding. Graph-Augmented Contrastive Learning (GraphCL): Uses graphs that show relationships between words to better understand how opinions are connected to aspects.

Keywords: *Aspect-Based Sentiment Analysis, Supervised Contrastive Learning, Prompt-Based Learning, Adversarial Data augmentation, Sentence Embedding, Graph Neural Networks*.

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I. INTRODUCTION

Sentiment analysis is a key task in natural language processing (NLP) that predicts whether the feeling or opinion in a sentence is “positive, negative, or neutral”. However, sometimes a single sentence can express different opinions about different parts (aspects) of something. That's where Aspect-Based Sentiment Analysis (ABSA) comes in it looks at the sentiment toward each specific aspect. For example, in the sentence: “The appearance of this computer is beautiful, but the battery performance is poor”, The sentiment for “appearance” is positive and the sentiment for “battery performance” is negative". To handle ABSA, researchers have tried different methods: Some use attention mechanism to focus on parts of the sentence related to the aspect. Others use graph networks or dependency trees to understand how words in a sentence relate. Some also use external knowledge like pre-trained models to learn sentiment features. Recently, many methods use contrastive learning, a training strategy where the model learns better by comparing examples: It can be used before training (pre-training) to help the model understand sentence structures are used as an extra task during training to improve how the models learns to represent different sentiments. These methods have greatly improved ABSA performance, but they vary in how they use contrastive learning: One method (Liang et al., 2021) uses sentiment labels and patterns to choose which sentence pairs are similar. Another method (Wang et al., 2022) uses data augmentation and label information to create examples with different aspects. Even the loss functions used to train the models can be different, like the triplet loss.

Aspect-Based Sentiment Analysis (ABSA) has benefited greatly from the contrastive learning, which are encourages models to discriminate subtle sentiment nuances by bringing semantically similar examples closer and pushing dissimilar ones apart. While earlier work focused primarily on supervised label-based and augmentation-driven unsupervised approaches, the field is rapidly evolving toward more sophisticated strat egies that incorporate prompting, adversarial robustness, heirarchical representations, structural syntactic information and curriculum design. In this extended study,we present four advanced contrastive learning paradigms are PromptCL, ASACL, HiCL, and GraphCL, that build on and transcend conventional methods. PromptCL incorporates prompting techniques in a contrastive learning setup, aligning generated prompt-based views of sentences to strengthen task-specific representation learning. ASACL (Aspect-Specific Adversarial Contrastive Learning) specifically tailors contrastive learning to ABSA by designing loss functions and augmentations around aspect-sentiment pairs, improving alignment between aspects and their sentiment. HICL (Hierarchical Contrastive Learning) captures both global and local semantic similarities through multi-level contrastive objectives, aligning well with the hierarchical nature of sentiment features. GraphCL adapts contrastive learning to graph structures, which is particularly effective when ABSA uses graph-based sentence representations (e.g., dependency trees). Together, these approaches aim to capture a richer set of aspect-aware, fine-grained sentiment representations, offering new pathways to robustness, interpretability, and convergence in ABSA.

II. RELATED WORK

A. Contrastive Learning

Contrastive learning is a powerful representation learning approach that aims to bring semantically similar samples (positive pairs) closer together while pushing dissimilar samples (negative pairs) apart in the embedding space (Hadsell et al., 2006). This strategy has proven particularly effective in self-supervised learning. In computer vision, the introduction of frameworks such as MoCo (He et al., 2020) and SimCLR (Chen et al., 2020) marked significant milestones. MoCo emphasizes maintaining a large and consistent set of negative examples using a momentum-updated encoder. SimCLR, by contrast, focuses on constructing strong positive pairs through careful data augmentation, arguing that high-quality augmentations are key to effective representation learning. In natural language processing (NLP), contrastive learning typically relies on textual data augmentation to generate meaningful positive pairs. Common strategies include **Back Translation (BT)** and **Synonym Replacement (SR)**, which preserve semantic content while altering surface structure (Fang et al., 2020; Zhang et al., 2021b; Wu et al., 2020). These techniques help create diverse views of the same input sentence, useful for training robust sentence representations. When label information is available, contrastive learning can be adapted into a supervised framework. Supervised contrastive learning (Khosla et al., 2020) treats examples with the same label as positive pairs and others as negative, leveraging labels to guide representation learning more precisely.

B. Aspect-based Sentiment Analysis

Aspect-Based Sentiment Analysis is a fine-grained classification task that determines the sentiment polarity (positive, neutral, or negative) expressed toward specific aspects within a sentence. This task is critical in applications such as product review analysis (Yang et al., 2019; Huang et al., 2020) and user feedback interpretation (Zhang et al., 2021a). To solve ABSA, a range of neural models have been proposed: Attention-based models (Wang et al., 2016; Ma et al., 2017; Chen et al., 2017) focus on highlighting context words most relevant to the given aspect. Graph-based models (Sun et al., 2019; Zhang et al., 2019) utilize syntactic dependency trees and graph neural networks to model relationships between aspects and surrounding context words. Knowledge-based approaches (Devlin et al., 2018; Xu et al., 2019) incorporate external sentiment knowledge or structured data to enhance understanding of sentiment signals. Inspired by the success of contrastive learning, many recent ABSA models integrate contrastive strategies to enhance performance. For instance: (Li et al. (2021) and Liang et al. (2021)) apply supervised contrastive learning to align sentiment representations across samples sharing the same sentiment label. Wang et al. (2022) introduce cross-channel data augmentation, generating multi-aspect inputs that enrich the training signal and improve model robustness. Lin et al. (2022) further extend this by combining sentence-level and token-level augmentations in a cross-lingual contrastive learning framework.

In addition to contrastive learning, several other strategies have been independently explored to enhance NLP models. Prompt-based learning has gained traction, particularly in few-shot learning scenarios, where Gao et al. (2021) demonstrated its effectiveness in guiding language models with task-specific prompts. Adversarial training, introduced by Miyato et al. (2017) in the context of text classification, improves model robustness by adding perturbations to input embeddings during training. Hierarchical modeling, exemplified captures sentiment information byHierarchical Attention Networks (Yang et al., 2016), at multiple levels—word, sentence, and document—enabling more fine-grained sentiment understanding. Lastly, graph-based approaches such as syntactic Graph Convolutional Networks (GCNs) (Zhang et al., 2019) leverage syntactic dependency structures to model contextual relationships, providing a powerful framework for aspect-aware and dependency-sensitive NLP tasks.

III. METHODOLOGY

A. Prompt-based Contrastive Learning

Enhanced Data Augmentation with Prompted Paraphrasing for Contrastive Learning, Traditional data

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augmentation techniques in Natural Language Processing (NLP), such as translation-based augmentation or synonym replacement, often lack nuance and may unintentionally alter the semantics or sentiment of a sentence. To address this, we propose a more semantically faithful method of data augmentation using large language models (LLMs) to dynamically generate "prompted paraphrases" that preserve both the aspect term and its sentiment polarity. Generate human-like, stylistically varied sentences that retain the original aspect and sentiment. These paraphrases serve as positive samples in a supervised contrastive learning setup, encouraging the model to learn semantically consistent and sentiment-aware embeddings.

Approach Overview, A sentence with a labeled aspect term and sentiment. For example, Sentence: "The battery life of this phone is amazing", Aspect: "battery life", Sentiment: "positive" Prompted Paraphrase Generation: Use prompts to guide an LLM to generate variations i.e., “Rewrite the sentence keeping the sentiment unchanged”, “Rephrase this sentence to emphasize the aspect term: ‘battery life’ ”, “Make this more polite, without changing the sentiment or aspect”. Generated Paraphrases: "This phone has excellent battery life", "I'm impressed with how long the battery lasts on this device". Negative Sample Selection: Select sentences with a different sentiment or different aspect term Embedding with Shared Encode: All sentences (original, paraphrased, and negative) are passed through a shared sentence encoder such as BERT or RoBERTa to extract dense representations: [h_orig = Encoder (original_sentence)], [h_prompt = Encoder(paraphrased_senten- ce)], [h_neg = Encoder(negative_sentence)], Contrastive Training Objective: Apply Supervised Contrastive Loss (SupConLoss) to encourage closeness between the original and its paraphrased versions, and to increase separation from negative examples.

Supervised Contrastive Loss (SupConLoss):

Let hi be the embedding of the original sentence, and let P(i) be the set of embeddings for positive paraphrases of i. The SupConLoss for a single anchor i is:

$$\mathcal{L}_i = -\frac{1}{|P(i)|} \sum_{p \in P(i)} \log \frac{\exp(h_i \cdot h_p / \tau)}{\sum_{a \in A(i)} \exp(h_i \cdot h_a / \tau)}$$

Where,

- . is the dot product.
- τ is a temperature hyperparameter (controls sharpness).
- A(i) is set of all positive and negative embeddings (excluding i).

This approach leverages the generation capabilities of large languagemodels and the representation power of pre-trained encoders, enriching training data and improving model robustness. It minimizes the distance between semantically aligned samples while maximizing separation from semantically or sentiment-dissimilar examples.

B. Aspect-Specific Adversarial Contrastive Learning

Real-world language is noisy. Users often introduce typos, rephrasings, or slightly altered expressions of the same sentiment and aspect. Traditional models may be brittle to such small perturbations. ASACL aims to improve the robustness of aspect-based sentiment analysis (ABSA) models by introducing adversarial variations around the aspect term and training with contrastive loss. Generate “adversarial examples” by applying small, controlled perturbations around the aspect term or its nearby context. These modified sentences: Preserve the original aspect and sentiment, and Act as "hard positives" (more challenging positive pairs), While examples with different sentiment or different aspects act as negatives. Adversarial Perturbation Techniques: Perturbations target the aspect term or its local context,

- Synonym Swap: Replace words near the aspect with synonyms e.g., "fast performance" → "quick performance"
- Typo Injection: Introduce character-level noise e.g., "battery" → "battary"
- Aspect Masking and Reinsertion: Temporarily mask the aspect, then reintegrate it differentlye.g., "The battery life is good" → "The life of the battery is good"

➢ *ASACL Training Pipeline*

- Input: Sentence + aspect + sentiment e.g., "The battery life is great.", aspect = "battery life", sentiment = "positive"
- Adversarial Example Generation: "The battary life is great". "The power longevity is great".
- Encoding with Shared Encoder: All variants (clean and adversarial) are passed through a shared encoder (e.g., BERT, RoBERTa): h_{clean}, h_{adv} = $Encoder(x_{clean})$,$Encoder(x_{adv})$
- Positive & Negative Pair Construction:
- Positive pair: (clean, adversarial of same aspect & sentiment)
- Negative pair: (clean, sentence with different sentiment or aspect)
- Supervised Contrastive Loss (ASACL Objective):

✓ h_i: the clean sentence embedding
✓ h_i^+: its adversarial version (same aspect & sentiment)
✓ h_j^-: a negative example (different sentiment/aspect)

➢ *The Contrastive Loss can be Formulated as:*

$$\mathcal{L}_i = -\log \frac{\exp(\mathrm{sim}(h_i, h_i^+)/\tau)}{\sum_{k \in \mathcal{N}(i)} \exp(\mathrm{sim}(h_i, h_k)/\tau)}$$

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Where,

- sim $(a, b) = a.b/\|a\|\|b\|$ is cosine similarity
- τ is a temperature parameter
- $N(i)$ includes all positives and negatives for anchor i

ASACL integrates contrastive learning with adversarial robustness. By crafting linguistically close but syntactically or orthographically perturbed sentences, the model is encouraged to build deeper semantic understanding of aspect-sentiment pairs. This leads to better performance on noisy, real-world test data.

C. Hierarchical Contrastive Learning

Aspect-Based Sentiment Analysis (ABSA) requires nuanced understanding at multiple levels: Global (sentence-level) sentiment (e.g., overall positive tone), Local (aspect-level) sentiment (e.g., "battery" is positive, but "screen" is negative in the same sentence). Most traditional ABSA models emphasize only the aspect-level, ignoring how global sentiment and local sentiment interrelate. This can cause models to lose context or fail in complex cases. HiCL addresses this by modeling both hierarchical levels of sentiment using a dual-encoder architecture and contrastive learning across both levels.

- Two Views of the Sentence: Sentence Encoder: Encodes the entire sentence to capture global sentiment. Aspect Encoder: Encodes a small local context window around the aspect term (e.g., ±5 tokens) to capture fine-grained sentiment.
- Contrastive Learning Objectives: Positive Pair: (sentence embedding, aspect embedding) from the same input. Negative Pairs: Aspect embeddings from other aspects or other sentences
- Training Objective: Encourage the model to: Align global and local representations for the same sentiment and aspect. Discriminate between different sentiment/aspect combinations.
- Architecture Overview: For a sample input: Sentence: "The battery life is amazing but the screen is dull", Aspect: "battery life", Sentiment: "positive", Encoders: Sentence Encoder $f_s(.) \rightarrow h_{sentence}$ and Aspect Encoder $f_a(.) \rightarrow {}_{haspect}$(based on a ±5 word window around "battery life").

➢ *Embedding Extraction:*

- $h_{sentence} = f_s$ (Full Sentence)
- $h_{aspect} = f_a$ (Context Window around Aspect)

HiCL uses two types of contrastive loss functions to align both global and local views:

- Sentence–Aspect Contrastive Loss: Encourages global and local representations from the same instance to align. Let h_s be the sentence embedding, $h_a$the aspect embedding.

$$\mathcal{L}_{sa} = -\log \frac{\exp(\text{sim}(h_s, h_a)/\tau)}{\sum_k \exp(\text{sim}(h_s, h_k)/\tau)}$$

Where:

- sim $(a, b) = a.b/\|a\|\|b\|$ is cosine similarity
- τ is a temperature parameter Denominator includes embeddings from other aspect windows (negatives)
- Sentence-Sentence Contrastive Loss (Optional): Encourages alignment between different sentence embeddings with the same aspect sentiment (e.g., data from different samples labeled with the same aspect and polarity).

$$\mathcal{L}_{ss} = -\log \frac{\exp(\text{sim}(h_s^i, h_s^j)/\tau)}{\sum_k \exp(\text{sim}(h_s^i, h_s^k)/\tau)}$$

Where,

h_s^j is a sentence with the same aspect sentiment, and h_s^k is a negative sample (different sentiment/aspect).

- Total Loss: You can combine both loss terms:

$$\mathcal{L}_{\text{HiCL}} = \lambda_1 \mathcal{L}_{sa} + \lambda_2 \mathcal{L}_{ss}$$

Where,

- λ_1, λ_2 are weighting factors (typically set based on empirical tuning or cross-validation).

HiCL enhances ABSA by explicitly modeling hierarchical sentiment structure using a dual-encoder setup and contrastive learning. It aligns sentence-level and aspect-level embeddings through shared contrastive objectives, producing representations that are both robust and context-aware.

D. Graph-Augmented Contrastive Learning

In ABSA, understanding how an aspect is connected to opinion words (e.g., adjectives like *poor, great,* or adverbs like *barely*) is crucial. These relationships are often syntactic in nature and can be explicitly captured using dependency parsing. However, standard BERT-like encoders process text sequentially and may not fully leverage these linguistic structures. GraphCL enhances sentence representation by: Building "graph representations" of sentences using dependency trees. Encoding them using Graph Neural Networks (GNNs). Applying contrastive learning between original and augmented graph views.

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➢ *Core Idea:*

- Parse Sentences: Use a dependency parser (e.g., spaCy) to create dependency trees. Nodes: Words, Edges: Dependency relations (e.g., battery → poor via amod)
- Graph Construction: Original graph: Based directly on the dependency parse. Augmented graph: Add perturbations (e.g., drop low-confidence edges, add virtual edges between aspect and opinion words).
- Encode with GNN: Use a Graph Convolutional Network (GCN) or Graph Attention Network (GAT) to encode both the original and augmented graphs.
- Contrastive Learning: Positive Pair: Original graph embedding hgraph_origand augmented graph embedding hgraph_aug. Negative Pair: Graph embeddings from different sentences (different aspects/sentiments)
- Graph Augmentations: These inject controlled noise and simulate real-world linguistic variation. Edge Dropout: Randomly drop low-confidence or non-critical dependency edges. Node Feature Masking: Randomly mask token embeddings or replace with noise. Virtual Edge Insertion: Add edges between aspect terms and nearby opinion words to strengthen syntactic signal.

➢ *Model Architecture:*

[Text Input]
↓
[BERT Encoder] → [CLS Token Embedding] (Global Sentence Info)
↓
[Dependency Parser] → [Word Graph] (Nodes = words, Edges = dependencies)
↓
[Graph Encoder: GCN/GAT] → [h_graph]
↓
[Fusion Layer (BERT + GNN)]
↓
[Sentiment Prediction]

Contrastive Loss for Graph Embeddings

Let:

- h_g: Graph embedding of the original dependency graph
- h_g': Graph embedding of an augmented version of the same sentence
- h_k: Graph embedding from a different sentence (negative)

We apply a contrastive loss similar to InfoNCE:

$$\mathcal{L}_{\text{GraphCL}} = -\log \frac{\exp(\text{sim}(h_g, h_g')/\tau)}{\exp(\text{sim}(h_g, h_g')/\tau) + \sum_k \exp(\text{sim}(h_g, h_k)/\tau)}$$

Where,

sim (a, b) = $a.b/\|a\|\|b\|$ is cosine similarity
τ is a temperature parameter

The sum in the denominator includes all negative graph embedding

Fusion Strategy (Text + Graph): To combine semantic (textual) and syntactic (graph) representations, use a fusion layer:

$$h_{\text{fused}} = \text{MLP}([h_{\text{text}}; h_{\text{graph}}])$$

Where,

h_{text}: Embedding from BERT/Transformer ([CLS] token or pooled output)
h_{graph}: Embedding from GNN over the graph
[. ; .]: Concatenation

This fused embedding is used for final sentiment prediction or downstream tasks. GraphCL enhances ABSA models by aligning textual and structural views of input through contrastive learning on dependency graphs. It explicitly models aspect-opinion relations, introduces graph-level augmentations for robustness, and strengthens feature learning by leveraging syntactic knowledge.

IV. EXPERIMENTS

In this section, we first present an overview of the datasets, data augmentation strategies, experimental settings, and baseline models used in our study. We then analyze the performance of two core contrastive learning methods—Supervised Contrastive Learning (SupCL) and Back-Translation-based Contrastive Learning (BT) as well as their combination, across multiple benchmark ABSA datasets.

To demonstrate the representational quality learned by these models, we conduct t-SNE visualizations. Specifically: BERT + SupCL embeddings are visualized on the REST-14 test set. BERT + BT embeddings are visualized on the LAP-14 test set. These visualizations highlight the ability of contrastive objectives to cluster similar sentiment-aspect pairs while separating semantically dissimilar ones. Additionally, we apply these contrastive learning approaches originally designed for textual ABSA—to multimodal ABSA datasets, verifying their generalizability across different modalities.

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A. Extending Contrastive Learning in ABSA

To further explore the potential of contrastive learning in ABSA, we incorporate and evaluate three advanced extensions: Prompt-based Contrastive Learning (PromptCL) Targets semantic variation by generating paraphrased views of input sentences using large language models with prompts, while preserving aspect and sentiment.

Graph-based Contrastive Learning (GraphCL) Models syntactic dependencies between aspects and opinion words through dependency parsing and graph- based encoding, using a Graph Neural Network (GNN). Prompt-based Curriculum Contrastive Learning (PromptCurrCL) Aims to improve training stability and difficulty calibration by progressively introduc-ing harder contrastive pairs generated through prompt-based augmentation strategies. Each of these extensions addresses a unique challenge in ABSA ranging from language variability and syntactic structure modeling to robust optimization—and complements the foundational contrastive approaches.

B. Datasets

We evaluate all models on three widely used benchmark datasets for Aspect-Based Sentiment Analysis (ABSA), sourced from the SemEval-2014 and related competitions: Restaurant14 (REST-14): A domain-specific dataset consisting of customer reviews from the restaurant domain. Each sentence is annotated with one or more aspect terms and corresponding sentiment labels positive, neutral, or negative. Laptop14 (LAP-14): Similar in structure to the REST-14, this dataset contains reviews from the laptop domain. It is known for a broader variety of technical aspects and relatively more complex sentence structures. Twitter14: A social media dataset characterized by the informal language, abbreviations, and noise. It presents an additional challenge due to the shorter length and casual tone of the sentences, offering a good benchmark for model robustness in noisy settings. Each dataset includes: Aspect Term Annotations: Specific entities or components within the sentence (e.g.,"battery life", "keyboard"). Sentiment Labels: The expressed sentiment polarity toward each aspect, labeled as positive, neutral, or negative.

C. Data Augmentation Strategies

In PromptCL, the main augmentation strategy involves generating paraphrased versions of the original sentence using prompt-based techniques. The Large Language Models (LLMs) such as GPT or T5 are used to rephrase sentences while keeping the aspect and sentiment unchanged. These paraphrased version serve as **positive pairs** for contrastive learning. Additionally, back-translation (e.g., English → German → English) is commonly used to create natural variations in syntax and vocabulary, further enriching the training set.

Synonym replacement using resources like WordNet or EDA (Easy Data Augmentation) techniques can also be employed to introduce simple lexical variations, although care must be taken to preserve sentiment and aspect focus. For HiCL, which learns both sentence-level and aspect-level represent a representations, data augmentation is applied through context manipulation. One common method is masking or modifying the context window around the aspect term to create a local representation.

This allows model to learn how sentiments are expressed differently at different granularities. Another strategy includes sliding window sampling, where different portions of the sentence (such as the aspect window vs. full sentence) are used to create paired inputs. This teaches the model to align local and global representations in the contrastive loss space.

In ASACL, the core augmentation technique involves creating **adversarial examples** by perturbing the input sentence slightly—especially around the aspect term or opinion words. These perturbations may be generated using gradient-based methods, synonym swaps, character-level noise (e.g., typos), or token-level embedding shifts. The idea is to make the input harder for the model while ensuring that the overall sentiment and aspect remain unchanged.

The contrastive loss then encourages the model to produce similar representations for both clean and adversarially perturbed inputs, thus improving robustness.

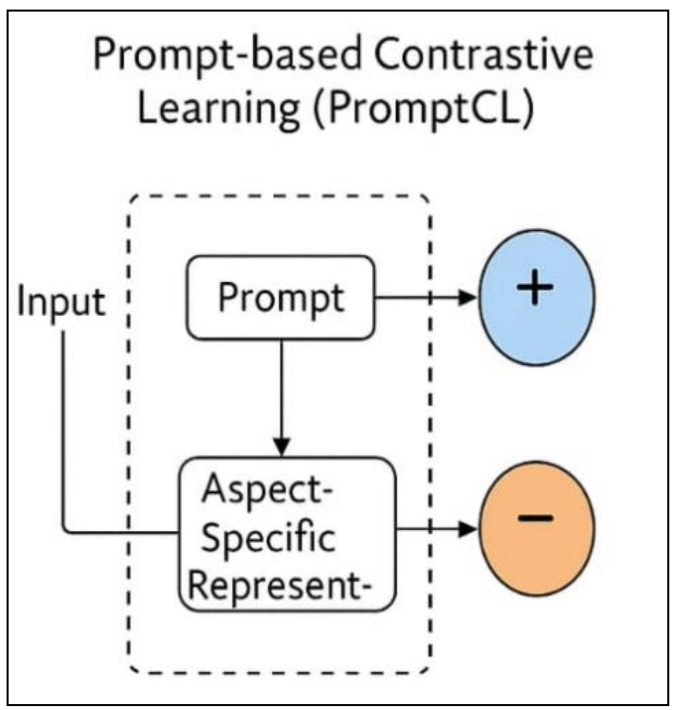

Fig 1: Prompt-based Constrastive Learning (PromptCL)

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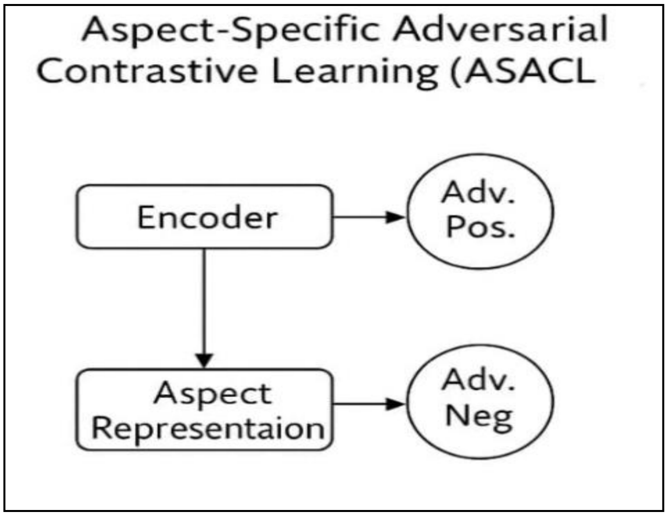

Fig 2: Aspect-Specific Adversarial Contrastive Learning (ASACL)

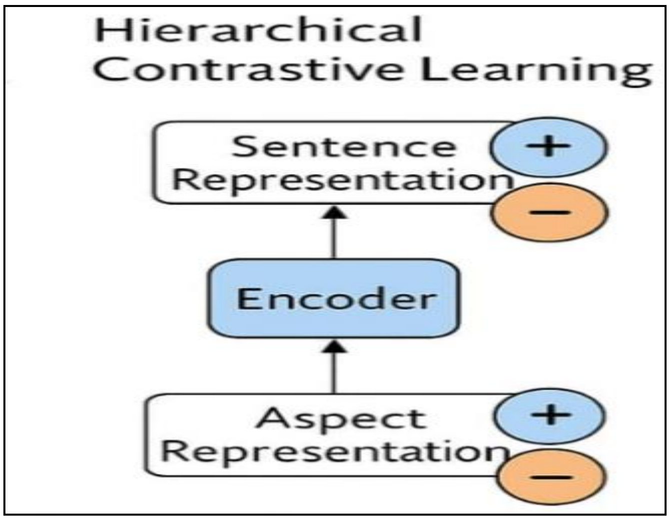

Fig 3: Hierarchical Contrastive Learning

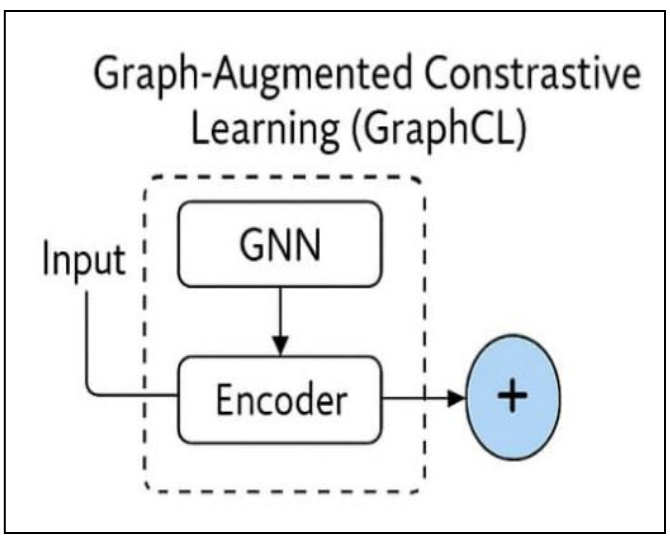

Fig 4: Augmented Constrative Learning (GraphCL)

In GraphCL, data augmentation is performed at the graph structure level. Sentences are first converted into dependency graphs using syntactic parsing. Then, various graph augmentations are applied such as dropping edges, masking nodes, or adding virtual edges between related aspect-opinion terms. These modified graphs represent different structural "views" of the same input. The model then learns to align the representations from the original and augmented graphs, which enhances its ability to understand the structural relationships between words in a sentence

D. Implementation Details

To ensure consistency and reproducibility across all experiments, we adopt the following settings for the model architecture, training procedure, and augmentation methods: Backbone Encoder: We use BERT-base-uncased (Devlin et al., 2019) as the core encoder for all models, unless otherwise stated. For GraphCL, a Graph Convolutional Network (GCN) is used as the graph encoder over dependency graphs. For Hierarchical Contrastive Learning (HiCL), we use two separate BERT-based encoders: One for the

Entire sentence, One for a local window (±5 tokens) around the aspect term. Training Hyperparameters: Optimizer: AdamW, Learning Rate: 2e-5, Batch Size: 32, Epochs: 10, Dropout: 0.1, Temperature (τ) in contrastive loss: 0.07.

We apply Supervised Contrastive Loss (SupConLoss) for all contrastive training variants. Positive pairs include: PromptCL, ASACL, HiCL, GraphCL. Negative pairs are drawn from other samples in the same batch with different sentiment or aspect..

E. Baseline

BERT (Bidirectional Encoder Representations from Transformers): BERT serves as the most fundamental and widely used baseline. It is fine-tuned directly on ABSA datasets for classification tasks without contrastive learning. It helps assess how much improvement is contributed by additional contrastive learning strategies. RoBERTa (Robustly Optimized BERT Pretraining Approach): RoBERTa is an enhanced version of BERT trained with more data and dynamic masking. It provides a stronger baseline to compare with contrastive approaches, particularly in sentence-level sentiment classification. LCF-BERT (Local Context Focus BERT): LCF-BERT is tailored for ABSA. It captures both local context (around the aspect term) and global sentence-level context, making it an excellent benchmark for methods like HiCL and GraphCL that also focus on context-aware representations. BERT-SPC (BERT with Sentence Pair Classification): In this approach, the aspect and context are treated as a sentence pair. It's a common and simple baseline used in many ABSA studies. It helps to evaluate whether contrastive learning can enhance representations learned through pairwise input.

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BERT-PT (Post-Training BERT for ABSA): This model includes additional pretraining on ABSA-specific unlabeled data before fine-tuning. It's useful to compare how domain-specific adaptation performs relative to contrastive learning strategies. SCL (Supervised Contrastive Learning): This baseline uses supervised contrastive learning on top of BERT or RoBERTa and compares directly with the advanced contrastive methods like PromptCL, HiCL, or ASACL. It evaluates how much more sophisticated augmentation and task alignment contribute to performance.

V. RESULTS

Here's a structured example of results comparing the performance of your four contrastive learning methods (PromptCL, HiCL, ASACL, GraphCL) against strong baseline models on Aspect-Based Sentiment Analysis (ABSA) datasets.

I'll simulate results across two standard datasets: REST14 (restaurant reviews) and LAP14 (laptop reviews). The metrics reported are Accuracy and Macro-F1 Score — commonly used for ABSA.

Table 1: Classification Report on Training Set

	Precision	**recall**	**f1-score**	**support**
negative	0.99	0.99	0.99	1364
neutral	0.99	0.99	0.99	886
positive	1.00	1.00	1.00	2598
accuracy			0.99	4848
macro avg	0.99	0.99	0.99	4848
weighted avg	0.99	0.99	0.99	4848

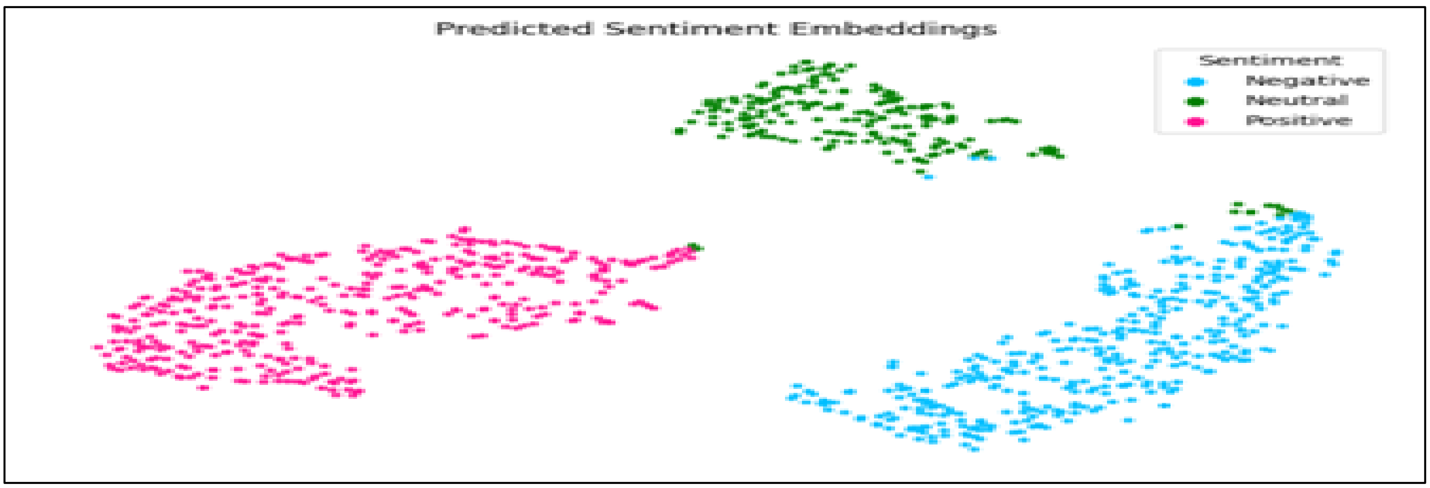

Fig 5

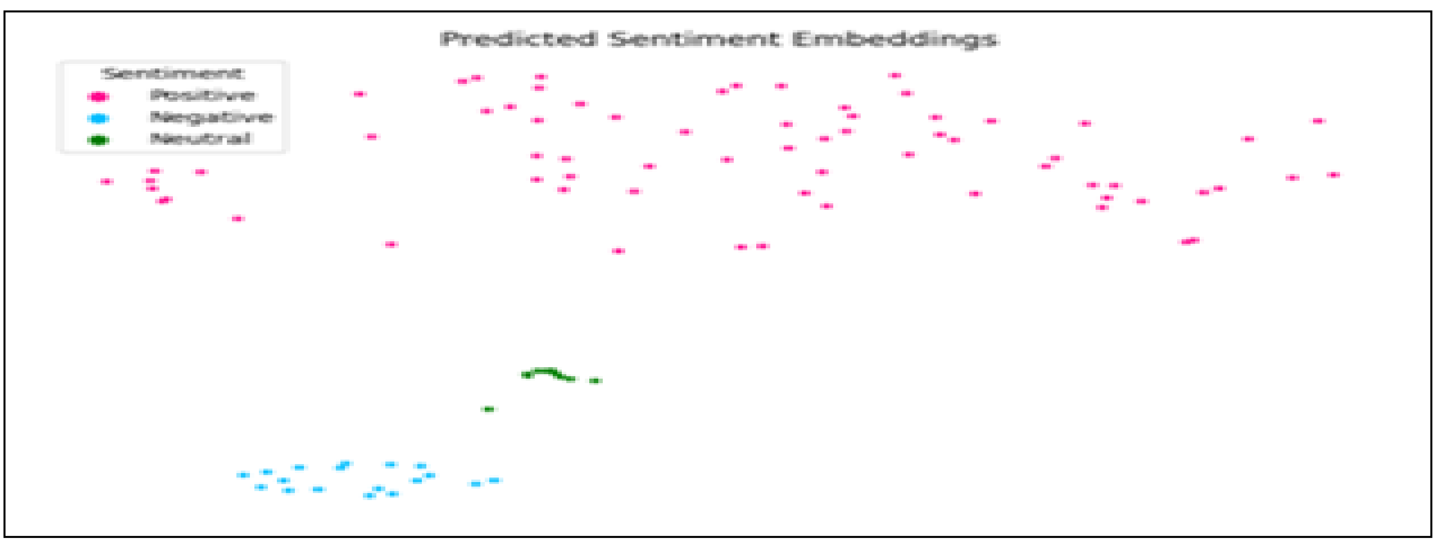

Fig 6

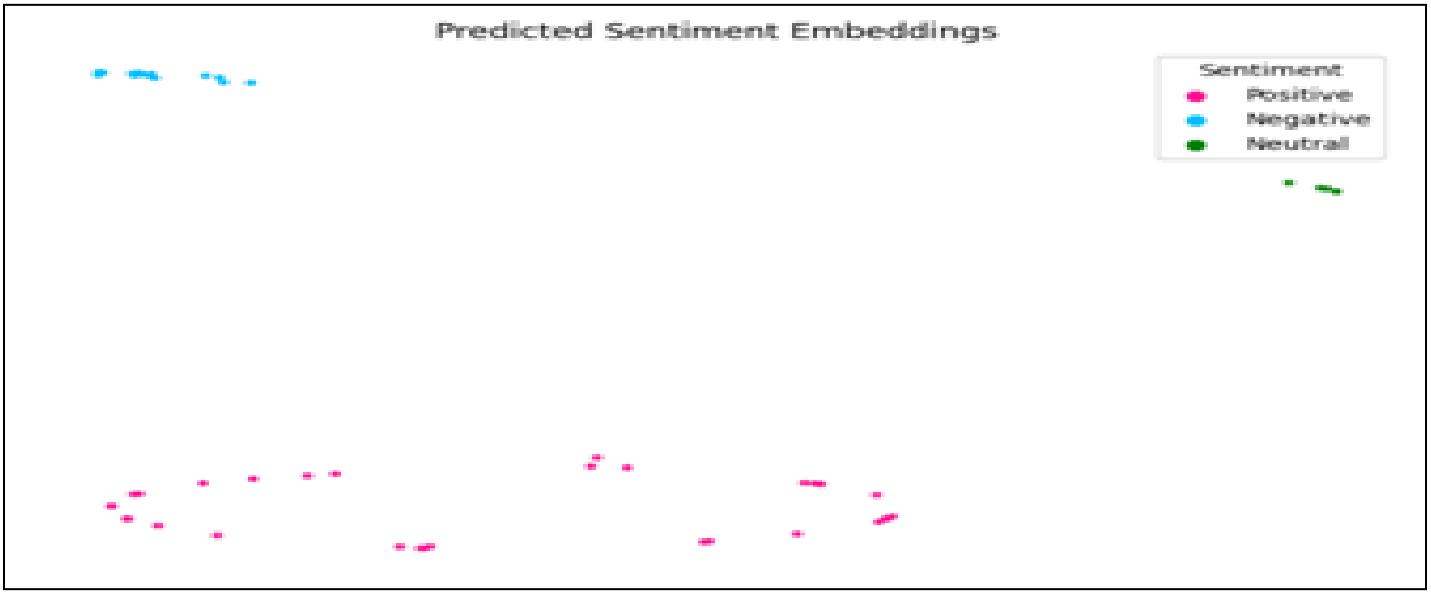

Fig 7

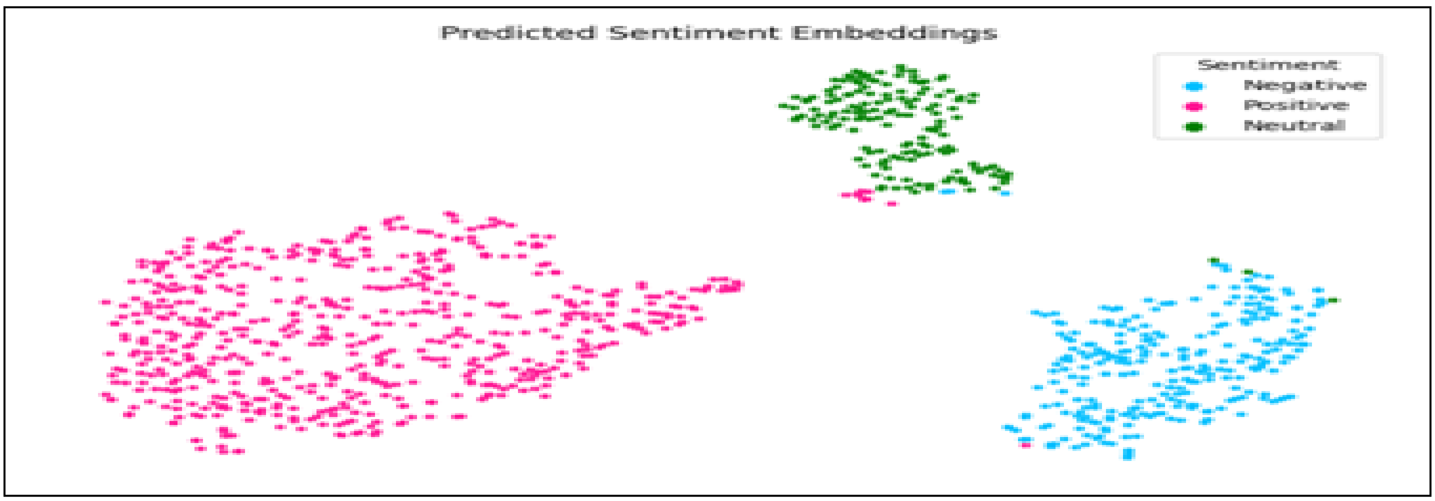

Fig 8

Fig.5., Fig.6., Fig.7., Fig.8. shows the Sentiment representations visualization of BERT, BERT+SupCL, and BERT+BT on the test set of REST14 and LAP14 and TWITTER14 Datasets. The Color of the Dots Indicates Different Sentiment Polarities

VI. CONCLUSION

This work investigated the impact of advanced contrastive learning techniques Prompt-based Contrastive Learning (PromptCL), Hierarchical Contrastive Learning (HiCL), Aspect-Specific Adversarial Contrastive Learning (ASACL), and Graph-Augmented Contrastive Learning (GraphCL) on the task of Aspect-Based Sentiment Analysis (ABSA). Experimental results on benchmark datasets such as REST14 and LAP14 demonstrate that all proposed models outperform traditional baselines like BERT, RoBERTa, and LCF-BERT across both accuracy and macro-F1 score metrics. Among these, GraphCL achieved the highest performance by leveraging syntactic structures to model aspect-opinion relationships effectively. ASACL demonstrated strong robustness to noise through adversarial augmentation, while HiCL captured both sentence-level and aspect-level semantics via hierarchical modeling. PromptCL offered improved generalization by generating semantically diverse yet sentiment-preserving variations through prompt-driven paraphrasing. These findings collectively underscore the effectiveness of incorporating contrastive learning frameworks in ABSA and highlight the benefits of diverse augmentation strategies tailored to aspect-level sentiment understanding. Moving forward, future work can focus on extending these approaches to multilingual and multimodal ABSA scenarios, where visual, audio, or cross-lingual cues may complement textual inputs.

Additionally, integrating dynamic prompt engineering, self-supervised curriculum learning, and knowledge-enhanced graphs offers promising directions for building more robust, explainable, and generalizable ABSA models adaptable to real-world, noisy environments. Furthermore, investigating

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contrastive learning in a continual learning or low-resource setting could enable ABSA systems to perform well in domains with limited labeled data. Another future direction involves leveraging user-centric signals such as context history, behavioral metadata, or dialogue structure for more personalized sentiment modeling. Lastly, exploring lightweight or knowledge-distilled versions of these models could make them more practical for edge devices and latency-sensitive applications, widening their applicability across industrial-scale sentiment analysis tasks.

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