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RESEARCH ARTICLE

Syntactic-Guided Chain of Thought for Iterative Implicit and Explicit Target Detection in Aspect-Based Sentiment Analysis

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ABSTRACT Prompt engineering is essential for optimizing the performance of large-language models (LLMs), particularly in tasks requiring complex interpretations such as aspect-based sentiment analysis (ABSA). However, existing methodologies often struggle to detect implicit targets, especially in multi-opinion sentences where sentiments are directed toward aspects that are not explicitly mentioned. This study addresses this gap by proposing the Iterative Syntactic-Guided Chain of Thought (IS-COT) framework, which integrates dependency parsing with modular prompt engineering to enhance LLMs' reasoning capabilities. IS-COT leverages syntactic structures and iterative refinement to detect both explicit and implicit targets while resolving ambiguities in multi-opinion contexts. Experimental evaluations on benchmark datasets, Sem-Eval 2015 (Res15) and Sem-Eval 2016 (Res16), demonstrated the effectiveness of the framework, achieving superior performance with 80.43 F1 scores on Res15 and 84.47 F1 scores on Res16, significantly outperforming state-of-the-art models. These results highlight IS-COT's potential of IS-COT as a comprehensive and interpretable solution for ABSA, addressing the critical limitations of existing approaches and advancing the field through innovative syntactic and semantic integration.

INDEX TERMS Aspect-based sentiment analysis (ABSA), prompt engineering, chain of thought (COT), explicit opinion, implicit opinion, target-aspect-sentiment (TASD), dependency relations.

I. INTRODUCTION

Aspect-based sentiment analysis (ABSA) has gained prominence in natural language processing (NLP) because of its ability to discern sentiments directed toward specific aspects of products or services [1], [2]. The challenge of identifying implicit targets, for example, the sentiment associated with the word *tasty,* remains significant, as it indirectly infers the aspect *Food Quality*, especially in sentences containing multiple opinions. Figure 1 illustrates an example sentence that contains both implicit and explicit opinions.

Recent studies have highlighted the necessity of advanced models to effectively address this complexity. For example, Gao, et al. [3]. emphasized the importance of multitarget tasks in reflecting the intricacies of fine-grained sentiment analysis.

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Furthermore, methodologies that incorporate grammatical rules and hybrid approaches have demonstrated efficacy in addressing both implicit and explicit aspects of sentiment analysis [4], [5], [6], [7]. Integration of contextual information and advanced neural network architectures has been proposed to enhance the detection of implicit sentiments that frequently lack explicit emotional indicators [8], [9]. Therefore, continued research is essential to enhance the precision and efficacy of the ABSA, particularly in complex scenarios involving implicit sentiments [10], [11].

Implicit target detection is a significant challenge in ABSA, particularly for sentences containing multiple aspects or sentiments. For instance, in multi-opinion sentences containing sentiments regarding various aspects, models frequently encounter difficulties in disambiguating which sentiment corresponds to which aspect. Furthermore, implicit targets, such as sentiments expressed without an explicit

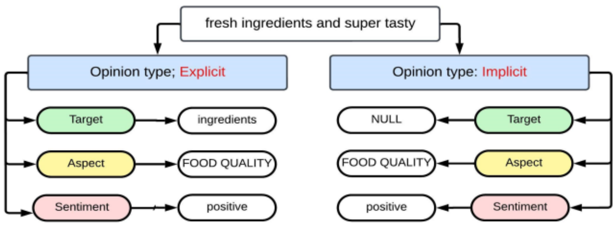


FIGURE 1. Multi-opinion sentence example.

opinion target, present a particular challenge because they rely on contextual or semantic information rather than direct syntactic cues [12]. Current methodologies in sentiment analysis, particularly those that utilize neural architectures and template-based prompts, frequently encounter challenges with implicit targets and complex relational nuances.

While Chain of Thought (COT) prompting demonstrates efficacy in explicit task scenarios, its methodology of decomposing problems into sequential subproblems exhibits limitations. This approach, which relies heavily on explicit target phrases, is less effective when addressing contexts that involve implicit sentiments or multiple opinions embedded within a single sentence [13], [14], [15]. This limitation is exacerbated by the lack of a broader semantic context, which is crucial for understanding implicit sentiments and managing overlapping opinions [12], [16]. The integration of Graph Neural Networks (GNNs) and attention mechanisms represents a significant advancement in deep learning research [17]. These innovative approaches have exhibited considerable potential for addressing existing challenges in the field. Specifically, they demonstrated an enhanced capacity to capture intricate relationships and subtle contextual nuances, thereby improving the overall performance of deep-learning models [13], [18]. However, further research is required to fully leverage these capabilities for implicit sentiment analysis and multi-opinion scenarios [6].

Moreover, recent advancements in large-language models (LLMs) such as GPT-3 have demonstrated their potential to execute various tasks with minimal fine-tuning. Nevertheless, challenges persist, particularly in comprehending implicit sentiments and navigating complex multi-opinion scenarios [19], [20]. This study proposes an innovative framework to enhance the reasoning capabilities of large-language models (LLMs) through a combination of iterative techniques, modular approaches, and advanced prompt engineering. The proposed methodology incorporates syntactic elements, including dependency parsing and semantic indicators, to augment the capacity of the model to infer implicit targets and resolve ambiguities in complex multi-opinion scenarios. The integration of these syntactic and semantic enhancements plays a pivotal role in improving the performance of LLMs in sophisticated sentiment-analysis tasks.

The primary contribution of this study is the development of an advanced prompt engineering methodology that effectively mitigates the limitations of the traditional approaches for detecting implicit targets. This framework incorporates dependency parsing into an iterative reasoning pipeline, enabling a more structured and accurate analysis of both the explicit and implicit targets. The modular design of prompts systematically guides LLMs through syntactic and semantic inferences, ensuring methodical decomposition of complex sentence structures. This iterative approach facilitates the refinement of reasoning at each stage, significantly enhancing interpretability and precision. By embedding syntactic dependencies directly into the reasoning process, the framework ensures that the hierarchical relationships within sentence structures are adequately represented, thereby facilitating a more comprehensive understanding of implicit sentiment associations. This contribution provides a more effective solution for ABSA tasks by improving both the accuracy and interpretability in detecting implicit targets. Furthermore, this technique surpasses existing approaches, such as COT and template-based prompt methods, by providing a more flexible and robust mechanism for handling multi-target and multi-opinion sentences, thereby advancing the state-of-the-art prompt engineering for ABSA.

II. RESEARCH OBJECTIVES

The main objective of this study was to develop an innovative approach to enhance ABSA by addressing the challenge of detecting implicit targets, particularly in multi-opinion sentences. The specific objectives of this study were as follows:

1) To improve opinion target detection by developing a method that leverages dependency parsing and syntactic information to enable LLMs to infer implicit targets that are not explicitly modified by sentiment words, but are identified through broader contexts and relationships.
2) To improve the model's capacity to handle sentences containing multiple opinions with distinct sentiment-target pairs.
3) Design of modular prompt engineering techniques to guide LLMs in reasoning over implicit sentiment-target relationships
4) To evaluate the effectiveness of the proposed method against state-of-the-art methods for Target Aspect Sentiment Detection (TASD) and assess its efficacy in comparison with COT prompt methods in terms of both accuracy and interpretability, utilizing the Sem-Eval 2015 Sem-Eval 2016 restaurant datasets.

III. LITERATURE REVIEW

LLMs have revolutionized natural language processing, demonstrating remarkable performance across various tasks [21], [22]. LLMs have evolved from task-specific to task-and-language-independent architectures, with model sizes growing from millions to trillions of parameters [23]. In ABSA, LLMs have shown promise in addressing challenges, such as domain specificity and labelled data reliance [24]. ABSA research has progressed from single-element analysis to compound tasks that involve multiple sentiment elements [25]. The primary tasks in ABSA include target aspect identification, where specific features or aspects of an entity are identified (e.g., ''food'' or ''service'' in restaurant reviews), sentiment polarity classification, which determines whether the expressed sentiment is positive, negative, or neutral, and opinion type identification, which distinguishes explicit opinions with clearly stated targets from implicit opinions that require inference based on context and external knowledge [26]. Approaches to ABSA include frequency-based, syntactic relation-based, and semantic similarity-based methods for aspect extraction [27]. The increase in deep learning has significantly enhanced these methods [28], [29]. The application of autoencoders has proven versatile across multiple domains, including sentiment analysis, highlighting their potential for tasks, such as image classification and text generation. Autoencoder architectures continue to evolve, addressing challenges in areas such as graph analysis and masked sequence modelling and demonstrating their adaptability [30]. Implicit aspect detection remains a challenge, with limited work compared with explicit aspect extraction [6]. As LLMs continue to advance, they face challenges in scalability, real-world deployment, and ethical considerations [21], [31].

Recent studies have explored efficient strategies to leverage LLMs without extensive retraining. Prompt engineering and in-context learning (ICL) have emerged as key techniques, allowing LLMs to adapt to various tasks through carefully designed prompts [32], [33]. These methods include the few-shot and zero-shot prompting, role-prompting, and COT approaches [34]. Techniques such as role-prompting and COT prompting have been shown to enhance the performance of LLMs by structuring the input in a manner that guides the reasoning process of the model [35]. Studies have demonstrated the effectiveness of demonstration selection, instruction formats, and knowledge augmentation in improving LLM performance, underscoring the versatility of prompt engineering [36].

Recent research has highlighted the importance of prompt engineering to enhance ABSA using LLMs. Prompt engineering involves designing effective input prompts to guide LLMs in sentiment-extraction tasks [37]. Studies have shown that LLMs such as GPT-3.5-Turbo and PaLM demonstrate competitive performance in ABSA tasks across various domains [24]. The integration of pretrained language models significantly improves the ABSA performance [25]. Researchers have proposed novel approaches such as prompt-enhanced sentiment analysis to better capture the relationships between aspects [38]. However, challenges persist in addressing complex scenarios involving multiple aspects and implicit sentiments [39]. As prompt engineering emerges as a crucial skill, there is a growing need to incorporate AI literacy and prompt engineering strategies into educational curricula [40], [41].

Techniques such as syntax-aware methodologies [20], [42] and knowledge graph augmentation [43] average both structural and semantic information to improve contextual understanding. These methodologies allow for a more nuanced interpretation of sentiment relationships, which is essential for accurately capturing the intricacies of sentiments in various contexts. Furthermore, task-specific prompt patterns have been developed to tailor LLMs to specific ABSA tasks, thereby enabling them to adapt more effectively to domain-specific requirements [20], [42], [44]. This highlights the critical role of prompt engineering in enhancing the capabilities of LLMs to discern subtle sentiment relationships and address the challenges unique to ABSA.

Despite these advancements, significant challenges persist, particularly in the management of implicit and multi-opinion cases. Implicit aspects, where sentiment targets are not explicitly stated, necessitate models to infer sentiment based on context and external knowledge, a task that remains challenging, even for advanced LLMs [42], [45]. Multi-opinion cases, which involve conflicting sentiments regarding different aspects or entities within a single text, further complicate the analysis because of the overlapping and intricate nature of opinions [44], [46].

Prompt engineering has emerged as a vital tool in addressing these challenges by crafting specialized input, prompting direct models to focus on implicit relationships, and disentangle overlapping sentiments [42], [43]. By integrating prompt engineering with external knowledge sources, syntactic and semantic analyses, and common sense reasoning, researchers are striving to develop fine-grained domain-adaptive ABSA solutions [42], [44]. The integration of advanced prompt engineering techniques with LLMs is a significant step forward in the ABSA. Although challenges such as implicit aspects and multi-opinion cases remain, ongoing research and development is focused on refining these methodologies to enhance the accuracy and applicability of sentiment analysis in real-world scenarios. The continuous evolution of these techniques is crucial for meeting the growing demands of various industries that rely on nuanced sentiment analysis.

Iterative prompt refinement has gained traction as a method to enhance the performance of LLMs. This technique allows the models to revisit and refine their initial responses by concentrating on various aspects or components of the input across multiple iterations. Such an approach is particularly beneficial for addressing challenges related to implicit target identification, as it enables LLMs to reassess context, syntactic cues, and sentiment expressions in a more nuanced manner [47]. Goyal et al. [48] highlighted that this iterative process can significantly improve the model's ability to discern implicit targets, which are often overlooked because of their reliance on surface-level syntactic cues rather than a deeper semantic understanding [47].

Despite advancements brought about by iterative refinement, LLMs still face notable limitations in implicit target identification. They frequently depend on superficial syntactic indicators, which can lead to inaccuracies in complex scenarios in which deeper semantic comprehension is

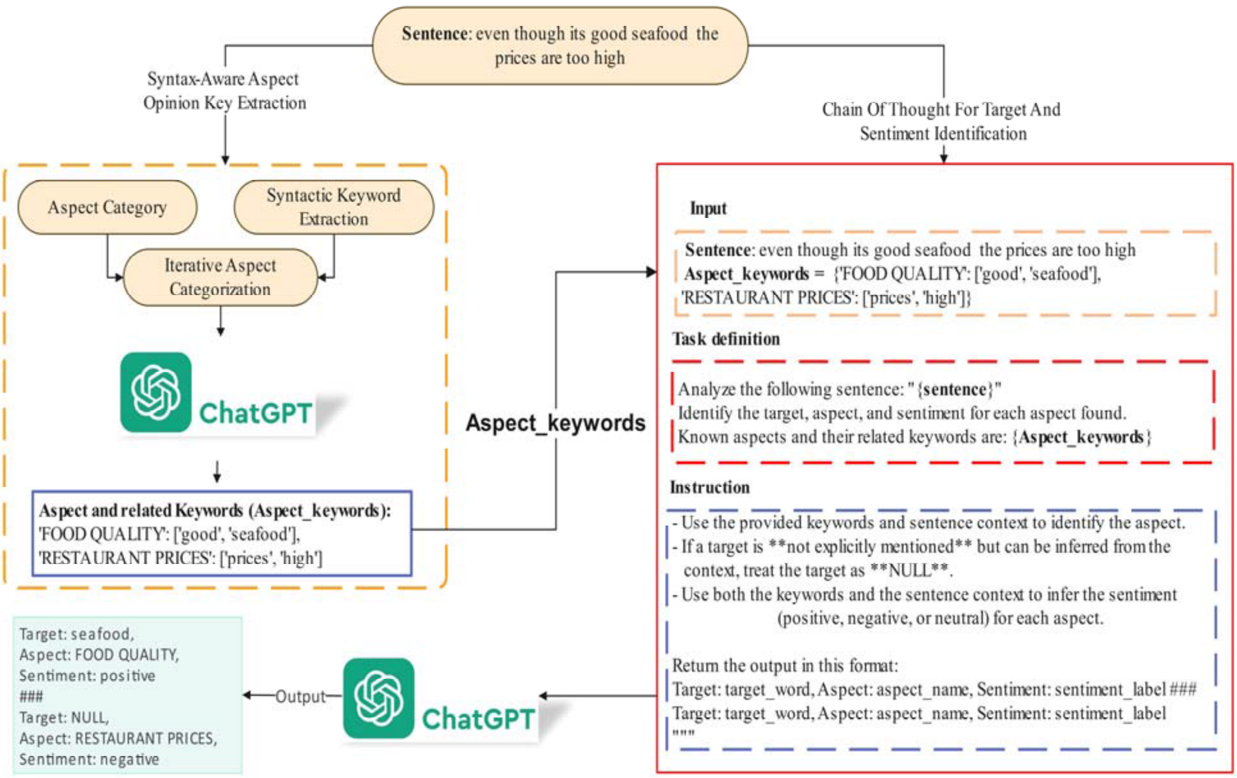


FIGURE 2. Framework overview of proposed iterative syntactic-guided chain of thought (IS-COT) for implicit and explicit target detection in aspect-based sentiment analysis.

required [49]. For example, handling multiple sentiments directed toward different components within a single sentence remains a significant challenge. Existing models often treat sentiments in isolation, neglecting the interdependencies between them [46], [50]. This oversight can result in a failure to accurately capture the sentiment landscape of a given text, thereby affecting the overall performance of sentiment analysis tasks [48]. Despite these advances, LLMs still have limitations in terms of implicit target identification, because they often rely on surface-level syntactic cues rather than deep semantic understanding, which can lead to errors in complex scenarios. In addition, handling multiple sentiments directed at various aspects of a single sentence remains challenging.

IV. PROPOSED METHODOLOGY

The proposed approach was designed to utilize LLMs and advanced engineering techniques to address ABSA challenges. This methodology specifically addresses the difficulties of identifying both implicit and explicit targets, processing multiple targets and opinions concurrently, and improving the sentiment classification accuracy. By implementing such prompting techniques, the model can effectively guide LLMs in emphasizing essential information, reducing ambiguity, and adhering to specific instructions. This process influences the calculation of the conditional probabilities in LLMs, thereby increasing their potential to generate Coherent and precise results were obtained in the present study. Incorporating this strategy facilitates the handling of complex sentence structures, thereby enhancing the ABSA task performance by capturing both overt and subtle relationships within the text, including targets, aspects, and sentiment detection for both implicit and explicit opinions.

The methodology employed in this study for Aspect-Based Sentiment Analysis (ABSA) provides a comprehensive approach for extracting fine-grained insights by identifying targets, aspects, and sentiments in text. This methodology integrates syntactic analysis, semantic reasoning, and large-language models (LLMs) to address explicit and implicit target detection, aspect categorization, and sentiment classification effectively. The process begins with syntactic keyword extraction, in which relevant nouns (potential targets) and adjectives (opinions) are identified using part-of-speech (POS) tagging and dependency parsing. The extracted keywords were then iteratively mapped to predefined aspect categories (e.g., food quality and service) using a context-aware matching function based on semantic similarity. Target and sentiment identification were subsequently conducted using a Chain of Thought (COT) framework, which identifies explicit targets, infers implicit targets where necessary, and refines target mappings. Sentiment classification (Positive, Negative, or Neutral) is achieved by leveraging prompts designed for LLMs. The final step involved formatting the results into a standardized structure: Target: target_word, Aspect: aspect_name, and Sentiment: sentiment_label. This approach offers a scalable and precise solution for ABSA tasks, particularly in Target Aspect Sentiment Detection (TASD), as depicted in Figure 2.

A. TASK DEFINITION

The objective of ABSA is to extract fine-grained insights from textual data by identifying specific targets, Aspect and Sentiment, which is analogous to the Target Aspect Sentiment Detection (TASD) task. This task encompasses both explicit targets, which are explicitly mentioned in the text, and implicit targets, which must be inferred from context. Formally, given an input sentence $S = (w_1, w_2, w_3, \ldots, w_n)$ composed of words w_i, the goal is to produce a structured output

$$R = (t, a, s)$$

where t represents the identified target, which can be explicitly mentioned in the text or inferred from the context; a denotes the corresponding aspect category; s is the sentiment polarity, categorized as Positive, Negative, or Neutral. The procedure is described in Algorithm 1.

B. SYNTACTIC KEYWORD EXTRACTION

In this step, the algorithm identifies keywords in a sentence using part-of-speech (POS) tagging, focusing on nouns that represent targets and adjectives that frequently express opinions. This approach ensures that the extracted keywords are syntactically relevant for the aspect and sentiment analyses. Dependency parsing, implemented with SpaCy, further enhances the extraction process by analyzing the grammatical structure of the sentence and preserving the relationships between words, such as adjectives describing nouns. Figure 3 illustrates the extracted keywords.

C. ITERATIVE ASPECT CATEGORIZATION

In this step, the algorithm systematically matches each keyword extracted in the previous syntactic keyword extraction step with the most contextually relevant aspect category from a predefined list. For each keyword in the set of extracted keywords, the algorithm queries a fine-tuned GPT-3.5 model utilizing a meticulously constructed context-specific prompt. The prompt explicitly incorporates the sentence, keyword, and a predefined list of aspect categories, thereby guiding the model to evaluate and determine the most semantically and contextually appropriate aspects of the keyword.

This iterative process ensures that each keyword is accurately assigned to an aspect category, based on its contextual relevance within a sentence. By combining semantic reasoning with iterative refinement, this step lays a durable foundation for subsequent target identification and sentiment analysis. The structure of the prompt used in this step is illustrated in Figure 4.

Algorithm 1 Iterative Syntactic-Guided Chain of Thought

Input: Sentence *S*,Aspect categories A = {rzj, *a*, •- - , a∗}
Output: Formatted results:Target : target word.
Aspect: aspect name, Sentiment:
sent iment label
Step 1: Syntactic Keyword Extraction
Tokenizc.S' and extract keywords TV ={A: | *k*G *S*,POS(fc) G {NOUN. ADJ}}
Step 2: Iterative Aspect Categorization
for each keywordG A do
Determine aspect *a*.G *A*that best matches *k*based on semantic similarity
Map keyword *k*.to aspect *a*
end for
Step 3: Chain of Thought for 'large! and Sentiment Identification
for each aspect a with associated keywords do
IO Identify explicit targets T∗ within *S*related to a
if no explicit targets found then
Infer implicit targets using contextual analysis
end if
Determine sentiment polarity associated with *ci*and its targets
end for
Step 4: Result Formatting
Format the results as: Target : target word.
Aspect: aspect name. Sentiment:
sent imentlabel
Step 5: Return Results
Return the formatted results

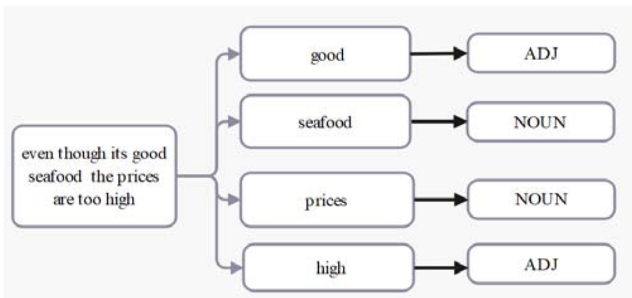
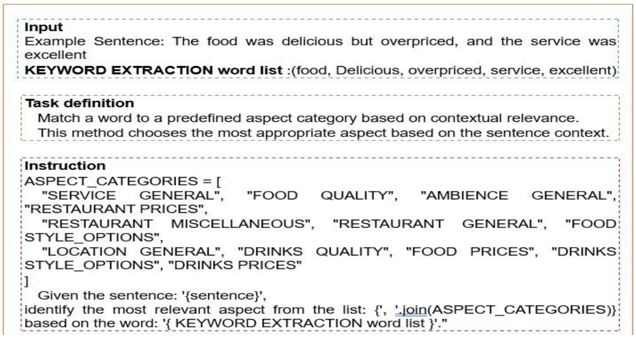


FIGURE 3. Extracted keywords list.

Figure 5 illustrates the final output achieved through the integration of syntactic features with the semantic capabilities of LLM. This integration ensures the preservation of both the meaning of the opinion and the sentence structure. The extracted results are constructed as a dictionary, where each key represents an aspect category and the corresponding value is a list of opinionated keywords associated with that category. For Example, given the sentence "even though its good seafood the prices are too high," the algorithm identifies opinion-related words (e.g., "good," "seafood") and maps



Input
Example Sentence: The food was delicious but overpriced, and the service was excellent
KEYWORD EXTRACTION word list :(food, Delicious, overpriced, service, excellent)

Task definition
Match a word to a predefined aspect category based on contextual relevance.
This method chooses the most appropriate aspect based on the sentence context.

Instruction
ASPECT_CATEGORIES = [
"SERVICE GENERAL", "FOOD QUALITY", "AMBIENCE GENERAL", "RESTAURANT PRICES",
"RESTAURANT MISCELLANEOUS", "RESTAURANT GENERAL", "FOOD STYLE_OPTIONS",
"LOCATION GENERAL", "DRINKS QUALITY", "FOOD PRICES", "DRINKS STYLE_OPTIONS", "DRINKS PRICES"
]
Given the sentence: '{sentence}',
identify the most relevant aspect from the list: {', '.join(ASPECT_CATEGORIES)}
based on the word: '{ KEYWORD EXTRACTION word list }'."

FIGURE 4. **Iterative aspect categorization prompt.**

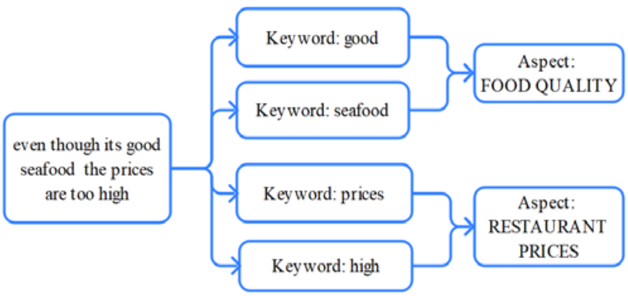


FIGURE 5. **Iterative aspect categorization prompt output.**

them to their most relevant aspect categories (e.g., ''food quality''). Similarly, other keywords such as ''prices'' and ''high'' are associated with the aspect category ''restaurant prices.'' The final output is a structured representation, such as

('food quality': ['good,' 'seafood'], 'restaurant prices': ['prices, ' 'high'])

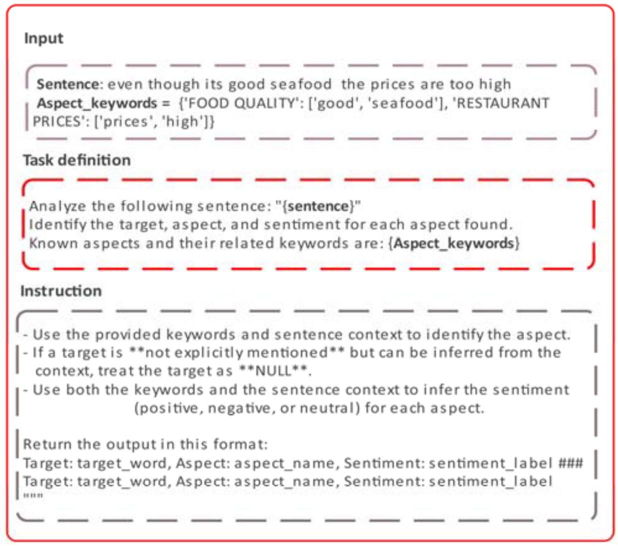
D. CHAIN OF THOUGHT FOR TARGET AND SENTIMENT IDENTIFICATION

This stage employs a structured Chain of Thought (COT) methodology to systematically identify targets, associate them with relevant aspects, and evaluate their sentiments within a given sentence. The prompt is designed as an organized framework to facilitate target identification, aspect mapping, and sentiment classification.

This section elucidates the construction and implementation of the prompt to ensure comprehensive and accurate analysis of the input sentence. Figure 6 illustrates the structure of the prompt. The prompt is dynamically generated based on the input sentence and predefined aspect keywords. The aspect_keywords dictionary delineates the recognized aspects and their associated keywords, ensuring a focused analysis. The construction of the prompt is illustrated in Figure 6.

E. INPUT SENTENCE AND ASPECT KEYWORDS

The first step involves initializing the input sentence (S) and aspect keyword dictionary (A). The input sentence is



Input
Sentence: even though its good seafood the prices are too high
Aspect_keywords = {'FOOD QUALITY': ['good', 'seafood'], 'RESTAURANT PRICES': ['prices', 'high']}

Task definition
Analyze the following sentence: "**{sentence}**"
Identify the target, aspect, and sentiment for each aspect found.
Known aspects and their related keywords are: **{Aspect_keywords}**

Instruction
- Use the provided keywords and sentence context to identify the aspect.
- If a target is **not explicitly mentioned** but can be inferred from the context, treat the target as **NULL**.
- Use both the keywords and the sentence context to infer the sentiment (positive, negative, or neutral) for each aspect.

Return the output in this format:
Target: target_word, Aspect: aspect_name, Sentiment: sentiment_label ###
Target: target_word, Aspect: aspect_name, Sentiment: sentiment_label
"""

FIGURE 6. **Cot prompt construction.**

represented as a string of texts containing n words.

$$S = (w_1, w_2, w_3, \ldots, w_n) \tag{1}$$

Aspect keywords are represented in a dictionary that maps each aspect (A) to a set of associated keywords (K_i):

$$A = \left\{a_1 : K_{1,} a_2 : K_{2,} \ldots, a_m : K_{m,}\right\} \tag{2}$$

where $K_i = (k_{i1}, k_{i2}, \ldots, k_{il})$ is the set of keywords for aspect a_i, that forms the foundation for constructing a dynamic and targeted prompt that enables systematic analysis.

The aspect keyword variable formats aspect keywords into a human-readable structure embedded in the prompt. Example of the resulting description.

- Aspect: FOOD QUALITY, Keywords: seafood, food
- Aspect: RESTAURANT PRICES, Keywords: price, high

F. TARGET IDENTIFICATION

After the aspect keywords are extracted, the model determines the target-aspect pairs, distinguishing between explicit and implicit targets.

G. EXPLICIT TARGET DETECTION

Explicit target detection is based on matching extracted keywords with a predefined list of aspect keywords (K). When a noun keyword from the extracted aspect keywords exists in K, it is classified as a target and its associated aspect category is assigned accordingly. The model analyzes sentences for explicit correspondence between the constituent words and keywords in the dataset. A valid correspondence establishes a target-aspect pair following the rule:

$$\text{If } w \in S \text{ and } w \in K_i, \text{ then Target} = w \text{ and Aspect} = a_i$$

For example, consider the sentence, "*Fresh ingredients and super tasty.*". The noun keyword with its modifiers, "*ingredients*," appears in both S and K, linking it to the FOOD QUALITY aspect. The dependency parser plays a crucial role by identifying "*ingredients*" as the head noun and recognizing its associated modifier "*fresh*," which enhances aspect categorization. Thus, the prompt correctly identifies "*ingredients*" as an explicit target, ensuring precise target-aspect mapping.

H. IMPLICIT TARGET DETECTION

Implicit target detection is crucial for identifying aspect-related sentiments when an explicit target noun is absent in a sentence. Unlike explicit target detection, which relies on direct keyword matches, implicit target detection infers a target using contextual reasoning and dependency parsing. This process allows the model to associate an aspect with a NULL target when no specific noun is mentioned; however, sentence structure implies an aspect. For example, consider the sentence "*Fresh ingredients and super tasty.*". The dependency parser plays a crucial role in identifying that "*super tasty*" lacks a direct target noun, requiring the model to infer the implicit target through contextual reasoning. The parser links "*tasty*" as an adjective modifier (*amod*), indicating a positive sentiment toward food without specifying a direct reference. In contrast, "*ingredients*" is identified as the head noun, with "fresh" as its modifier, reinforcing its classification under FOOD QUALITY. Thus, the prompt correctly identifies "ingredients" as an explicit target, while assigning NULL as the target for "*super tasty*", ensuring precise target-aspect mapping. Output after Target Identification

Target: ingredients, Aspect: FOOD QUALITY ###
Target: NULL, Aspect: FOOD QUALITY

I. TARGET-ASPECT PAIRS AND SENTIMENT CLASSIFECATION

This step involves finalizing the relationships between the identified targets and their corresponding aspects from the sentence, followed by sentiment classification for each target-aspect pair. This process was structured to ensure that both explicit and implicit relationships were captured accurately. Guiding Prompt for Target-Aspect Pairs and Corresponding Sentiment: The model is as follows.

"Use both the keywords and the sentence context to infer the sentiment (positive, negative, or neutral) for each aspect."

J. RESULT CONSOLIDATION

The results from all opinions are aggregated to produce the final output, R, which contains mappings of the form (t,a,s), where t is the target (explicit or implicit), a is the aspect, and s is the sentiment (Positive, Negative, or Neutral). The final output is as follows:

Target: t_1, Aspect: a_1, Sentiment: s_1 ###
Target: t_2, Aspect: a_2, Sentiment: s_2

K. MODULAR PROMPT DESIGN AND ITERATIVE REFINEMENT FOR IMPLICIT TARGET DETECTION

The Iterative Syntactic-Guided Chain of Thought (IS-COT) framework employs modular prompts to iteratively refine the target-aspect mapping, thereby ensuring accurate explicit and implicit target detection. Unlike single-pass methods, the IS-COT dynamically adjusts prompts based on sentence complexity, syntactic dependencies, and contextual cues.

A key advantage of this approach is the integration of LLM reasoning, which enhances context-aware inference, ambiguity resolution, and aspect-assignment refinement.

Modular prompts function in three stages: keyword extraction, aspect categorization, and target identification. Explicit targets are identified through direct keyword matching, whereas implicit targets require contextual inference and reasoning from the LLMs. When an implicit target is unclear, the IS-COT leverages LLMs' semantic understanding of LLMs to reassess dependencies, examine co-occurrence patterns, and refine aspect assignments through multiple iterations. Different implicit target types require adaptive refinement through LLM reasoning.

- Adjective-Based Implicit Targets: In "*The food was incredibly fresh and tasty.*" Keyword Extraction identifies "food" (noun) and adjectives "fresh" and "tasty." Aspect Categorization assigns "*fresh*" to FOOD QUALITY since it explicitly modifies "*food*," but "*tasty*" lacks a direct noun. Since no noun is linked to "*tasty*," The iterative aspect categorization step, guided by LLM semantic reasoning, refines the assignment by recognizing adjective-noun dependencies and linking "*tasty*" to FOOD QUALITY. However, since "*tasty*" does not have an explicit noun, Target Identification assigns NULL to mark an implicit target, and iterative aspect categorization step confirms the aspect linkage while preserving NULL for the target
- Contextually Implied Targets: In "*Too expensive!",* Keyword Extraction identifies "*expensive*" as a sentiment-bearing adjective. Aspect Categorization iteratively evaluates sentence-wide meaning and leverages LLMs' ability to infer the missing opinion target to correctly assign the RESTAURANT PRICES. However, because no explicit noun is present, target inference becomes difficult. Target Identification assigns NULL to mark an implicit target, and Iterative Aspect Categorization confirms the aspect linkage while preserving the NULL for the target.
- Multi-Opinion Sentences: In "*Fresh ingredients and super tasty.*" Keyword Extraction identifies "ingredients" (noun) and adjectives "*fresh*" and "*tasty*." tasty'. Aspect Categorization assigns "*fresh*" to FOOD QUALITY since it explicitly modifies "ingredients," while "*tasty*" tasty lacks a direct noun link. Since "*fresh*" has an explicit target, Target Identification correctly assigns the first opinion as:

Target: ingredients, Aspect: FOOD QUALITY

However, as "*tasty*" has no explicit noun, Target Identification assigns NULL to indicate an implicit target for the second opinion:

Target: NULL, Aspect: FOOD QUALITY

Thus, Target Identification correctly maps both explicit and implicit targets, whereas Iterative Aspect Categorization refines the aspect category using LLM reasoning.

- Ambiguous Expressions: In "*The waiter was friendly, and the drinks were amazing!*", the initial prompt may misassign "*amazing*' to the SERVICE GENERAL. LLM reasoning analyzes semantic context and dependency structures, ensuring "*amazing*" is linked to DRINKS QUALITY.
- Target–aspect Pairs and Sentiment Classification: The final step establishes target-aspect relationships and assigns sentiment polarity, ensuring the correct categorization of both explicit and implicit targets before sentiment classification. The model determines sentiments using a guiding prompt

"*Use both the keywords and the sentence context to infer the sentiment (positive, negative, or neutral) for each aspect.*"

Since "*fresh*" and "*tasty*" and relevant context indicate positive sentiment, the final sentiment mapping is:

Target: ingredients, Aspect: FOOD QUALITY, Sentiment: Positive

Target: NULL, Aspect: FOOD QUALITY, Sentiment: Positive

By leveraging LLMs' capacity for complex reasoning, IS-COT enhances target inference beyond syntactic dependencies, allowing for a deeper contextual understanding, robust implicit target detection, and more precise aspect categorization. This iterative refinement approach significantly improves the sentiment classification accuracy, making IS-COT a scalable and adaptive solution for ABSA.

L. SYNTACTIC AND SEMANTIC INTERPLAY IN IS-COT

The modular design of IS-COT enhances both syntactic parsing and semantic inference through an iterative refinement process. This approach ensures accurate target-aspect mapping, particularly in cases involving implicit targets, sentiment ambiguity, and multi-opinion structures. However, the interaction between syntactic and semantic inferences within this iterative process is crucial for understanding IS-COT's comprehensive functionality of the IS-COT. The IS-COT first extracts syntactic dependencies from the input text to establish relationships between targets, aspects, and sentiment-bearing expressions. This ensures that explicitly stated sentiment targets, such as "food" in "The food was tasty," are correctly assigned.

However, syntactic analysis alone is insufficient for dealing with implicit or complex sentence structures. Unlike traditional models that rely solely on syntactic structures, IS-COT integrates semantic inference using LLM-driven reasoning to refine the aspect categorization and sentiment segmentation. This is particularly important in cases in which the model must infer missing sentiment targets based on contextual clues, such as in the sentence "Too expensive!" where IS-COT correctly assigns the aspect RESTAURANT PRICES despite the absence of an explicit noun. Similarly, ambiguous expressions like "The drinks were amazing!" may lead to syntactic misclassification, assigning "amazing" to SERVICE GENERAL instead of DRINKS QUALITY, but semantic inference ensures that the correct aspect is identified.

TABLE 1. **Is-cot handling of multi-opinion sentences.**

Sentence	Gold Label (T, A, S)	Predicted Label (T, A, S)	Type
Terrible service, food ok, pricey.	(food, FOOD QUALITY, neutral)	(food, FOOD QUALITY, neutral)	Explicit
	(service, SERVICE GENERAL, negative)	(service, SERVICE GENERAL, negative)	Explicit
	(NULL, RESTAURANT PRICES, negative)	(NULL, RESTAURANT PRICES, negative)	Implicit
Excellent food, nice ambience, fairly expensive.	(ambience, AMBIENCE GENERAL, positive)	(ambience, AMBIENCE GENERAL, positive)	Explicit
	(food, FOOD QUALITY, positive)	(food, FOOD QUALITY, positive)	Explicit
	(NULL, RESTAURANT PRICES, negative)	(NULL, RESTAURANT PRICES, negative)	Implicit

In addition, the IS-COT ensures accurate sentiment classification in multi-opinion sentences by utilizing extracted keywords through a dependency parser and leveraging the sentence context to infer sentiments related to specific opinions. This approach enables the model to correctly associate sentiments with their target aspects, while maintaining structural coherence. For instance, in the following examples, IS-COT effectively separates opinions within a sentence and accurately classifies the sentiment for each target-aspect pair.

As shown in Table 1, the IS-COT effectively associates the correct sentiment with its respective aspects by ensuring that sentiment expressions remain confined within their respective clauses. For example, in "Terrible service, food ok, pricey," IS-COT correctly classifies SERVICE GENERAL as negative and FOOD QUALITY as neutral, and implicitly recognizes that RESTAURANT PRICES carries a negative sentiment. This demonstrates the ability of IS-COT to distinguish sentiment-bearing elements within a sentence without sentiment misattribution.

Similarly, in "Excellent food, nice ambience, fairly expensive," IS-COT accurately maps AMBIENCE GENERAL and FOOD QUALITY to positive sentiment while identifying RESTAURANT PRICES as negative, reinforcing its ability to manage implicit sentiment relationships effectively. To ensure accuracy, IS-COT iteratively refines its predictions by dynamically adjusting the aspect mappings based on both syntactic and semantic structures. Through modular prompting, IS-COT systematically reassesses dependency relations, examines co-occurrence patterns, and refines aspect assignments, ensuring that aspect categorization and sentiment classification remain both structurally and contextually aligned.

This iterative process strengthens the IS-COT's ability to resolve ambiguities in multi-opinion sentences by reinforcing clear sentiment-aspect pairings, reducing misclassification, and improving sentiment consistency in complex sentence structures. The interplay between syntactic parsing and semantic inference within the IS-COT's modular framework enables contextually grounded target detection, accurate sentiment classification, and improved aspect assignment. This hybrid approach mitigates errors caused by syntactic overreliance and semantic ambiguity, making IS-COT a scalable and adaptive solution for complex sentiment analysis tasks.

V. EXPERIMENTS

For all the experimental evaluations, the fine-tuned ft:gpt-3.5-turbo variant of the GPT-3.5 model [51] was employed to implement and validate the proposed methodology. The F1 score was chosen as the primary evaluation metric in these experiments because of its widespread adoption and effectiveness in measuring both the precision and recall performance. This metric is extensively used to evaluate ABSA tasks and offers a balanced assessment of the precision and recall. Thus, the F1 score is particularly well-suited for the evaluation of ABSA models.

A. DATASETS

This study used two restaurant review datasets for evaluation: Sem-Eval 2016 Task 5 (Res16) [52] and Sem-Eval 2015 Task 12 (Res15) [53]. These datasets comprised original review sentences, annotated opinion targets (explicit and implicit), aspect categories, and sentiment polarity (Positive, Negative, or Neutral). Key statistics revealed that the Res15 test dataset contained approximately 27.4% implicit targets, whereas the Res16 test dataset contained approximately 22.4% implicit targets that featured explicit targets.

A high percentage of implicit targets indicates that this poses a significant challenge for sentiment analysis systems that potentially require sophisticated techniques to identify and analyze the sentiments associated with these implicit targets. Furthermore, 38.1% of the sentences in the Res15 test dataset and 35.3% in the Res16 test dataset contained multiple opinions, demonstrating the complexity of sentence structures.

The datasets encompass diverse sentence structures that capture explicit opinions with clearly identified targets and implicit opinions where the targets must be inferred from the context. Table 2 provides detailed statistics on the number of reviews, annotated opinion targets, and aspect categories for both the datasets. These datasets are widely recognized as benchmarks for various subtasks within the ABSA and provide a robust foundation for evaluating explicit and implicit target identification.

TABLE 2. Statistics of RES15 and RES16 dataset splits, including targets and sentiment distribution.

Dataset		Total Sentences	Opinion Type		Sentiments		
			Implicit Targets	Explicit Targets	Neg	Neu	Pos
Res15	Train	1041	332	1369	396	48	1257
	Test	535	218	577	305	37	453
Res16	Train	2117	729	2566	877	125	2293
	Test	544	179	620	176	40	583

B. STATE-OF-THE-ART METHODOLOGIES FOR COMPARISON

The ABSA has witnessed significant advancements in recent years, with researchers developing sophisticated methodologies to improve the accuracy and granularity of sentiment detection. These state-of-the-art approaches frequently employ advanced natural language processing techniques and deep learning models, such as Bidirectional Encoder Representations from Transformers (BERT), to effectively capture the complex interplay between targets, aspects, and sentiments within textual data.

The integration of these advanced models has enabled a more nuanced and context-aware sentiment analysis, thereby addressing the challenges posed by the inherent complexities of human language and sentiment expressions. Several state-of-the-art techniques have addressed the challenges of implicit and multi-opinion target identification, specifically in TASD tasks. TAS-BERT [54] models target-aspect relationships to improve TASD accuracy of TASD. MEJD [55] combines BERT, Bi-LSTM, and GACN with POS-tagged information. GAS [56] treats TASD as text generation that uses sequence-to-sequence learning.

PARAPHRASE [57] predicts sentiment quads through end-to-end paraphrase modelling. LEGO-ABSA [58] employs a multitask framework with prompt-based approaches. Seq2Path [59] reformulated the TASD for path generation. MVP [60] uses multi-view prompts for aspect-sentiment tuple prediction. SimCPD [61] used contrastive prompts for target aspect-sentiment detection. ATCAD [26] incorporates syntactic information and dependency relations for context-aware aspect term detection. These approaches have significantly advanced the field of target-aspect sentiment detection by offering diverse strategies to address complex linguistic challenges.

To evaluate these models, we employed a widely used metric: the Macro-Averaged F1 Score (F1). The Macro-Averaged F1 Score balances precision and recall across all categories, and is calculated as the average of the F1 scores for each category:

$$F1 = \frac{1}{N} \sum_{i=1}^{N} \frac{2 \cdot Precision_i \cdot Recall_i}{Precision_i + Recall_i} \tag{3}$$

where N is the number of categories, $Precision_i$ is the precision for category i_1, and $Recall_i$ is the recall for category i. Precision and recall are based on the number of correctly predicted target aspect–sentiment tuples, ensuring a comprehensive evaluation of the model's performance.

VI. RESULTS

This study evaluates the Iterative Syntactic-Guided Chain of Thought (IS-COT) framework, designed to address key challenges in Aspect-Based Sentiment Analysis (ABSA), particularly in identifying both implicit and explicit targets. By integrating syntactic parsing, iterative reasoning, modular prompts, and dynamic chain-of-thought (COT) reasoning, IS-COT enhances the detection of opinion targets in complex multi-opinion sentences.

To assess its performance, experiments were conducted on the Res15 and Res16 benchmark datasets with the F1 score as the primary evaluation metric. Table 3 presents the comparative performance of IS-COT against the baseline models, demonstrating that IS-COT consistently achieved the highest scores. These results confirm its robustness in Target-Aspect Sentiment Detection (TASD) tasks, particularly in cases involving implicit sentiment expressions.

TABLE 3. Comparative performance of IS-COT and baseline models on Res15 and Res16 datasets for TASD task, measured using F1 scores.

Authors	Methods	Res15	Res16
Wan, et al. [54]	TAS-BERT	57.51	65.89
Wu, et al. [55]	MEJD	57.76	67.66
Zhang, et al. [56]	GAS	60.63	68.31
Zhang, et al. [57]	PARAPHRASE	63.06	71.97
Gao, et al. [58]	LEGO-ABSA	62.3	71.8
Mao, et al. [59]	Seq2Path	65.2	72.1
Gou, et al. [60]	MVP	64.74	72.76
Ke, et al. [61]	SimCPD	59.31	68.95
Radi, et al. [26]	ATCAD	71.17	76.04
Current Study	IS-COT	**80.43**	**84.47**

The IS-COT achieved an F1 score of 80.43 Res15 and 84.47 Res16, outperforming all baseline models. Compared with the second-best performing model, ATCAD and IS-COT exhibited an improvement of 13% on Res15 and 11.09% on Res16. These significant improvements highlight the ability of the framework to effectively leverage iterative refinement, syntactic parsing, and modular prompts, resulting in superior performance in both implicit and explicit target-detection tasks. The consistently high scores across datasets validate IS-COT's adaptability of IS-COT to diverse sentence structures and multi-opinion contexts. In addition to quantitative improvements, IS-COT outperforms existing models owing to several key points. First, iterative refinement enables IS-COT to dynamically reassess implicit target assignments, unlike static single-pass models that struggle with ambiguous sentiment expressions. Second, IS-COT's syntactic parsing mechanisms of IS-COT allow it to accurately disambiguate multi-opinion sentences, ensuring that each sentiment-bearing word is mapped to the correct target.

Example 1
Sentence: And they packaged everything nicely so it didn't spill.
Gold Label: (NULL, SERVICE GENERAL, positive)
Prediction : (NULL, FOOD QUALITY, positive)

Example 2
Sentence: drinks are suberb and i feel like i am in a third world country when i walk in the door
Gold Label: (NULL, AMBIENCE GENERAL, positive),
(drinks, DRINKS QUALITY, positive)
Prediction : (NULL, AMBIENCE GENERAL, positive),
(drinks, DRINKS QUALITY, negative)

Example 3
Sentence: while I could have done without the youth who shared the evening with us, our wonderful server and food made the experience a very positive one.
Gold Label: (NULL, RESTAURANT MISCELLANEOUS, positive)
Prediction : (food, FOOD QUALITY, positive)

FIGURE 7. Error Examples in IS-COT Predictions. Incorrect predictions in red highlight errors for TASD task.

Third, modular prompting enhances the ability of the IS-COT to guide LLMs through structured reasoning steps, thereby reducing misclassification errors. Fourth, the integration of COT reasoning allows IS-COT to dynamically adapt aspect assignments based on contextual and syntactic cues, thereby improving its performance in implicit sentiment classification. Finally, comprehensive target-aspect pairs and sentiment mapping ensure that both explicit and implicit opinions undergo accurate sentiment classification, thereby increasing the overall prediction consistency. The consistent performance gains across Res15 and Res16 confirm IS-COT's robustness and scalability of the IS-COT in handling complex multi-opinion scenarios. These results justify IS-COT's advancement over existing state-of-the-art methods and establish it as a comprehensive high-precision solution for nuanced ABSA tasks.

A. ERROR ANALYSIS

To gain deeper insights into IS-COT's prediction behavior of IS-COT, we conduct an error analysis by categorizing misclassified predictions into four key groups: Target Detection, Aspect Category Detection, Sentiment Detection, and Multi-Opinion Detection. The errors analyzed below reflect the key limitations of the IS-COT in handling implicit targets, aspect overlaps, sentiment boundary detection, and multi-opinion segmentation. A sentence may exhibit multiple error types simultaneously. Figure 7 shows the selected misclassified cases with the corresponding gold labels and model predictions.

Figure 7 highlights the key challenges in IS-COT prediction, particularly in aspect category, multi-opinion, and target detection. In Example 1, the aspect category was incorrectly classified under FOOD QUALITY, instead of SERVICE GENERAL. This misclassification suggests that the IS-COT relies heavily on adjective-based aspect alignment rather than dynamic dependency relations, leading to errors when an action (e.g., "packaged") lacks an explicit adjective modifier but conveys an aspect-relevant meaning.

Since "packaging" is a service-related action rather than an indicator of food quality, IS-COT fails to dynamically associate verbs with their correct aspect categories. This highlights a fundamental limitation of the dependency-parsing approach, in which aspect categorization is biased toward adjective-based cues, even when the verb itself encodes a service-related function. To address this, integrating semantic role Labelling (SRL) or dependency-based refinement is necessary to improve aspect classification, particularly in cases where verbs, rather than adjectives, determine the aspect assignments.

IS-COT misclassifies DRINKS QUALITY as negative in Example 2 because of its failure to properly separate sentiment structures across conjunctions ("and") and clauses. The LLM's contextual understanding is limited by its lack of explicit syntactic segmentation, causing it to incorrectly propagate negativity from "third-world country" to "drinks" drinks', despite being in separate clauses. This issue arises because IS-COT relies on contextual associations rather than explicitly modelling clause boundaries to isolate sentiment expressions. Without clause-aware sentiment segmentation, the model fails to prevent sentiment spillover across conjunctions, leading to misclassifications. To address this, contrastive learning and enhanced syntactic parsing are required to ensure that sentiments remain structurally confined within their respective clauses, thereby preventing unintended sentiment influences across targets.

Another recurring issue is target detection, particularly in Example 3, where IS-COT incorrectly identified "food" as the sentiment target instead of the overall experience in the sentence: "While I could have done without the youth who shared the evening with us, our wonderful server and food made the experience a very positive one." Here, the IS-COT defaulted to the nearest explicit noun ("food") instead of recognizing the implicit sentiment target ("experience"). This suggests a limitation in the IS-COT's implicit target inference capabilities, which can be improved by integrating co-reference resolution techniques to capture unstated sentiment-bearing entities better.

Overall, although the IS-COT demonstrates strong structured reasoning capabilities, it requires further improvement in hierarchical aspect categorization, implicit target detection, sentiment segmentation, and multi-opinion processing. Future enhancements should focus on refining syntactic parsing to better handle structural dependencies, improving contextual sentiment inference to mitigate sentiment spillover, and integrating contrastive learning techniques to enhance opinion separation and aspect alignment.

B. EFFECTIVENESS ANALYSIS OF SYNTACTIC-GUIDED CHAIN OF THOUGHT FOR ITERATIVE IMPLICIT AND EXPLICIT TARGET

This study evaluated the effectiveness of the IS-COT compared to the COT prompt, focusing on TASD tasks. The performance of the prompts was measured using F1 scores on benchmark datasets Res15 and Res16. The objective of evaluating the effectiveness of the IS-COT framework was to assess its impact on opinion identification, particularly implicit elements. Table 4 shows the results for the comparative performance effectiveness, where IS-COT demonstrates superior performance in opinion detection tasks, excelling in extracting opinion triples and identifying targets.

TABLE 4. . Statistics of Res15 and Res16 dataset splits, including targets and sentiment distribution.

Dataset	Methods	Opinion			
		Opinion triple	Target	Aspect	Sentiment
Res15	COT	78.45	74.74	71.45	89.18
	IS-COT	**80.43**	82.97	71.03	87.80
Res16	COT	82.41	77.57	77.61	92.03
	IS-COT	**84.47**	84.64	77.22	91.58

For opinion triples, the IS-COT outperformed the COT by 2.53% for Res15 and 2.06% for Res16. For target identification, the IS-COT achieved notable improvements of 10.99% for Res15 and 9.09% for Res16. Although both methods perform similarly in aspect identification, COT demonstrates a slight edge in sentiment classification, achieving 1.38% higher accuracy on Res15 and 0.45% on Res16. The slight difference in COT highlights a fundamental limitation in its design. It evaluates the components of the opinion triple (target, aspect, and sentiment) individually without adequately considering their interrelationships.

By isolating these elements, COT sacrifices its ability to capture contextual dependencies and cohesive structures inherent in natural language. This narrow focus may result in better sentiment classification accuracy in explicit scenarios, but struggles with the complexities of implicit or intertwined opinion expressions. Overall, IS-COT is more effective for comprehensive opinion detection tasks, excelling in capturing complete opinion structures and targets, whereas COT offers a modest advantage in terms of sentiment accuracy.

C. EFFECTIVENESS AND COMPUTATIONAL OF IS-COT

To assess the computational efficiency of IS-COT and COT, we analyzed three key metrics: execution time, which measures the time taken for inference; memory usage, which tracks peak resource consumption during execution; and F1 Score, which evaluates model performance, particularly in target detection. These metrics provide a comprehensive comparison of the trade-offs between efficiency and accuracy in both the models. The results of the benchmark experiments are presented in Table 5.

IS-COT proved to be a highly effective approach for implicit target detection and multi-opinion sentence analysis, significantly improving the target F1 score from 77.57% to 84.64% compared with COT. This improvement is critical in

TABLE 5. Effectiveness and computational of IS-COT.

Dataset	Methods	Opinion			
		Opinion triple	Target	Execution Time (s)	Memory Usage
Res15	COT	78.45	74.74	0.686949	0.00131
	IS-COT	80.43	**82.97**	3.374071	0.00321
Res16	COT	82.41	77.57	0.9663	0.000708
	IS-COT	84.47	**84.64**	3.2220	0.003407

ABSA, where many targets are not explicitly mentioned, but must be inferred from the context. By leveraging dependency parsing and syntactic analysis,

The IS-COT ensures greater precision in identifying target-aspect-sentiment relationships, making it more reliable for real-world applications. The higher computational cost of IS-COT is justified by its ability to accurately separate multiple opinions within a sentence, thereby preventing errors where an opinion is misattributed to the wrong target. Unlike COT, which relies on direct sentiment-target mapping, IS-COT performs context-aware reasoning, requiring additional inference steps. This added complexity results in a more accurate sentiment classification, particularly in cases where targets are implied rather than explicitly stated. Another key advantage of the IS-COT is its improved interpretability. The structured dependency-based approach ensures that sentiment classification is linguistically grounded, making it easier to explain and justify model predictions.

In applications, such as business intelligence, customer feedback analysis, and market research, explainability is as important as accuracy. Although IS-COT demands a slightly higher execution time and memory usage, this trade-off is necessary to achieve state-of-the-art precision in sentiment analysis. Despite the increased computational burden, IS-COT remains a strong choice for high-accuracy sentiment applications, where the precision outweighs the raw speed. Future optimizations, such as pruning dependency paths, refining prompts, and implementing caching, can help reduce the processing time while preserving accuracy. By balancing computational efficiency with sentiment classification accuracy, IS-COT represents a necessary advancement in ABSA, ensuring scalability and reliability in real-world sentiment analysis tasks.

VII. DISCUSSION

The Iterative Syntactic-Guided Chain of Thought (IS-COT) framework significantly advances ABSA by addressing challenges in detecting opinion targets and analyzing multi-opinion sentences. By combining syntactic parsing with iterative reasoning, the IS-COT bridges the gap between syntactic analysis and semantic inference, allowing it to capture subtle and indirect sentiment expressions. This capability marks a notable improvement over traditional COT frameworks, which often struggle with implicit targets owing to their reliance on explicit syntactic dependencies.

The IS-COT modular design effectively handles sentences with multiple opinions, and iteratively refines the target and sentiment mappings for better accuracy and contextual relevance. Evaluations on benchmark datasets, such as Sem15 and Sem16, demonstrated their superiority over state-of-the-art methods, achieving higher F1 scores, particularly for target detection. While sentiment classification accuracy shows a slight decline compared to COT, this trade-off is offset by IS-COT's improvements in target detection and handling of multi-opinion ambiguities.

Despite its strengths, the IS-COT has limitations, including reliance on English syntactic norms, which may hinder multilingual applications and increase computational complexity owing to iterative reasoning. Future research could explore multilingual adaptations, optimization of scalability, and application of IS-COT to other tasks that require nuanced semantic inference. Overall, the IS-COT offers a robust and adaptable framework for ABSA, providing a solid foundation for further advancements in the field.

VIII. CONCLUSION

The IS-COT framework represents a significant advancement in the field of ABSA, addressing long-standing challenges in implicit target detection and multi-opinion sentence analysis. By integrating syntactic parsing with an iterative Chain of Thought reasoning, IS-COT enhances the interpretability and performance of ABSA tasks, as evidenced by its superior results on benchmark datasets.

The ability of this framework to accurately detect implicit targets and resolve ambiguities in complex sentence structures demonstrates its potential as a comprehensive solution to opinion mining. Although there are minor limitations such as sentiment classification accuracy and scalability, IS-COT sets a solid foundation for future innovations in the ABSA and related NLP domains. In conclusion, IS-COT not only advances the state-of-the-art in ABSA, but also exemplifies the potential of combining syntactic and semantic reasoning in iterative frameworks. Their modular design and effectiveness highlight their adaptability and applicability to a wide range of NLP challenges, thus paving the way for further research and development.

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